A STUDY OF BRAIN NETWORKS ASSOCIATED WITH SWALLOWING VIA ELECTROENCEPHALOGRAPHY SIGNALS

by

Iva Jestrovic

B.S. in Electrical Engineering, University of Belgrade, 2011M.S. in Electrical and Computer Engineering, University of Pittsburgh, 2013

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This dissertation was presented

by

Iva Jestrovic

It was defended on

March 22, 2016

and approved by

Ervin Sejdic, PhD, Assistant Professor, Department of Electrical and Computer

Engineering

Zhi-Hong Mao, PhD, Associate Professor, Department of Electrical and Computer

Engineering

Amro El-Jaroudi, PhD, Associate Professor, Department of Electrical and Computer

Engineering

Thomas E. McDermott, PhD, Assistant Professor, Department of Electrical and Computer Engineering

James Coyle, PhD, Associate Professor, Department of Communication Science and

Disorders

Dissertation Director: Ervin Sejdic, PhD, Assistant Professor, Department of Electrical and Computer Engineering

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Swallowing and swallowing disorders have garnered continued interest over the past several decades. While physiological origins of the swallowing activity are well understood, it remains uncertain how this activity affects the central nervous system and brain activity. Electroencephalography (EEG) systems can enable our study of cerebral activation patterns during the performance of swallowing tasks, and can also possibly allow us to make inferences about the nature of abnormal neurological conditions causing swallowing difficulties. EEG also lends itself to techniques for analysis which provide insight into the interactions between brain regions, and enables the measuring and analysis of functional interactions between different brain regions by way of the graph theoretical and signal processing on graph approach. In this dissertation we provided better insight into the neurology of swallowing by focusing our research towards the three main areas of investigation. First, we showed that the EEG signals during the swallowing can be considered as non stationary. These findings provided an answer about choosing an appropriate technique for forming connectivity brain networks. Second, using graph theory and signal processing on graphs we showed that there are differences between swallowing in the neutral and chin-tuck head positions, between swallowing of different stimuli, between normal swallowing and swallowing with a distraction, and between consecutive swallows. Lastly, we improved an algorithm used to calculate the vertex-frequency information from the signals on graph that we used in our investigation. Particularly, we overcame the limitations of the computational complexity and the fixed window size associated with the windowed graph Fourier transform.

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1.0 INTRODUCTION

1.1 MOTIVATION

1.1.1 Dysphagia - definition and occurrence

Dysphagia (swallowing difficulties) refers to any swallowing disorder [1], typically occurring in patients who suffer from a variety of neurological conditions (stroke [2], cerebral palsy [3], Parkinson's disease and other neurodegenerative diseases [4]), head and neck cancer and its treatment [5], and iatrogenic conditions or trauma [6]. Dysphagia can also occur due to genetic predispositions or congenital craniofacial syndromes [7]. The signs and symptoms of dysphagia include subjective difficulty in swallowing food or liquids, choking or coughing before, during, or after swallowing due to impaired clearance of swallowed material from the throat into the digestive system, which can cause malnutrition [8], dehydration [9], failure of the immune system [10], psycho-social degradation, [11, 12] and in general, a decreased quality of life [13]. A major consequence of dysphagia is aspiration of food and liquids into the airway past the vocal folds and into the respiratory system which often leads to airway obstruction, pneumonia, and on increased risk of mortality resulting from both [14, 15].

1.1.2 Prevalence and costs of the treatment

According to the American Speech Language Hearing Association (ASHA), there are approximately 15 million people suffering from dysphagia. Dysphagia is especially prevalent among the elderly. For instance, studies suggest that up to 75% of nursing home residents experience some degree of dysphagia, and that almost the half of all Americans over 60 will experience dysphagia at some point after this age [16]. 50% to 75% of stroke patients and

60% to 70% of patients who undergo radiation therapy for head and neck cancer have dysphagia [17,18]. Also, dysphagia is prevalent in 20% to 40% of the patients with Parkinson's disease, and over 30% of individuals with multiple sclerosis experience swallowing problems [4,19]. In addition, over 60,000 people yearly die from complications associated with swallowing dysfunctions [20].

Complications that are caused by dysphagia increase the costs of healthcare. Emergency room visits, extended hospital stays, the need for long-term institutional care, and the need for expensive respiratory or nutritional support are common extra expenses that follow dysphagia [21]. The cost of managing a patient with a feeding tube is reported to average over \$31,000 per patient per year [22]. The total annual cost for enteral feeding supplies was more than \$670 million, in a year period [23]. Overall, together with the costs incurred by hospitals, costs of dysphagia in the healthcare care system exceed billion dollars per year, and are increasing rapidly. According to a recent study, the prevalence of feeding tube usage is also rising steadily [24].

1.2 ANATOMY AND PHYSIOLOGY

1.2.1 Normal deglutation and stages of deglutition

In humans, swallowing is an essential motor activity by which food, liquids, and saliva pass from the oral cavity to the stomach. It is considered one of the most complex adrodigestive sensorimotor activities due to the high level of coordinated efforts needed to accomplish the swallowing task over a very short period of one to two seconds, and the multiple central and peripheral subsystems it involves. The system that plans, coordinates and executes the oropharyngeal swallowing sequence actively targets muscle groups in the head and neck and upper thorax via activation of a broad range of regions in the brain and brainstem [25, 26].

In an effort to discretely describe the numerous sensorimotor events that occur during the relatively short duration of an oropharyngeal swallow, Logemann [1] described four distinct swallowing phases that occur in a somewhat overlapping temporal sequence (Figure 1).



Figure 1: Four swallowing phases: (a) oral preparatory phase; (b) oral transit phase; (c) pharyngeal phase; (d) esophageal phase.

The first swallowing phase, the oral preparatory phase, is entirely voluntary, while the oral transit phase, is initiated voluntarily and completed involuntarily. During the oral preparatory phase, solid food is reduced into a swallowable form by being chewed, mixed with saliva, and formed into a cohesive bolus, while tactile, kinesthetic, proprioceptive, and taste sensory input are delivered to brainstem and cortical centers [27]. Meanwhile, lingual and palatal musculature contain the bolus in the oral cavity in varying manners, preventing inadvertent gravity-dependent flow of material from the oral cavity to the pharynx [28]. Depending on the information collected by sensory receptors about the food or liquid being prepared, these receptors generate signals that stimulate activation of salivatory nuclei in the pons and medulla to produce salivation in the oral cavity, and motor nuclei that produce masticatory motor activity in the head and neck. Furthermore, the signals generated by the sensory receptors elicit limbic-mediated emotions related to the act of feeding while this cumulative sensory afferent information is processed in the pontomedullary swallowing centers in preparation for the subsequent phases of swallowing [29].

During the oral transit phase, intrabolus pressure generated by the tongue propels the bolus posteriorly by compressing the bolus against the palate, while the posterior linguapalatal value is opened to enable transfer of the pressurized bolus into the pharynx [30,31]. In healthy young individuals, the onset of the next phase, the pharyngeal phase, begins before the leading edge (head) of the bolus enters the pharyngeal cavity, while in older individuals pharyngeal motor activity is observed after the bolus head enters the pharynx [27]. The duration between the entrance of the bolus head into the pharynx and the onset of pharyngeal motor activity is referred to as the duration of stage transition [32]. After processing, this information is received by the trigeminal and solitary nuclei and associated reticular formation, and a motor plan is produced by the swallowing central pattern generator, after which the muscles involved in the pharyngeal phase are automatically activated [33].

The third phase, the pharyngeal phase, is nearly entirely a combination of voluntary and involuntary activity that involves numerous biomechanical events, which continuously transfer intrabolus pressure to the inferior pharynx, inhibiting resting closure pressure of the upper esophageal sphincter (UES), displacing the unprotected airway out of the path of the oncoming bolus, covering the inlet to the airway, sealing the superior nasopharynx at the velopharyngeal port, and applying the necessary traction forces on the UES to enable adequate duration and diameter of opening for complete bolus clearance into the digestive system.

The fourth phase, the esophageal phase, is a totally involuntary process mediated by vagal efferents and a somewhat internal esophageal nervous system that produces propulsive sequential superior to inferior motor activity, propelling the bolus toward the lower esophageal sphincter, which then momentarily relaxes and enables clearance into the stomach [34].

1.2.2 Neurological origins of swallowing and dysphagia

Historically, it was believed that only the brainstem centers were responsible for controlling swallowing; however, later studies emphasized the importance of the cerebral cortex during swallowing [35]. Other parts of the brain which later demonstrated activity during swallowing include: the facial areas of the sensorimotor cortices, the premotor cortex, the anterior

cingulate cortex, the insular cortex, the frontal operculum, the cerebellum, etc. [36–41]. It is well known that swallowing is mediated by both cerebral cortical and brainstem activity. However, recent studies have produced evidence emphasizing the importance of the role of cerebral cortex in both the involuntary and voluntary parts of the swallow [38], which demonstrates neuronal activation of different parts of the cerebral cortex, namely the sensory and motor cortices, the cingulate gyrus and the insula [37, 42].

Neurogenic dysphagia is primarily caused by lesions in disparate cortical and subcortical regions [9], and these lesions occur most frequently in people who are suffering from neurological conditions such as stroke [2], brain injuries [43], cerebral palsy [3], Parkinson's and other neurodegenerative diseases [4]. Even though many different specific cortical lesions that produce dysphagia have been identified [44, 45], one previous study showed that the insular cortex is the most common cerebral lesion site in patients with stroke-related dysphagia [46], and conjectured accordingly that the insular cortex may be the most important region of the brain activated during swallowing in general.

1.3 TECHNIQUES FOR STUDYING OF THE NEUROLOGICAL ORIGINS OF SWALLOWING AND DYSPHAGIA

Advanced techniques, such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), magnetoencephalography (MEG), and electroencephalography (EEG) provide significant insight into brain activity during swallowing. Since fMRI and PET provide good spatial representations of brain changes, they are considered to be the gold standards for investigating central neural activation during swallowing.

fMRI provides a safe, noninvasive method for exploring how the human cerebral cortex processes information during a certain task. In particular, fMRI allows a detailed investigation of the functional neuroanatomy of the human brain with a spatial resolution of 2 mm or less [36]. The underlying principles behind fMRI relate to the sensitivity of detecting slight physiological alterations in neuronal activation via a complex function of changes in blood flow, blood volume, and blood oxygenation [47]. The magnetic resonance signal changes depend predominantly on the concentration of blood deoxyhemoglobin, which acts as an intravascular contrast agent. Even though this technique is very precise in providing information about spatial brain structure, its high price makes it unavailable to many smaller hospitals [48].

PET is another imaging modality that is commonly used in studies investigating brain activity during certain tasks [49]. Although PET does not provide a direct measure of neural activity, it offers a correlate in the form of haemodynamic and metabolic changes locally within the brain tissue by detecting the radioactive signal from a suitable radiolabelled tracer. This radiotracer might be water as a surrogate marker of blood flow, or fluorodeoxyglucose, which provides an image of the rate of regional glucose metabolism. As the local rate of energy metabolism or blood flow is believed to be coupled to neural activity, these surrogate changes are thus used to assess cortical activation and produce functional brain images. A drawback of this technique is high price, and it is considered as invasive since radionuclide must be injected into a subject's veins [50, 51].

Even though there are few documented studies about characterization of EEG during swallowing, EEG is considered as one of the few possible techniques that can be used for evaluating cortical brain activity during swallowing [52,53]. EEG records electrical activity in the brain [54]. Neural activity in the brain generates electrical signals, which can be recorded by electrodes (i.e., sensors) placed on the surface of scalp [55]. Brain EEG waves form sinusoidal shapes where certain frequencies are more dominant depending on the brain activity during different tasks [56,57]. Using sophisticated computerized analysis tools, it is possible to determine brain mapping for specific activities from the EEG time series [58]. This is called quantitative EEG [58]. With quantitative EEG, it is possible to determine spatial structures and localize areas with brain activity and abnormality [59,60]. Even though this spatial representation is characterized by bad resolution, EEG has some advantages, such as low price and high temporal resolution, which makes this technique very attractive for use both in clinic and in research.

1.3.1 Evaluating data obtained by techniques for studying of the neurological origins of swallowing and dysphagia

Traditionally, techniques such as fMRI, PET, or EEG were very useful for gaining the information about which part of the brain is involved in a swallowing task. Very good fMRI and PET image representation of the brain enabled examination of brain anatomy, and determined precisely which part of the brain is handling critical functions such as thought or movement, while EEG with high temporal performance was able to identify brain regions involved in short and fast brain activation, such as in sensation. Thus, studies have provided consistent evidence that swallowing is a complex human function, which transports food from the oral cavity via pharynx and esophagus to the stomach, and involves many parameters that cause activity across several regions of the central nervous system [36, 38, 61–65].

After defining the brain regions involved in the swallowing activity, an important step forward would be understanding the relationships and interactions among brain regions during swallowing. The concept of brain connectivity (how brain regions communicate with each other) during swallowing is central to understanding the organized behavior of brain regions, even beyond the simple mapping of their activity. The human brain exhibits specific functional interconnection patterns linking different brain regions or individual cortical neurons [66]. These interconnections form a complex network consisting of highly interconnected processing regions. Since there are many different brain regions involved in swallowing activity, analyzing the brain network could provide a better understanding of brain specialization and pathways of integration during swallowing. A graph theoretical approach and signal processing on graphs recently shown promise as methods for the analysis of neuroanatomical networks [67–71], and therefore these methods could usher in the next level of understanding swallowing.

The first of the two popular methods used for analyzing neuroanatomical networks is the graph theoretical approach [67–69]. Graph theory mathematically describes the relationships between and among vertices (i.e., nodes) [72]. Studies have shown that graph theory is suitable for analyzing functional connectivity in the human brain network [73], and it has been widely used in different human and animal neuroscience studies, as it facilitates easier

analysis of the differences and similarities of brain networks [74–77]. Thus, the graph theoretical approach could be useful for investigating neuroanatomical networks during swallowing. Interconnections between vertices are accomplished by edge connections whose strength depends of synchronization between nodes (brain regions). For functional interactions between different brain regions, graph theory provides an opportunity to determine the connective relationships between and among neighborhoods of vertices, providing information about topological properties of the network. The difference in the topological properties between networks that are formed during various swallows could provide important insight into the core of human brain function during swallowing.

Signal processing on graphs, the second of the two popular methods for analyzing neuroanatomical networks, is an extension of the classical graph theory approach, which enables deeper insight into the structure of the graphs and provides advanced information exceeding the information about the topological properties of the graph. Signal processing on graphs is useful for the representation, processing, and analysis of structured datasets represented by graphs. In the signal processing on graph notation, besides information about the strength of connection between nodes, a graph also carries information about the values of the nodes. These values of the nodes represent signals on a graph. At a high level, solving problems of such structures can be adopted to in a signal processing context [70,71]. Since swallowing is one of the most complex human functions [25,26], brain networks that are formed with the signals during swallowing will most likely have complex and irregular structures. Signal processing on graphs enables spectral graph analysis, providing deep insight into these complex structures.

Spectral graph analysis is very similar to classical signal processing notation [70, 71]. The Laplacian matrix enabled the implementation of basic signal processing operations in graph settings (i.e., the Fourier transform on graphs, signal filtering on graphs, and signal shifting [70, 71]). Thus, this approach also enables vertex-frequency analysis of the signals on graph, providing information about the changes of the signal frequency among the nodes. Vertex-frequency analysis can lead to advanced graph analysis, such as finding a specific sub-graph in a larger graph [78], detecting very dense or frequently-occurring sub-graphs [79, 80], or detecting a certain behavioral pattern [81].

Analyzing data sets using signal processing on graphs has already been demonstrated in clinics to detect anomalies in graphs [82–84]. Thus, signal processing on a graph could likewise be worthwhile for analyzing brain networks formed during swallowing activities. In the future, signal processing on graphs could establish ways for finding abnormalities in the brain networks of a dysphagic population, and potentially lead to the development of new diagnostic and screening techniques.

1.4 DIRECTIONS AND GOALS

Nearly 15 million Americans are affected by the swallowing disorder dysphagia [1,85]. As many as 40,000 people die each year in the United States from aspiration pneumonia, a medical complication strongly associated with dysphagia [20]. This leads us to conclude that early diagnosis and an appropriate treatment is paramount. Studies showed that therapy and rehabilitation of patients with neurogenic dysphagia is highly correlated with the brain's plasticity and ability to reorganize the sensory and motor cortex after events such as stroke [86]. Consequently, to obtain good diagnoses and treatment methods, we should have a better understanding of swallowing and swallowing therapy techniques from the prospective of brain activity.

Even though fMRI and PET are considered the gold standard for investigating central neural activation during swallowing, these two modalities have some drawbacks. fMRI and PET machines are expensive (i.e. \$500,000 to \$3 million depending on the resolution) [87,88]. Also, the average cost of PET and fMRI scans (i.e., technical scan and professional charges) ranges from approximately \$900 to \$1400 [89]. This means that smaller hospitals cannot likely provide this equipment, and also people with small or no income could not afford the necessary care. Apart from the high price, the poor temporal resolution of fMRI and PET fails to clearly recognize the difference between the motor component and sensory feedback during swallowing. Another drawback of fMRI and PET is that although fMRI gives information about changes in the blood flow [90], and PET gives information about metabolic activity [91], which are both indirect markers of brain activity, both of these

techniques are highly sensitive to contamination by foreign metal objects being placed in the scanner with the subject. Additionally, another significant drawback of fMRI and PET is that during testing, the patient is required to be in the supine position, which is a dangerous and unnatural position for dysphagic patients to assume while swallowing.

EEG demonstrates some advantages when compared with other techniques. The price of the EEG equipement is around \$30,000 to \$80,000 [92], which is significantly cheaper than fMRI and PET machines. Besides having good temporal resolution, EEG records neural brain activation, which is considered to be the direct link to brain activity. Another advantage of EEG is that it is not sensitive to interactions or proximity to any material, and it also enables patients to remain in a natural body position during testing. Several studies have already used EEG to identify brain regions that are involved in swallowing control [52,53,93,94]. Therefore, we believe that EEG is a worthwhile technique for analyzing cortical activation while a person is swallowing.

Besides identification of the brain regions involved in the swallowing activity, we believe that using the EEG time series for investigation of the interactions between brain regions during swallowing by graph theory and signal processing on graph approach could give important insight into the neurological origins of swallowing. At this moment, similar studies have yet to be conducted on the EEG data during swallowing. Thus, in order to provide a better understanding of brain activity during swallowing using the graph theoretical and the signal processing on graph approach, a number of questions remain and must be answered. For example, what are the EEG signals' stationarity characteristics during various swallows? Then, depending on the EEG signals' stationarity, what is the best method for forming the graphs which represent the swallowing brain network? How are topological properties different between various swallowing brain networks? How do therapeutic techniques affect swallowing brain networks? How can we extract information about the identity of the signals on graphs from the swallowing brain network? How can we improve methods for extracting information about this identity? How are signals on graphs different between various swallowing brain networks? The goal of this investigation is to provide some of the answers to these questions.

1.5 DISSERTATION SCOPE

In order to have the most reliable results it is important to choose an appropriate method for forming connectivity brain networks during the swallowing. There are several methods that are commonly used for forming connectivity matrices from the data obtained with the EEG time series (e.g., coherence, directed transfer function, adaptive directed transfer function, synchronization likelihood, time-frequency based phase synchrony measure, etc. [95–99]). The choice of method will mostly depend on the signals' stationarity characteristics. Therefore, one of the first steps in our study should be investigation of the EEG signal stationary characteristics during swallowing.

After investigation of the EEG signals' stationary characteristics and choosing the method for forming the brain networks, an important part of the investigation is to determine how various swallows influence the brain networks formed with the EEG signals. Particularly we want to know how common therapeutic techniques, such as the swallowing of the thicker liquids and swallowing in the chin-tuck head position, influence topological properties of the brain networks formed from the EEG signals. Also, we want to know what the characteristics of the swallowing brain network are during conditions that influence swallowing activity, such as compromised attention. Studies showed that increasing the bolus viscosity and swallowing in the chin-tuck position eliminates aspiration 50% of the time [100, 101]. Defining the characteristics of the brain networks formed during these commonly employed therapeutic techniques could potentially demonstrate whether there is a central explanation for the limited efficacy of this technique at eliminating aspiration. Also studies showed that patients who had altered attention or impaired cognitive functions due to some brain damage such as stroke, often manifested changes in the swallowing action [102, 103]. Defining and understanding the difference between brain networks for normal swallows and for swallowing with distraction could potentially lead to the development of better rehabilitation strategies for dysphagia patients who also have altered attention or impaired cognitive functions due to some neurological disorder.

In addition we want to investigate the differences between consecutive swallows. These findings could potentially explain why some dysphagic patients have a higher risk of aspiration after a few swallows [104–106]. Since the classical graph theory approach cannot recognize differences between consecutive swallows (Section 9.1), we want to employ signal processing on graphs in order to analyze the structural properties of the swallowing brain networks. Signal processing on graphs could provide information about identity of the brain network that exceeds information about topological properties of the network. A previous study developed a vertex-frequency analysis technique based on the windowed Fourier transform from classical signal processing [107]. The windowed graph Fourier transform (WGFT) has been shown to be a useful method for extracting frequency information from the signals on a graph. Applied to our data, the WGFT could provide convenient information about signals' oscillations on the graphs, which are formed with the swallowing EEG signals. However, lack of the window size choice, computational complexity, and required computational time make this technique not very efficient. Therefore, developing a method for automatic choice of the best window size, as well as decreasing the required computational time, could provide a significant contribution towards the study of neural origins of the swallowing.

1.6 MAIN CONTRIBUTIONS

To address these goals we will make the following contributions:

- Investigate stationarity of the EEG signals during various swallowing tasks.
- Investigate difference in brain network between swallowing in neutral and chin-tuck position, and between different fluid viscosities.
- Develop the fast WGFT.
- Develop a method for optimizing window size for the *WGFT* and investigate differences among consecutive swallows.
- Investigate differences in brain networks during normal swallowing and swallowing with distractions.

1.7 DISERTATION ORGANIZATION

Chapter 2 details the background information necessary (i.e., EEG and EEG studies related to swallowing) to understand the principles discussed in later chapters. Chapter 3 describes open questions to be addressed throughout our investigation of swallowing using the EEG modality. Chapter 4 - 8 describe our results and discussions of the proposed studies. And finally, future work and the proposed research will be described in Chapter 9.

2.0 BACKGROUND

With kind permission of Journal of Neural Engineering, this chapter was excerpted in entirety from the following journal article:

Jestrović, I., Coyle, J.L., Sejdić, E. (2015). "Decoding human swallowing via electroencephalography: a state-of-the-art review." *Journal of Neural Engineering*, vol. 12, no. 5, pp. 1-15, 2015 The homepage of *Journal of Neural Engineering* is located at this page. The publisher's copyright information can be found at Copyright Clearance Center, Inc.. This article can be found on the publisher's website by clicking here.

2.1 ELECTROENCEPHALOGRAPHY (EEG)

2.1.1 Definition and reasons for investigation

EEG is a time domain acquisition modality that records neural electrical activation along the interface of the scalp [55], with electrodes positioned according to the 10 - 20 international electrode system [108] (Figure 2). As a noninvasive and affordable technique, EEG is broadly used in both clinics for diagnosing and investigating a wide range of diseases and also in research [109–113]. Jordan described five important reasons for using EEG in the monitoring of brain activity [111]. EEG describes temporal and spatial representations of the cortical excitatory potential and the inhibitory potential, as well as their interaction with and influence on the cerebral metabolism. This means that EEG can directly describe the immediate outcomes associated with cerebral metabolic activity. Normal human EEG representation has a histological pattern, and this representation is very sensitive to cerebral changes and cerebral abnormalities, such as injuries, ischemia, or hypoxia. The 10 - 20 international system for EEG electrode placement provides a consistent correlation with brain topography. Another advantage of EEG is that it can register neural abnormalities when they are still at a reversible stage.



Figure 2: Example of international 10-20 electrode system placement (64 electrodes).

The EEG power spectrum is controlled by the brain's homeostatic system, which produces rhythmic electrical activity of various frequencies controlled by population of neurons and the neurotransmitters [114–116]. Pacemaker neurons located throughout the thalamus are known to oscillate in the frequency range 7.5 - 12.5 Hz. Efferent projections located throughout the cortex produce electrical activity in the range 8 - 16 Hz, which is known as the *Alpha* range. This *Alpha* range is most dominant when a healthy person is in a resting state. When neurons from the thalamus hyperpolarize due to the effects of neurotransmitter gamma-aminobutyric acid, the dominant frequency range of the brain's electrical activity becomes 4 - 8 Hz, which is known as the *Theta* range. Oscillation of the neurons in the deep cortical layers and in the thalamus produce low frequency electrical activity up to 4 Hz; this low frequency band is known as the *Delta* range. Brain activity precipitated by specific information processing produces the fastest brain activity in the *Beta* range from 16 - 32 Hz [117].

Event related potentials (ERP) are positive and negative voltage deflections, which are observed as positive and negative changes or excursions in the waveform. ERP waveforms are very often investigated in EEG studies. ERP is made of averaged ongoing EEG signals which are time-locked to the response event, and ERP gives information about discharges of large populations of neurons related to some cognitive or sensory-motor processes [118]. Portions of an ERP waveform can be classified as either positive (P) or negative (N). Using this polarity classification (i.e., positive or negative), the name designator for an ERP waveform can be constructed in two possible ways: by order of occurrence, or by mean latency in milliseconds (e.g., see "Findings" in Table 2). For example, the first positive-polarity ERP waveform with a mean latency of 130 ms takes on the name "P1" when designating the waveform according to its order of occurance (i.e., "1" corresponds to the first occurrence). If the same positive-polarity ERP waveform were to be classified according to mean latency, its name would be "P310". Different ERP are qualified and quantified depending on their latency and maximum amplitude, observed from the pre-stimulus baseline. An example of an observed ERP is shown in Figure 3. Three separate time ranges/windows (i.e., the three vertical rectangular boxes shown to exist between roughly 100 - 300 ms in Figure 3) each capture respectively the peak of one of the three EEG signals. However, the aforementioned description is, of course, specific to the set-up. ERP waveforms can be different depending on the design of the experiment, stimuli type, and cognitive task being performed.

Bereitschafts potential (BP) and movement-related cortical potentials (MRCP) are characteristic features of EEG signals which describe the cortical activity associated with motor response. Kornhuber and Deecke [119] explained the BP as the negative potential which occurs 1-2 seconds before the voluntary motor action, and that it is possible to record BP along the scalp. The amplitude of the BP potential depends on the motor demands of the task. The first of two components in the BP occur symmetrically on both brain hemispheres, and these components happen 1 - 1.5 seconds before motor action onset. The second of two components occurs 0.5 seconds before the motor action, and this component of the BP is positioned contralaterally to the activated hemisphere, depending on the movement [120–122]. Previous studies showed that the first component of the BP is generated mostly in the supplemental motor area, while the second component is generated in the primary motor cortex [123]. Furthermore, this BP component of MRCP has been shown to be a valuable tool for investigations in the field of swallowing, such as the initiation of deglutitive behavior [52].

The MRCP is used for investigating cortical activation during movement activities (e.g., swallowing) [119, 121, 124]. MRCP contains two components: the BP and the negative slope (Figure 4). Because of the high signal-to-noise ratio of electrical activity in the brain neurons, cortical activations recorded from the scalp enable the investigation and evaluation of the MRCP. The contingent negative variation (CNV) is a negative cortical potential with a slow drop, which occurs between two successively instructed tasks [125, 126]. CNV and MRCP have functional differences in the cognitive process which occurs at the beginning of the movement. Studies showed that MRCPs are generated in the primary sensorimotor cortex, supplementary motor area proper, and pre-supplementary motor area [127–130], while CNVs are generated in the prefrontal cortex [131].

2.2 EEG STUDIES RELATED TO SWALLOWING

2.2.1 Smell

Previous studies reported that EEG signals are sensitive to changes in odor, suggesting that EEG is suitable for investigating and analyzing brain activity during olfaction [132–134]. Most of the olfactory EEG studies reported changes in signals for different stimuli. The reported observed changes in EEG signals were not ubiquitous across all of the EEG olfactory studies due to differences in employed investigation methodologies. Moncrieff published one of the earliest studies to report these EEG signal changes due to olfactory stimuli [135]. Moncrieff used five subjects with eight bilaterally placed electrodes on each subject. The results of his study showed changes in the alpha band of the signals for almost all stimuli. Moncrieff used anachronistic EEG recording procedures, and a large number of stimuli. Also, the experimental conditions were not very well controlled, which accounts for the differing results observed in recent studies.

Even though recent studies have improved the standards for experimental control, differing results exist among the reported studies. Loring et al. [136] and Klemm et al. [134] found no changes in the alpha activity, while Loring et al. [137] later reported a reduction in the alpha power activity for different stimuli. Also, other studies reported conflicting results: a reduction [133, 138] and an increase [134] of the theta activity for differing odor stimuli. In one portion of their study, Loring et al. [136] found that for different stimuli, alpha and theta activity exhibited changes along different brain hemispheres. Reasons for these observed differences could include environmental conditions during recording sessions, the specific odor stimuli used, the number of electrodes, and that the recording durations all differed among studies. One study by Martin [139] investigated the influence of food's odor on the EEG signals. Martin found that theta activity was significantly reduced for chocolate stimuli in comparison to both almond and cumin stimuli. He also found similar results (i.e., reduced theta activity) for spearmint when compared with the control (i.e., no odor). These results could be attributed to psychological experience of the pleasant odor property. The results of these studies are summarized in Table 1.

2.2.2 Taste and texture

Recent EEG studies that investigated the gustatory brain waveform concentrated on investigating the ERP. The first positive (P1) gustatory ERP peak for a salt stimulus was reported by Mizoguchi et al. [140] and Wada [141], and the P1 gustatory ERP peak for electric taste (applying an electrical current to the participants' tongue) was reported by Olha et al. [142, 143]. Each of these studies reported the P1 gustatory ERP peak between latencies spanning 130 and 150 ms. In these studies, the P1 deflection was higher for frontal electrodes, where this deflection is assumed to have origins in the insula, the middle temporal gyrus, and the anterior cingulate cortex [143]. The first negative (N1) deflection for a latency time of 200 ms was reported by Olha et al. [142, 143] for an electric taste stimuli in the regions of the cranial vertex and bilateral insula. Mizoguchi et al. [140] reported the N1 deflection for salt at a latency of 256 ms in the region of the cranial vertex. Early ERP studies that focused on ERP deflection (i.e., Min and Sakamoto [144], and Franken et al. [145]) were hindered by gustatory and tactile stimulation, which influenced their interpretation of the reported results. These studies were not concentrated on brain regions where deflection occurred, but rather on the difference in potential between different tastes. It was found that sweetness in stimuli influenced the evoked potential. P1 deflection at latencies higher than 500 ms was reported by Funakoshi and Kawamura [146], Kobal [147], Plattig et al. [148], Hummel et al. [149], and Singh et al. [150]. However, it is not known if these late peaks have origins from the same process that produces early peaks, nor is it known whether their origins are due to variations in the administration of different stimuli. The results of these studies are summarized in Table 2.

2.2.3 Cortical pre-motor ativation in swallowing

The supplementary motor area is not frequently the focus for analysis during swallowing, but it is known that the supplementary motor area is involved in the planning and initiation of the voluntary movement phases in swallowing [151]. Knowing this leads us to the investigation of MRCP in the case of volitional swallowing. This investigation could provide us information about sequential cerebral processing, and it could also enable us to distinguish between cortical motor preparation, cortical control of swallowing execution, and cortical swallowing regulation. However, Yoshida et al. [152] has shown the importance of MRCP in the diagnosis of oral motor dysfunction, and their results could be instrumental in the treatment of dysphagia. CNV gives information about cognitive functions in the case of swallowing activities initiated by a command, and together with MRCP, CNV gives important information about brain activity.

In the analysis of MRCP, it was assumed that the MRCP can provide information about cortical motor planning. Similar assumptions were used in the case of analyzing volitional activity such as finger movement. Huckabee et al. [52] were the first to use the EEG technique in a swallowing study, and they investigated the role of the cerebral cortex in the motor planning of swallowing as well as the initiation of swallowing. They found the BP before the onset of volitional swallowing at the supplementary motor cortex. The same study by Huckabee et al. also claimed that, contrary to other volitional activities, the primary motor cortex is not involved in the volitional swallowing task. Satow et al. [93] later reported BP activity in both hemispheres (i.e., the central area of the cranial vertex with additional involvement of the cerebral cortex) during a swallowing activity. They found that the role of the cerebral cortex during a swallowing activity is very similar to its role involving tongue movement. This difference in results between Huckabee et al. and Satow et al. could be attributed to the choice of stimuli which were used in each of the two studies. Huckabee investigated dry swallowing (i.e., saliva swallowing), while Satow used water as a stimulus. Hiraoka [53] later documented differences in cortical activation during saliva and water swallows. He showed that the amplitude of the positive potential is significantly higher for water swallowing compared with that in saliva swallowing. This can be attributed to the bolus size used in the study. In this study it was assumed that the saliva bolus was smaller than the water bolus. These results signify that information registered with different types of receptors in the oral cavity and oropharynx activates different cortical processes, where the particular activated cortical process depends on the type of information registered by the receptors. With these results, he claimed that the cortical preparatory process greatly depends on the type of the swallowing task.

Satow also found the BP in the case of swallowing and tongue movement. There was not a difference in the BP's amplitude between these two tasks. However, in the case of swallowing activities, the BP occurred earlier than in the case of tongue movement. Several years after Satow, Nonaka et al. [94] investigated brain activity in the case of volitional and command swallowing. He compared CNV waveforms during the command swallowing task with the MRCP during the volitional swallowing task. He found that the CNV, in the case of the command swallowing task, had both larger amplitude and longer duration when compared with the volitional swallowing task. This finding was observed from the Cz electrode signal, which reflects the activity of the supplementary motor area. This means that supplementary motor area activation starts earlier and has greater activation in the case of complex motor tasks. The results of these studies are summarized in Table 3.



Figure 3: ERP activation across different time ranges.



Figure 4: Scheme of MRCP.

Table 1: Summary of published studies which investigated the human response to odor using EEG.

\mathbf{Study}	Number of subjects	Stimuli	Electrodes	Findings
Moncrieff (1962) [135]	5	Floral perfume, alco- hol, lavender, methyl antrhrantilate, lemon- grass oil, cinnamon, citral, pyridine, ammo- nium sulphide	4 on the left side and 4 on the right side	Changes in alpha band activity
Stacher et al. (1979) [138]	16	Chives placed on bread and butter, frying but- ter, eggs, bacon	F7, F8, T5, T6	Reduction in theta band activity
Lorig et al. (1988) - first part [136]	13	Spiced apple, eucalyp- tus, lavender	Cz	Reduction in theta band activity
Lorig et al. (1988) - second part [133]	10	Five fragrances diluted with distilled water	F7, F8, T5, T6	Increase or decrease of alpha and theta ac- tivity along different hemispheres
Loring et al (1991) [137]	16	Different concentra- tions of spiced apple, lavender oil	F7, F8, T5, T6	Reduction in alpha band activity
Klemm et al. (1992) [134]	16	Birch tar, galbanum, jasmine, heliotropine, lavender, lemon, pep- permint, room-air	FP1, FP2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, O2, Fz, Cz, Pz	Increase in theta band activity
Martin (1998) [139] - first part	21	Chocolate, spearmint, almond, strawberry, vegetable, garlic, onion, cumin	FP1, FP2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, O2, Fz, Cz, Pz	Reduction in theta band activity

Table 2: Summary of published studies which investigated the human response to taste using EEG.

Study	Number of subjects	Stimuli	Electrodes	Findings
Kobal (1985) [147]	5	acetic acid	12 electrodes	P300, N410, P660, N860
Plattig et al. (1988) [148]	21	NaCl, tartaric acid, sucrose, quinine HCl, Water	Cz	N1000, P2300 for NaCl; P2300 for tar- taric acid; N2300 for quinine HCl
Min and Sakamoto (1998) [144]	10	NaCl, sucrose, tartaric acid, quinine HCl, arti- ficial saliva	Cz	P50, P180
Mizoguchi et al. (2002) [140]	5	NaCl	Fz, Cz, Pz, T3, T4	P127, N263, P432
Wada (2005) [141]	11	glucose, NaCl, artificial saliva	Cz	P72197 for glucose, P84188 for NaCl
Olha et al. (2009) [142]	17	11.5 μA electrogustatory stimuli	64 electrodes	P130, N220, P390
Olha et al. (2010) [143]	17	11.5 μ A and 360.5 μ A electrogustatory stimuli	64 electrodes	P134, N219, P390 for 11.5 μ A; P124, N186, P347 for 360.5 μ A
Hummel et al. (2010) [149]	17	70% acetic acid, $100%$ acetic acid	Cz, Fz, Pz	N390, P601 for 100% acetic acid
Singh et al. (2011) [150]	17	NaCl, MSG	Fz, Cz, Pz, C3, C4	N506, P718 for NaCl
Table 3: Summary of published studies which investigated the human response to odor using EEG.

Study	Number of subjects	Stimuli	Electrodes	Findings
Huckabee at all. (2003) [52]	20	saliva swallowing	$\begin{array}{llllllllllllllllllllllllllllllllllll$	BP at the supplemen- tary motor cortex
Satow at al. (2004) [93]	8	Water swallowing	$\begin{array}{l} {\rm Fp1, \ Fp2, \ F7, \ F3,} \\ {\rm Fz, F4, F8, T3, C3,} \\ {\rm Cz, \ C4, \ T4, \ T5,} \\ {\rm P3, Pz, P4, T6, O1,} \\ {\rm O2} \end{array}$	BP in both hemi- spheres at the central area of the cranial vertex; Activation of cerebral cortex
Hiraoka (2004) [53]	7	saliva swallowing, wa- ter swallowing	C3, Cz, C4	higher positive poten- tial amplitude for wa- ter swallowing com- pared with saliva swal- lowing
Nonaka et al. (2009) [94]	10	Command saliva swal- lowing, volitional saliva swallowing	Fz, Cz, Pz, C3, C4	higher amplitude and longer duration of the CNV for the command swallowing task com- pared to the MRCP for volitional swallow- ing task

3.0 AREAS OF INVESTIGATION

Based on the literature review, six open problems have been identified as described in the next six subsections. For each of the problems we provided motivation to address this problem, and the action plan of how to address it.

3.1 THE EFFECTS OF INCREASED FLUID VISCOSITY ON STATIONARY CHARACTERISTICS OF ELECTROENCEPHALOGRAPHY SIGNALS IN HEALTHY ADULTS

3.1.1 Motivation

Stationarity describes whether a signal's statistical behavior from the future is the same as the statistical behavior from its past. In recent years, evidence reporting the weak but significant non-stationary properties of EEG signals and their interdependencies was published [153–155]. However, it is still unknown whether EEG signals during swallowing can be characterized as stationary or non-stationary. Answering this question will provide important directions for our future investigations of brain activity during swallowing.

One way EEG signals are analyzed is by investigating brain networks. There are several methods currently used for constructing brain networks from EEG signals [98,99,156–158], which in essence measure the synchronization between signals from two EEG electrodes. Choice of the method depends of the behavior of the EEG signals. Therefore, we must first assess the stationarity of EEG signals produced during swallowing activity, before we can implement the appropriate network building method.

On the other hand, investigating the stationarity of EEG signals during swallowing activity may also hold clinical significance. The stationarity of a signal could change due to the effects of a pathological condition. These changes may contain certain tell-tale patterns (e.g., different types of background activity) that elucidate the underlying nature of neurogenic dysphagia, and becoming familiar with these patterns could provide a pathway to new intervention strategies for neurogenic dysphagia caused by abnormal brain activity during swallowing. By monitoring the post-processed EEG waveforms it could be possible to recognize these clinically significant changes through visual inspection or another, automated method. In order to test the viability of such a screening tool, we have also investigated if EEG signal stationarity would be significantly affected by sex, age, different brain regions, and by the viscosity of the swallowed liquids.

3.1.2 Plan of action

The data acquisition process has been done as a part of the previous study, and the data are available for use. The study was approved by The Institutional Review Board at the University of Pittsburgh. 55 healthy adults (28 males and 27 females), aged 18 to 65, participated in the data acquisition process. Each participant signed consent forms, and they provided information about age and gender. EEG signals were recorded while participants performed four different types of swallowing tasks, each with a unique viscosity fluid. Saved data were pre-processed. Pre-processing involved some standard pre-processing steps such as: downsampling of the signal, filtering of the signal, removing DC offset, and removing artifacts. Artifacts were removed using Independent Component Analysis [159]. From the pre-processed signal, stationarity will be tested with surrogates, which is a time-frequency approach proposed by Borgnat et. al [160] for testing wide-sense stationarity. The essence of this approach is to compare the local spectra statistics of each signal with the global spectrum of that signal. Depending on the results of this comparison, the stationarity of the time scale can be determined.

3.2 DIFFERENCE IN BRAIN NETWORK BETWEEN SALIVA SWALLOWING IN NEUTRAL AND CHIN-TUCK HEAD POSITION

3.2.1 Motivation

Performing a swallow in the chin-tuck position is the most common method of compensating for specific swallowing abnormalities [161, 162]. It has been reported to eliminate aspiration approximately 50% of the time in patients who aspirate thin liquids due to delay onset of the pharyngeal response, provided that aspirated material did not originate in the hypopharyngeal recesses that lie beside and behind the inlet to the larynx (pyriform sinuses) [101]. When the head is in the chin-tuck position, the tongue is drawn forward due to gravity, and the valleculae expands. A larger valleculae pushes the tongue base closer and the flexed posture moves the posterior pharyngeal to the tongue base which provides better swallowing control [163]. Studies showed that these anatomical changes have been very helpful in protecting the airway for some patients [1,162,164].

While studies have given a physiological explanation of anatomical changes in the pharynx during chin-tuck swallows, it remains unclear how this maneuver affects brain activity. It is hypothesized that the chin-tuck maneuver operates via one of two pathways. Physically, it may simply modify the configuration of the oropharyngeal mechanism, and as a result, the swallowing profile. Alternatively, it may affect the activation of the muscles involved in swallowing caused by a transformation in cerebral function prompted by the postural change.

The neurological conditions that cause dysphagia are not necessarily localized conditions. The areas damaged by the underlying pathology may also damage the brain regions involved in the control of the chin-tuck maneuver. Defining characteristics of the brain network and defining brain regions involved in these commonly deployed compensatory maneuvers could potentially explain whether there is a single explanation for the limited efficacy of this technique at eliminating aspiration. Therefore, we hypothesize that the brain network changes its configuration when swallowing in either a neutral or chin-tuck position.

3.2.2 Plan of action

The data acquisition process has been done as a part of the previous study, and the data are available for use. From each participant, EEG brain activity was recorded during swallowing in the neutral and chin-tuck head positions. After standard pre-processing of the EEG time series, connectivity matrices will be formed for each frequency band of interest from the EEG time series using the time-frequency based phase synchrony measure [99]. Matrices formed like this will be weighted undirected connectivity matrices. Constructed weighted undirected connectivity matrices are thresholded in order to form binary networks. For a binary undirected network, a_{ij} refers to the connection between node i and node j. If a connection exists between two nodes (i.e., node i and node j), then $a_{ij} = 1$, but if $a_{ij} = 0$, then there exists no connection between two nodes (i.e., node i and node j). When comparing network measures, only matrices containing the same number of edges can be considered. Because there is no single accepted method for choosing a threshold value, we chose to form binary networks by thresholding the weighted networks according to the percent of their density of connections (e.g., if a threshold is set to 10%, then this means that 10%of the strongest connections in the connectivity matrix will be assigned a value of 1 while the remaining 90% connections will be assigned a value of 0). For each of the constructed networks, network measures (e.g. clustering coefficient, characteristic path length, local efficiency, small-worldness) will be calculated and then compared to extracted differences and similarities between swallowing in the neutral and chin-tuck head positions.

3.3 EFFECTS OF FLUID VISCOSITY ON THE BRAIN NETWORK DURING SWALLOWING

3.3.1 Motivation

Previous studies indicated that thicker liquids can reduce the amount of material that is aspirated when certain individuals aspirate thinner liquids while swallowing [100]. There are several clinical explanations for this trend. For example, with higher viscosity liquids, it is known that the duration of the contact between tongue base and pharyngeal wall increases, oral and pharyngeal transit time is longer, pharyngeal delay time decreases, duration of the peristalic waves is longer, the upper esophageal segment opening is longer, etc. However, thicker liquids can also subjectively improve swallowing symptoms in some individuals who have dysphagia with ordinary liquids.

While we are familiar with anatomical changes during swallowing performance of higher viscosity fluids, it is still unknown how those diet changes affect brain activity. We still do not know if better control of swallowing for higher viscosity fluids is due to anatomical control of the larynx or due to better communication between brain regions for this swallowing task. Understanding the changes in brain activation with healthy people during swallowing of different viscosity fluids could potentially allow us to apply this information to existing neurogenic dysphagia treatment methods.

Furthermore, a patient's neurological disorder may also damage brain regions that affect swallowing control. Therefore, it would be informative to determine whether the effects of increased fluid viscosity on swallowing signal characteristics produce useful information that might add value to brain networks as a screening method.

3.3.2 Plan of action

Data from the previous study, where EEG signals were recorded while participants performed 3 different types of swallowing (i.e., water swallowing, nectar-thick swallowing, and honeythick swallowing) in the neutral and chin-tuck head positions, are available for use. Preprocessing of the EEG signals, forming connectivity matrices, thresholding, and extraction of the network measures will be done as is described in Section 3.2.2. Extracted network measures will be calculated and then compared between different conditions.

3.4 INFLUENCE OF ATTENTION AND BOLUS VOLUME ON BRAIN ORGANIZATION DURING SWALLOWING

3.4.1 Motivation

In order to provide better rehabilitation for the dysphagia patient, it is important to understand events that can influence swallowing activity. Studies showed that patients who have altered attention or impaired cognitive functions due to brain damage, such as those caused by stroke, often manifest changes in the swallowing action [102, 103]. This means that the swallowing process may require certain attentional and cognitive resources involved in this motor behavior. However, this area of study has not been well explored. Thus, there are still open questions regarding the influence of attention and cognitive demands on the swallowing activity. In order to understand how attention influences swallowing activity, we should compare brain organization during normal swallowing and swallowing with distraction. These findings could potentially lead to the development of better rehabilitation strategies with dysphagia patients who also have altered attention or impaired cognitive functions due to neurological disorders.

3.4.2 Plan of action

Data will be collected from 15 healthy male subjects, aged from 18 to 35. All participants will provide informed consent, and information about age, height, and weight. After the participants give consent, first, EEG electrodes will be attached to the scalp using noninvasive surface recording electrodes, then the accelerometer will be attached to the ventral side of the subject's neck using surgical tape. Participants will be asked to consume ten 1ml water swallows, ten 5ml water swallows, and ten 10ml water swallows. Then, participants will be asked to do the same thing, but this time while they watching a video which occupies their attention and involves cognitive demands. All stimuli will be served chilled (3-5C) in separate cups, and participants will be instructed to consume stimuli in their self selected time base between each swallow. Pre-processing of the EEGs, forming connectivity matrices,

thresholding, and extraction of the network measures will be done as is described in section 3.2.2. Extracted network measures will be calculated and then compared between among conditions.

3.5 FAST WINDOWED GRAPH FOURIER TRANSFORM

3.5.1 Motivation

Even though topological properties of the swallowing brain network could provide important insight into the neurological origins of the swallowing, in some cases we need a more advanced approach. For example, we have shown that the classic graph theoretical approach could not find the difference between consecutive swallows (Section 9.1). Therefore, employing signal processing on a graph could provide deeper insight into the functional brain network during the swallowing.

Previously, the WGFT [107] has been shown as a convenient method for extracting vertex-frequency content from the signals on graphs. However, one disadvantage of the WGFT is its computational complexity, particularly for big graphs. A more efficient algorithm for computing the windowed Fourier transform would make EEG analysis more attractive as a potential screening tool for dysphagia. Therefore, we aim to develop a faster algorithm for computing the windowed Fourier transform.

3.5.2 Plan of action

Data from the last study are available for use in this study, which will enable testing the new and fast algorithms for calculating the WGFT. The algorithm will be developed following the idea proposed in [165]. Essentially, the required computational time will be decreased by operating on the Fourier spectrum of the signal on a graph, and also operating on the Fourier spectrum of the window used for calculating the WGFT.

3.6 DIFFERENCE IN THE BRAIN NETWORK BETWEEN CONSECUTIVE SWALLOWS

3.6.1 Motivation

In order to have a better understanding of swallowing we should also understand the differences between consecutive swallows. The differences between consecutive swallows have not been considered much in previous swallowing studies, even though it could possibly influence swallowing control for the people who have impaired clearance of swallowed material from the throat, or impaired muscles that are involved in swallowing control. For example, due to fatigue in the muscles of the larynx involved in swallowing or due to residue in pharynx, patients with dysphagia could have higher risk of unsafe swallowing immediately after completing a swallowing action [104–106, 166–168]. Therefore, investigation of the differences between consecutive swallows could lead us to better understanding of swallowing neurology and improve swallowing therapy.

It was already mentioned that the classical graph theory approach cannot register differences in the brain networks between the first, second, and third swallows (Section 9.1). Therefore, for this investigation we want to employ signal processing on graphs. Signal processing on graphs enables the extraction of distinctive features, such as vertex-frequency content from the graphs. This information could be extracted using the WGFT [107]. However, like in classical signal processing, the WGFT has a limitation regarding the fixed window size. Choosing too wide or too narrow a window can result in poor resolution of the representation of the graph's frequency content. Therefore we want to implement a method which will calculate the optimal window for extracting frequency information from signals on a graph. Calculating optimal window size automatically will enable more efficient extraction of the frequency content from the graphs formed during swallowing.

3.6.2 Plan of action

Data from healthy subjects are available for this study. After standard pre-processing of the EEG signals, connectivity networks will be formed from each swallow using the timefrequency based phase synchrony measure [99]. Weighted undirected connectivity networks will correspond to the connection between nodes, while the mean value from each EEG electrode will be attributed to each node. From such data sets, the graph Laplacian will be formed. Using the graph Laplacian, it is possible to define some basic signal processing operations on graphs, such as the graph Fourier transform, translation, modulation, as well as WGFT [107]. The optimal window for the WGFT will be calculated using an algorithm based on concentration measure, which will optimize size of the window. The algorithm for calculating an optimal window for WGFT will be used for calculating the vertex-frequency representation brain network during swallowing. These vertex-frequency representations will then be compared between the consecutive swallows.

4.0 THE EFFECTS OF INCREASED FLUID VISCOSITY ON STATIONARY CHARACTERISTICS OF ELECTROENCEPHALOGRAPHY SIGNALS IN HEALTHY ADULTS

With kind permission of Elsevier, this chapter was excerpted in entirety from the following journal article:

Jestrović, I., Coyle, J.L., Sejdić, E. (2015). "The effects of increased fluid viscosity on stationary characteristics of EEG signal in healthy adults." *Brain Research*, vol. 1589, no. 1, pp. 45-53, 2014 The homepage of *Brain Research* is located at this page. The publisher's copyright information can be found at Copyright Clearance Center, Inc.. This article can be found on the publisher's website by clicking here.

4.1 MOTIVATION

Recognizing a non-stationary process in the EEG and identification of the components that are responsible for affecting the signal's stationarity could be important for different reasons. For example, by monitoring the post-processed EEG waveforms, it could be possible to recognize clinically significant changes that may influence the treatment of patients with neurogenic dysphagia, either by visual inspection or even by some other automatic method (i.e., software tools for automatic detecting of changes). On the other hand, these components may contain certain telltale patterns (e.g., different types of background activity) that elucidate the underlying nature of neurogenic dysphagia, and becoming familiar with these patterns could provide a pathway to new intervention strategies for neurogenic dysphagia caused by abnormal brain activity during swallowing. Additionally, it could provide information about appropriately selecting techniques which should be used for forming brain connectivity matrices.

4.2 METHODS

4.2.1 Data acquisition from participants

55 healthy adults (28 males and 27 females), aged 18 to 65, participated in the data acquisition process. Each participant signed consent forms, and they provided information about age, gender, height, and weight. The Institutional Review Board at the University of Pittsburgh approved this study.

EEG data was collected with a 64 channel system, arranged according to the 10-20 international electrode system [108], using actiCAP active electrodes and an actiCHamp amplifier (BrainProducts, Germany). The impedance of each electrode was below 15 k Ω , and the electrode marked P1 was chosen as the reference electrode. All data was recorded with the PyCorder acquisition software, which provided a 10 kHz sampling rate on each channel. In order to determine the swallowing segments (i.e., the starting and ending points of the swallow), the EEG signal was recorded during swallowing simultaneously while dual axis accelerometer sensor attached to the anterior side of the participants' necks overlying the larynx recorded vibratory signals associated with laryngeal movement that occurs during swallowing. The methods describing the implementation of the accelerometer, pre-processing steps, and swallowing segmentations are described in a previous study [169].

After appropriately affixing the accelerometer and EEG cap along with the rest of the system (Figure 10), participants were asked to perform five swallows with fluids of four different viscosities. Fluids were served chilled (between $3^{\circ} - 5^{\circ}$ C) in individual cups filled to approximately 30 ml. Participants were instructed, after the instructor signaled for the participant to begin the swallowing task, to then pause 2-3 seconds between each swallow.



Figure 5: The experimental setups used in the study.

The order of presentation of the four conditions was not randomized. Each participants swallowed five saliva boluses, followed by five water boluses (viscosity of water is 1 cP), followed by five mildly thick (nectar-thick, Nestlé Health Care Inc., Florham Park, N.J.) liquid boluses with a viscosity of 150cP, and followed finally by five moderately thick (honey-thick, Nestlé Health Care Inc., Florham Park, N.J.) liquid boluses (400cP). Bolus volume was not controlled for or measured, and participants were asked to consume a comfortable bolus volume as there are sex based differences in a comfortable bolus size [170].

4.2.2 Pre-processing steps

Pre-processing of the EEG signals were performed using the EEGlab [171] toolbox running on MATLAB Version 2013a. The first step in pre-processing of the EEG signals began with downsampling the signal to 256Hz. Next, the signal was filtered using a short bandpass elliptical IIR filter with a cutoff frequency between 0.1Hz to 100Hz. To remove power supply noise, the EEG signal was filtered with a short notch elliptical IIR filter with a bandwidth between 58Hz to 62Hz. Next, the signal was segmented into separate swallows using segmentation points based on the accelerometer signal. Lastly, artifacts were removed. Previous studies have shown that independent Component Analysis (ICA) [172] implemented in EEGlab is a convenient method for removing EEG artifacts [159, 173, 174]; therefore, this same method was used to remove artifacts in the EEG signals collected in this study. Only the channels, which were contaminated with artifacts, were considered for the ICA algorithm. ICA components corresponding to artifacts were identified by visual inspection and then removed.

4.2.3 Stationarity and time-frequency approach test

Assume that each EEG channel is represented as separate discrete time series of the length $n, X(t) = \{x_1, x_2, ..., x_n\}$. In this case X(t) is a family of real-valued random variables and t is an integer $(t \in \mathbb{Z})$. If the statistical properties of the given data series are shift-invariant,

$$f_{X_{t_1}, X_{t_2}, \dots, X_{t_n}}(x_1, x_2, \dots, x_n) = f_{X_{t_{1+h}}, X_{t_{2+h}}, \dots, X_{t_{n+h}}}(x_1, x_2, \dots, x_n),$$
(4.1)

where $h \in \mathbb{Z}$, then we would say that this time series is *strongly* or *strict-sense* stationary [175]. However, if only the first two moments of the series are time-invariant,

$$E(X_{t_1}) = E(X_{t_{1+h}}), (4.2)$$

$$Cov(X_{t_1}X_{t_2}) = Cov(X_{t_{1+h}}, X_{t_{2+h}}),$$
(4.3)

then the time series would have a *weakly* or *wide-sense* stationarity.

Testing stationarity with surrogates is a time-frequency approach proposed by Borgnat et al. [160] for testing wide-sense stationarity. The essence of this approach is to compare the local spectra statistics of the signal with the global spectrum of the signal. Depending on the result of this comparison, the stationarity of the time scale can be determined. The local spectra of the signal is calculated using the multitaper spectrogram, which is defined as:

$$S_{g,K}(t,f) = \frac{1}{K} \sum_{k=1}^{K} S_g^{(h_k)}(t,f), \qquad (4.4)$$

where $S_g^{(h_k)}$ is the spectrogram computed with the k-th Hermite function, and is defined as:

$$S_g^{(h_k)}(t,f) = \left| \int g(s) h_k(s-t) e^{-i2\pi f_s} ds \right|^2,$$
(4.5)

where $h_k(t)$ is k-th Hermite function of the length T_h .

A surrogate data set is formed by multiplying the amplitude of the Fourier transform of the original signal by independent identically distributed phase sequence. After this multiplication, the inverse Fourier transform is applied to the result. A total of J of realizations is obtained. After obtaining J different surrogate realizations, the distance between the local spectra and the global spectrum (GS) is calculated. Mathematically, GS can be expressed as:

$$GS = E[s_{g,K}(t,f)]_t = \frac{1}{T} \sum_{i=1}^T S_{g,K}(i,f)$$
(4.6)

The distance between the local spectra and the global spectrum are defined as [176]:

$$D_{KL}(L,G) = \int_{\Omega} (L(f) - G(f)) log \frac{L(f)}{G(f)} df, \qquad (4.7)$$

$$D_{LSD}(L,G) = \int_{\Omega} \left| log \frac{L(f)}{G(f)} \right| df, \qquad (4.8)$$

respectively, where L(f) is the local spectrum and G(f) is the global spectrum, and f is the frequency variable over the space Ω . Next, the distance of our interest is computed as:

$$D(L,G) = D_{KL}(\tilde{L},\tilde{G}) \cdot (1 + D_{LDS}(L,G))$$

$$(4.9)$$

where \tilde{L} and \tilde{G} are the normalized parameters for L and G, respectively. For the original signal and each surrogate signal, N distances between N local spectra and GS were calculated. Furthermore, from this set of N distances, the variance was calculated. The variance for the distances of the original signal is indexed as Θ_1 , while the variance for the distances of each surrogate is indexed as vector Θ_0 . Since elements of the vector Θ_0 has Gamma distribution [160], it enables determination of the value for threshold γ . This means that for all values above γ the null hypothesis is rejected.

$$d = \begin{cases} 1 & \text{if } \Theta_1 > \gamma : \text{"non stationary"} \\ 0 & \text{if } \Theta_1 < \gamma : \text{"stationary"} \end{cases}$$

In the case when null hypothesis is rejected, we can calculate the index of non-stationarity (INS), which is defined as:

$$INS := \sqrt{\frac{\Theta_1}{E[\gamma]}},\tag{4.10}$$

where $E[\gamma]$ is the average value of the random variable. This value is approximated as the average value from the vector Θ_0 . In the case of stationary signals, *INS* is close to one, while non-stationary signals have higher *INS* values. As the signal gets more non stationary, *INS* increases.

4.2.4 Data analysis

In order to determine statistical difference between stationarity of different conditions, statistical tests were applied on indices of non-stationarity. The Kruskal-Wallis test [177] was used for testing the statistical differences between each type of swallowing task (i.e., saliva, water, nectar-thick, and honey-thick). Next, the Wilcoxon rank-sum test [178] was used for determining the statistical differences of the index of non-stationarity between different fluids, genders, and different brain regions (left frontal, right frontal, left back, and right back). A standard linear regression was used to examine the effects of age on percent of stationarity test statistic values [179].

4.3 RESULTS

We examined the stationarity of 64209 EEG channel signals using the time-frequency approach with surrogates. Figure 6 shows the percentage of non-stationarities in EEG for different stimuli. Figure 7 shows boxplots with the distribution of index of non-stationarity values for different types of fluids. According to our results, it can be seen that saliva swallowing contained more non-stationarity than other stimuli.



Figure 6: Percentage of non-stationary in EEG signals for the different fluid stimuli.

Statistical tests failed to show differences for the index of non-stationarity only between nectar-thick and honey-thick swallows (p = 0.63). All other pairwise comparisons between different stimuli (i.e., saliva and water; saliva and nectar-thick; saliva and honey-thick; water and nectar-thick; water and honey-thick) showed significant differences (p << 0.01). Sex differences were absent only for water swallows (p = 0.44), while male participants exhibited a higher non-stationarity for all other swallows (p << 0.01). Comparisons between the left and right frontal sides, as well as comparisons between left and right back sides (Figure 8.) did not show statistical difference (p > 0.05) for each respective comparison pair. However, both the left and right frontal sides have a higher index of non-stationarity than both the left and right back sides ($p \ll 0.01$). According to the linear regression, age did not affect the percent of stationarity test statistic values (p = 0.65).



Figure 7: Distribution of the index of non-stationarity for different fluid stimuli.

According to Figure 9 most of the non-stationarity can be attributed to a change in the mean over time (50 - 60%). Less than 10% of EEG demonstrated time-dependent variance alone. Changes in both mean and variance significantly contributed to the non-stationarity (i.e., 15 - 25%), as well as unknown causes (15 - 21%). However, the time-varying mean was a major cause of non-stationarity.

4.4 DISCUSSION

Our hypotheses, that sex, liquid viscosity, and brain region would significantly affect the EEG signals stationarity, were supported in most comparisons, while our hypothesis that age affects the EEG signals stationarity was not supported. The fact that swallowing is one



Figure 8: Distribution of the index of non-stationarity for each brain region for different fluid stimuli.

of the most complicated tasks performed by the central nervous system [38, 180], led us to intuitively expect non-stationarities in its EEG representation. EEG signals tend to be more non-stationary with increasing fluid viscosity. This means that the collected EEG signals during swallowing tasks using thicker liquids contain more changes in mean and variance along the signal sample duration [175]. Studies that have investigated brain activity related to eating have discovered neurons that are capable of responding to either the viscosity or the taste of food, and to both the viscosity and the taste [181]. The neuronal responses to increasing fluid viscosity during swallowing tasks manifest as modulations of the response



Figure 9: Distribution of the index of non-stationarity for each brain region for different fluid stimuli.

from the neurons (i.e., the increase or decrease), or even as activation thresholding where neurons respond only for a range of fluid viscosities [182]. The cumulative effect of neuronal activity in a given area of the cortex will proportionally change the behavior of the EEG signal and subsequently affect the number of stationary test statistic values [55].

Additionally, our results reported that sex affects the stationary test statistic values. Even though there exists little documented information about sex differences in brain activity for food stimuli [183], there is evidence of sex differences regarding the ability to inhibit brain activation elicited by food stimulation [184]. In women, it was shown that the brain regions responsible for processing visual and taste sensations showed greater activity to food stimuli than the same brain regions for men [185]. Food stimuli are associated with greater activity in the orbitofrontal cortex and prefrontal dorsolateral cortex regions of the brain; these regions are responsible mostly for emotions/rewards with regard to decision making and memory, respectively. It is known that the frontal cortex is associated with the presence of sex hormone levels during the menstrual cycle during a memory task in women [186, 187]. This leads to the conclusion that modulation of brain activity (i.e., when recording with EEG equipment) during a swallowing task (i.e., food) in these regions is correlated with sex and explains our result. This means that one of our future investigations could focus on the characterization of swallowing EEG signals with females at known points in the menstrual cycle and testing for differences. Also, this difference in stationarity between sex could be attributed to bolus size. It was shown that comfortable bolus sizes are different between men and women [170]. Men have significantly larger self-determined bolus volume than women. This difference may produce different brain activation patterns during swallowing activity. There is also evidence of possible sex differences in certain aspects of peripheral swallowing kinematics and physiology including the duration of laryngeal closure during the swallow in both healthy adults and those with dysphagia [188–191]. However it remains uncertain whether these are actual sex differences caused by anatomic and physiologic differences between adult females and males, or rather artifacts of experimental design that did not correct for proportional differences in average adult female and male aerodigestive tract caliber and size.

One of the challenges in the investigation of swallowing's neural origins is determining the brain regions involved in swallowing activities. Advanced imaging techniques, such as fMRI, PET, and MEG, provided significant contributions to the swallowing field and were used to identify many different origins of swallowing within the brain [36–41]. Our findings showed differences in stationarity between the frontal and the back part of the brain. Luan et al. [192], in their fMRI studies related to swallowing, summarize 23 different brain regions that are activated during swallowing activities. According to their report, it can be seen that the brain regions involved in swallowing are mostly concentrated in the frontal portion. This explains the statistical difference for stationarity in our data.

Stationarity describes whether a signal's statistical behavior from the future has the same statistical behavior from the past. Our investigation of stationarity determined that EEG signals during swallowing can be considered as non-stationary, and changes in mean of the signal are mostly responsible for producing the non-stationarities. Studies that investigated artifacts in EEG signals showed that swallowing activities produce a burst of brain activity with higher frequency content (compared with the baseline) and a differing amplitude variation (again, compared to the baseline) [193]. This variation of the amplitude explains origins of non-stationarities related to changes in the mean. This provides us an answer which allows us to appropriately select which technique and which signal duration length we should use in future analyses of EEG (i.e., the wavelet-based approach [194], time-frequency based phase synchrony measure [99], which are suitable for analysis of non-stationary signals). Clinically, choosing the appropriately technique for analysis is very important, because the proper choice can significantly reduce the number of false-positive and false-negative detections of swallowing abnormalities. The major future goal for this research and for all future investigations is to obtain a faster and more efficient method to determine abnormalities in patients with dysphagia. It is our aim to reduce the clinical burden associated with dysphagia screening and diagnosis, and increase its accuracy and efficiency. To expound on the direction of our aims, further investigation would determine and recognize exact components which cause non-stationarity and their origins. Furthermore, these investigations would aim to determine if those components are repeating and to what extent (i.e., does the signal have a noticeable pattern or are the patterns random), and also determining whether these components are important, or rather need to be removed from our EEG signals.

The clinical implications of this line of research may lead to yet unexplored avenues of intervention for people with swallowing disorders. Currently, revived interest in the afferent/sensory portion of the sensorimotor systems subserving swallowing function. Early research investigating peripheral stimulation of sensory receptors produced equivocal evidence of a transient increase in motor output in dysphagic patients after high doses of stimulation [195–198]. However, only recently are methods of measuring the central effects of peripheral stimulation increasingly available. Electroencephalography, a relatively portable and noninvasive procedure, may offer significant value in the treatment of neurogenic dysphagia, if researchers could elucidate whether central plasticity can be shown to occur as a result of sensorimotor treatments, and if manipulation of the process of reorganization might improve clinical outcomes. A shortcoming of our study is that the volume of swallowed boluses was not controlled for, so the possibility that bolus volume affected signal stationarity cannot be excluded. Also, in this study, swallowing tasks are administered in a specific order (saliva, water, nectar-thick, honey-thick) which leaves an open question about the influence of order on our results. In order to eliminate these limitations, a future study could include investigations with specific bolus size, and also randomize the order of administered stimuli.

4.5 CONCLUSION

In this study we investigated the stationarity of EEG signals during swallowing activities. Swallowing EEG signals were collected from 55 healthy adults who performed four different types of swallowing tasks, each with a unique viscosity fluid. We demonstrated that the EEG during swallowing tasks, can be considered as non-stationary. Additionally, we found that the viscosity of the fluids, sex, and different brain regions, all affect the index of nonstationarity values. Lastly, we found that the origins of non-stationarities were mainly due to variations in the mean.

5.0 DIFFERENCE IN BRAIN NETWORK BETWEEN SWALLOWING IN NEUTRAL AND CHIN-TUCK HEAD POSITION

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5.1 MOTIVATION

Swallowing in the chin-tuck position (head and neck flexion) is one of several different postural techniques that allow some patients with specific swallowing abnormalities to swallow more safely [161, 162]. The chin-tuck maneuver involves flexing the head and neck approximately forty-five to sixty degrees, approximating the chin to the anterior upper chest while swallowing. This posture has been shown to produce several biomechanical advantages during swallowing, for patients who have impaired ability to maintain posterior containment of food and liquids in the oral cavity until he or she is ready to swallow, or who have delayed onset of the pharyngeal stage of the swallow. Both of these conditions expose the unprotected airway to aspiration. This posture also repositions the posterior wall of the pharynx in closer proximity to the tongue base, which narrows the pharynx and subsequently the inlet to the laryngeal vestibule, thereby reducing aspiration risk and increasing airway protection [1,162–164]. In the first study of its efficacy, swallowing in the chin-tuck head position eliminated aspiration in 50% of patients who were aspirating liquids due to a delayed onset of the pharyngeal stage of swallowing [199]. However, studies showed that therapy and rehabilitation of patients with neurogenic dysphagia is highly correlated with the brain's plasticity and ability to reorganize sensory and motor cortex after events such as stroke [86]. This neural reorganization produce compensatory changes in the swallowing sensory and motor subsystems [200, 201]. Therefore, efforts to better understand the potential central nervous system effects of therapeutic interventions used to restore swallow function, might elucidate how maneuvers like the chin-tuck posture influence cerebral plasticity for swallowing after stroke and other neurological diseases.

We seek to investigate whether there are differences in brain networks when individuals swallow while in these two postures. While studies have given a physiological explanation of anatomical changes in the pharynx during swallowing in the chin-tuck position, it remains unclear whether or how this maneuver affects brain activity. Investigating this brain activity during swallowing could explain whether better control of swallowing in the chin-tuck position is simply due to the artificially modified configuration of the oropharyngeal mechanism caused by the change in posture, or if is due to alterations in muscle activity caused by a transformation in cerebral function prompted by the postural change itself. Areas of brain damage induced by neurological pathologies that cause dysphagia may overlap with the brain regions involved in the control of swallowing in the chin-tuck position. Defining characteristics of the brain network and defining brain regions involved in these commonly deployed compensatory maneuvers could potentially explain whether there is a central explanation for the limited efficacy of this technique at eliminating aspiration.

In a brain network, vertices refer to brain regions of interest, while edges are solely the functional connections between two brain regions. The position of the vertices and edges in networks define the topological structure of the brain network. Topological structures will determine whether synchronization of neural activity between brain regions is organized more regularly or more randomly. Regular and random networks have different local clustering and interconnection path length characteristics. Regular networks are characterized by higher local clustering and longer path length between brain regions. This organization provides greater functional connectivity among the brain regions; however, communication efficiency is reduced between brain regions. Random networks have a lower local clustering and shorter path length between any two connected brain regions, which provides efficient communication between brain regions, but poorer overall functional connectivity in the brain. Brain regions which are optimally organized have so-called small-world architecture topological properties. Small-world architecture topologies share some characteristics with regular networks as well as with random networks [73]. Networks characterized by small-worldness have strong local clustering (a characteristic of regular networks) and a short path length connecting any two brain regions (a characteristic of random networks). Modeling studies have shown that neural networks with small-world properties are characterized by more efficient communication between neurons [202, 203], which correlates to optimally synchronized neural activity between different brain regions within a brain network. Investigation of small-worldness is of particular interest for analysis in dysphagia research, because it could explain how neural reorganization occurs after cerebral injury, and lead researchers to interventions to both speed and optimize recovery from stroke and other neurological diseases. The small-word properties of constructed brain networks and the differences in these brain networks for each of the two head positions will also form the basis of our research. We aim to determine if better small-world properties of the brain networks for swallowing in chin-tuck position provides a neurological explanation as to why the chin-tuck head position is an effective therapeutic technique for treating dysphagia. Therefore, we hypothesized that brain networks in both the neutral and the chin-tuck head positions have small-world proprieties, and that the brain network is different for swallowing in the neutral head position than when compared with the brain network for swallowing in the chin-tuck head position.

5.2 METHODOLOGY

5.2.1 Data acquisition from participants

Data was collected from 55 healthy subjects aged from 18 to 65, all of whom provided informed consent, as well as information about age, gender, height, and weight. The protocol was approved by the Institutional Review Board at the University of Pittsburgh.

In this study, signals were collected from 64 EEG electrodes positioned according to the 10-20 international electrode system [108]. Electrode positioning was accomplished using actiCAP active electrodes (BrainProducts, Germany), and signal amplification was performed using an actiCHamp amplifier (BrainProducts, Germany). The P1 electrode was chosen as the reference (i.e., EEG voltage potentials are referenced to P1). During the entire course of the data collection, the electrode impedance was below 15 k Ω . The PyCorder acquisition software provided a 10 kHz sampling frequency, and this software was also used for saving collected data on a computer hard drive. During EEG recording, a dual-axis accelerometer was used to record vibratory correlates of pharyngeal motor activity associated with individual swallows. It also provided temporal evidence regarding the beginning and end of each swallowing event, which was then used to enable segmentation of the EEG signals into swallow-specific data sets. It was positioned on the anterior aspect of the neck at the level of the cricoid cartilage of each participant. The method for determining swallowing segments with the dual-axis accelerometer is described in detail in one of our previous studies [169]. After proper set-up of all EEG equipment was complete, participants were asked to perform five saliva swallows in their self selected time base between each swallow, first in the neutral head position and then five saliva swallows in the chin-tuck head position (Figure 10).

5.2.2 Pre-processing steps

Collected data was pre-processed with the EEGlab MATLAB toolbox [171]. All signals were downsampled to 256 Hz, and then band-pass filtered from 0.1 Hz to 100 Hz with an elliptical infinite impulse response (IIR) filter. Next, in order to remove noise associated with the power supply, all signals were filtered with an elliptical IIR notch filter with cut-



Figure 10: The experimental procedure used in this study.

off frequencies at 58 Hz and 62 Hz. Individual swallows were identified according to the segmentation points provided by the accelerometer signal. Segmented swallows were then visually inspected for the presence of possible artifacts, which could be produced by electrode activation from any source which is not cerebral activity (e.g., noisy nearby equipment and instruments, bodily movement, etc. that can produce undesirable artifacts in the EEG signal) [204]. All present artifacts were removed using the Independent Component Analysis (ICA) algorithm [172]. EEG data samples that containing an artifact that could not be removed by the ICA algorithm without significantly damaging the signal were excluded from the study. Less than 5% of EEG data samples were excluded due to excessive artifact.

5.2.3 Network constructions

Pre-processed signals were filtered with an elliptic band-pass filter into the commonly used frequency bands: Delta (< 4Hz), Theta (4 – 7Hz), Alpha (8 – 15Hz), Beta (16 – 31Hz), and Gamma (> 32Hz). The time-frequency based phase synchrony measure was used for computing connectivity matrices for each of the bands of interest.

5.2.4 Time-frequency based phase synchrony measure

Since we have shown that EEG signals during swallowing activity are non-stationary [205], connectivity matrices were formed using time-frequency based phase synchrony measure proposed by Aviyente et al. [99]. This method is called a reduced interference Rihaczek distribution.

Synchronization between any two signals can be estimated as the instantaneous phase of the signals around a certain desired frequency point. The signal in the time-frequency domain can be represented as:

$$X(t,\omega) = a(t)exp(j(\omega t + \phi(t))), \qquad (5.1)$$

where a(t) is amplitude and $\phi(t)$ is the phase of the signal. From the vantage point of the time domain for a desired frequency, the organization of two signals, x and y, can be estimated by the difference in their phase:

$$\Phi_{xy}(t) = |n\phi_x(t) - m\phi_y(t)| \tag{5.2}$$

where n and m are ratios of the locking frequencies, and ϕ_x and ϕ_y are phases of the signals, x and y, respectively.

In the event that we have a signal able to be presented as a sum of independent signals, such as, $s(t) = s_1(t) + s_2(t)$, the Rihaczek time-frequency distribution is defined as:

$$C(t,\omega) = \frac{1}{\sqrt{2\pi}} (s_1(t)S_1^*(\omega)e^{-j\omega t} + s_2(t)S_2^*(\omega)e^{-j\omega t} + s_1(t)S_2^*(\omega)e^{-j\omega t} + s_2(t)S_1^*(\omega)e^{-j\omega t})$$
(5.3)

where $S(\omega)$ is the Fourier transform of the signal. The last two terms in the equation (5.3) are the cross-terms. The problem associated with cross terms is that they exist at the same time points as original signal, and furthermore, that these cross terms occupy the same frequency bands occupied by the original signal. In order to remove the cross-terms, the Choi-Williams (CW) kernel function, which is defined as $\phi(\theta, \tau) = exp(-(\theta\tau)^2/\sigma)$, is applied to the Rihaczek distribution [206]. As a result, we obtained the reduced interference distribution of Rihaczek distribution which can be written as:

$$C(t,\omega) = \iint e^{(-(\theta\tau)^2/\sigma)} e^{(j(\theta\tau)/2)} A(\theta,\tau) e^{-j(\theta t + \tau\omega)} d\tau d\theta$$
(5.4)

where $A(\theta, \tau) = \int s(u + (\tau/2))s^*(u - (\tau/2))e^{j\theta u}du$. The $A(\theta, \tau)$ term is the ambiguity function of the original signal, and the $e^{(j(\theta\tau)/2)}$ term is the kernel corresponding to the Rihaczek distribution.

After defining the time-varying phase spectrum, the phase difference between two signals is computed as:

$$\Phi_{12}(t,\omega) = \arg\left[\frac{C_1(t,\omega)C_2^*(t,\omega)}{|C_1(t,\omega)||C_2(t,\omega)|}\right]$$
(5.5)

Calculated values for the phase difference between signal pairs are used for calculating the phase locking value (PLV). PLV is a measure of the phase difference between signal pairs, and is defined as:

$$PLV(t,\omega) = \frac{1}{N} \left| \sum_{k=1}^{N} exp(j\Phi_{12}^{k}(t,\omega)) \right|$$
(5.6)

where N is the number of trials. PLV values are in range from 0 to 1, inclusive. PLV values tend to be higher when the phase difference does not vary significantly between trials.

5.2.5 Network measures

Formed weighted undirected connectivity matrices are typically converted into binary undirected matrices. This study considers the use of binary undirected networks for the purpose of calculating network measures. Constructed weighted undirected connectivity matrices are thresholded in order to form binary networks. For a binary undirected network, a_{ij} refers to the connection between node *i* and node *j*. If a connection exists between two nodes (i.e., node *i* and node *j*), then $a_{ij} = 1$, but if $a_{ij} = 0$, then there exists no connection between two nodes. When comparing network measures, only matrices containing the same number of edges can be considered. Because there is no single accepted method for choosing a threshold value, we chose to form binary networks by thresholding the weighted networks according to the percent of density of their connections (e.g., if a threshold is set to 10%, then this means that 10% of the strongest connections will be assigned a value of 0). In this study, binary networks were constructed by thresholding from 5% (i.e., sparse connections) to 100% (i.e., full connections) of the connections using increments of 5%. For each of the constructed networks, network measures were calculated and then compared in order to extract differences and similarities between swallowing in the neutral and chin-tuck head positions. We used the Brain Connectivity Toolbox (BCT) [207] running in MATLAB to calculate each of the discussed network measures:

• The degree of the node, D_i , is the number of the edges that node *i* has with the rest of the nodes in the graph. The degree parameter is one of the fundamental network parameters in graph theory. Degree distribution is the summation of the degrees of all nodes from the network, while the mean degree is the average of all of the degrees of all nodes in the network.

$$D = \frac{1}{N} \sum_{i \in N} D_i, \tag{5.7}$$

where N is the number of nodes.

• The clustering coefficient of the *i*-th node is C_i . The clustering coefficient is a measure that describes the ratio between the number of existing edges between the nearest neighbor of the node and the maximum number of possible edges [208]. For a binary network, the clustering coefficient is calculated as:

$$C_i = \frac{2E_i}{D_i(D_i - 1)},$$
(5.8)

where E_i is the number of existing edges between adjacent nodes of node *i*, and D_i is the degree of the *i*-th node. In the case of a random network, the clustering coefficient is relatively low, whereas a higher clustering coefficient is found in networks containing more densely connected clusters [209]. The mean clustering coefficient is defined as:

$$C = \frac{1}{N} \sum_{j=1}^{N} C_j.$$
 (5.9)

• Shortest path length, L_i , is the minimum number of edges needed for one node to be connected to another node [210,211]. The mean shortest path length is the average shortest length between all possible combinations of only two nodes in the graph. Mathematically, the mean shortest path length between two nodes is defined as:

$$L_{i,j} = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} d_{i,j},$$
(5.10)

where $d_{i,j}$ the shortest path length between node *i* and node *j*.

Furthermore, the mean characteristic path length is calculated as the average of all of the shortest path lengths:

$$L = \frac{1}{N} \sum_{i \in N} L_i.$$
(5.11)

• The local efficiency, E_{local} , is defined as the mean of the efficiencies of the subgraphs which are formed from the neighborhoods of each node [212]. The local efficiency can be calculated as:

$$E_{local} = \frac{1}{N} \sum_{i \in N} E(G_i), \qquad (5.12)$$

where $E(G_i)$ is the efficiency of the subgraph, G_i .

Clustering coefficient, C, and mean characteristic path length, L, are the two parameters used to describe small-worldness. A network is considered to have small-world proprieties if it is characterized by a high clustering coefficient and short characteristic path length. Networks with small-world proprieties will have high formations of clustered subnetworks [213]. Mathematically, small-world attributes should satisfy two conditions:

$$\gamma = \frac{C}{C_{random}} \gg 1, \tag{5.13}$$

and

$$\lambda = \frac{L}{L_{random}} \approx 1, \tag{5.14}$$

where C_{random} and L_{random} are the mean clustering coefficient and the mean characteristic path length of the random network, respectively. Random networks are characterized by a low clustering coefficient and a long characteristic path length. C_{random} and L_{random} are calculated by generating many random networks for each considered network using the Markov-chain algorithm [77, 214]. Finally, small-worldness is calculated as:

$$S = \frac{C/C_{random}}{L/L_{random}},\tag{5.15}$$

where the network can be said to possess small-world proprieties if S > 1.

5.2.6 Data analysis

To determine the categorical statistical differences between features in different head positions, the Wilcoxon rank-sum test was used [178].

5.3 RESULTS

We analyzed 252 swallows in the neutral head position, and 233 swallows in the chin-tuck head position. Results of the network measures are presented as a mean value \pm standard deviation, as the function of percent of network connections.

Figure 11 summarizes the mean value for clustering coefficient for different connection densities (i.e., from 5% to 100%). The clustering coefficient did not exhibit statistically significant differences between different head positions for the *Delta*, *Theta*, and *Beta* frequency ranges (p > 0.05). Swallowing in the chin-tuck head position showed a higher clustering coefficient for a 30% connection density in the *Alpha* frequency range (p = 0.02) when compared to swallowing in the neutral head position. Furthermore, swallowing in the chin-tuck head position showed a higher clustering coefficient for connection densities of 40%, 45%, and 50% in the *Gamma* frequency range (p < 0.03) when compared with swallowing in the neutral head position.

Figure 12 summarizes the mean value for characteristic path length for different connection densities. For connection densities of 20%, 30%, 35%, 40%, 45%, 50%, 55%, and 60% in the *Alpha* frequency range, swallowing in the chin-tuck position showed a higher mean value for characteristic path length than did swallowing in neutral head position (p < 0.05). In all other frequency bands (i.e., *Delta*, *Theta*, *Beta* and *Gamma* bands) there were no significant differences between different head positions (p > 0.05).



Figure 11: The value of mean clustering coefficient, C, for different threshold percentages and for different frequency bands.

Figure 13 summarizes the mean local efficiency, and Figure 14 summarizes the mean normalized clustering coefficient, γ , and mean normalized characteristic path length, λ , for different connection densities. None of these parameters showed statistically significant differences in different head positions. However, it should be noted from Figure 14 that the swallowing activity in both head positions has the small-world proprieties.

5.4 DISCUSSION

Our hypothesis, that the constructed brain network for swallowing in the neutral and chintuck head positions has small-world properties, was supported by our results. However, our hypothesis, that the brain network is different for the swallowing in the neutral head position



Figure 12: The value of mean characteristic path length, L, for different threshold percentages and for different frequency bands.

compared with the brain network constructed for the swallowing in chin-tuck head position, was partly supported for only some of the features (i.e., clustering coefficient and shortest path length).

Studies which previously investigated the origins of the EEG frequency bands suggested that the *Alpha* EEG band is associated with inhibitory control required for efficient performance of cognitive and motor tasks [215–217], while the *Gamma* EEG frequency band is associated with preforming cognitive and motor tasks [55,218,219]. Our results showed differences in the *Alpha* and *Gamma* EEG bands. These results could be attributed to the higher cognitive demand and inhibition of the swallowing task in the chin-tuck head position. Even though the chin-tuck postural technique is considered a comfortable maneuver for a patient, performing swallowing in the chin-tuck position is not natural. The unnatural position used



Figure 13: The value of local efficiency, E_l , for different threshold percentages and for different frequency bands.

when performing the chin-tuck technique results in changes in pharyngeal dimensions [220]. These pharyngeal dimensional changes affect the attention and evoke inhibition of the person who is performing swallowing in the chin-tuck position as well as potentially altering afferent and resultant efferent signals emanating from cerebral centers involved in processing the sensorimotor activities involved in each of the two conditions. While most aspects of normal swallowing in healthy people occur spontaneously (i.e., with no conscious effort), swallowing in the chin-tuck position demands additional cognitive contributions compared with neutral swallowing. Chin-tuck position swallowing recruits additional neural regions in the brain because this type of swallowing carries a higher cognitive demand and attention to swallowing activity and a higher degree of inhibition, which explains the differences in our results.


Figure 14: The value of mean normalized clustering coefficient γ , and the mean normalized characteristic path length, λ , for different threshold percentages and for different frequency bands.

A higher clustering coefficient for swallowing in the chin-tuck head position in the Gamma EEG frequency band could also be attributed to changes in muscle recruitment for this position. The Gamma EEG frequency band is well known to be modulated by muscular recruitment demands [55, 218, 219]. During swallowing in the chin-tuck position, the various regional muscles exhibit different pre-contraction length, which can produce a change in the resultant force of their contraction [55, 164]. This change leads to a possible explanation of the differences we found in the Gamma EEG band between these two head positions. This means that decreased muscular recruitment in the chin-tuck head position correlates to greater functional connectivity in the brain, as evidenced by a higher clustering coefficient for the Gamma EEG frequency band when compared with the neutral head position. That is to say, changes in posture that reduce muscular control for a swallowing task may increase the central functional motor control for the swallowing task in the brain.

A shortcoming of this study is that participants were instructed to perform five consecutive swallows in quick succession, which limits the amount of saliva that can accumulate between swallows. It is possible that saliva-bolus volumes differed as a result of the allotted time for re-accumulation of saliva during the data collections for swallowing tasks. We also did not counterbalance the order of the two experimental, chin-tuck and control (neutral posture) positions when participants were swallowing. In order to overcome these limitations, future studies should investigate swallowing activities with other fluids with a specific bolus volume, and consistency (i.e., water, nectar-thick, honey-thick juice), or sufficiently allow saliva to re-accumulate to a specific range of volume, as well as imposing a random or counterbalanced order of presentation of these conditions. Furthermore, a future study could also investigate differences in the brain networks constructed for each of the consecutive swallows.

5.5 CONCLUSION

In this study we investigated the differences between the constructed brain networks during saliva swallowing in both the neutral and chin-tuck head positions. Swallowing EEG signals were collected from 55 healthy adults, each of whom performed five saliva swallows in both of these head positions. We demonstrated that the constructed brain networks during these two tasks exhibit small-world properties. We also demonstrated that there exists a difference between swallowing in neutral and chin-tuck position within the *Alpha* and *Gamma* frequency bands; therefore, this difference should be considered in future investigations concerning swallowing.

6.0 INFLUENCE OF VISCOSITY ON BRAIN NETWORK CHARACTERISTICS

This chapter was excerpted partly or in entirety from the following submitted journal article: Jestrović, I., Coyle, J.L., Perera S., Sejdić, E., "Functional connectivity patterns of normal human swallowing: difference among various viscosity swallows in normal and chin-tuck head positions," Experimental Brain Research, submitted in March, 2016. This article is currently under review with Experimental Brain Research.

6.1 MOTIVATION

Previous studies indicated that thicker liquids can reduce the amount of material that is aspirated when individuals aspirate thin liquids while swallowing [100] or subjectively improve swallowing symptoms in some individuals who have dysphagia with ordinary liquids. During the pharyngeal swallowing stage, the pharynx generates pressure in order to drive the bolus further into the pharynx. This pressure increases as the bolus viscosity increases. Thus, the viscosity of the bolus can change oropharyngeal swallowing coordination by utilizing a greater pressure to clear the thicker food from the pharynx, which provides safer swallowing. There are a number of studies that have investigated the influence of viscosity on swallowing characteristics using different techniques, in attempt to provide deeper insight into the physiology of this therapeutic technique [31, 169, 182, 221, 222]. However, we still do not understand how swallowing of the various fluid viscosity affects brain activity. Therefore, we are interested in analyzing difference in the brain network structure between swallowing of the various viscosity fluids. Our findings could give better explanation for the neurological origins that provide safer swallowing using this technique (i.e., increasing fluid viscosity).

6.2 METHODOLOGY

6.2.1 Data acquisition from participants

The study was approved by the Institutional Review Board at the University of Pittsburgh. 55 healthy people, aged from 18 to 65, participated in the data acquisition process. All of them signed a consent form and provided information about age, gender, height, and weight. Setup of the data collection process is described in the section 5.2.1.

After setting up all devices, participants were instructed to perform three different tasks in two different head positions. They were first asked to keep their head in neutral position and to perform five water swallows, then five nectar-thick apple juice swallows (nectarthick, Nestlé Health Care Inc., Florham Park, N.J.), and then five honey-thick apple juice swallows (honey-thick, Nestlé Health Care Inc., Florham Park, N.J.). Later, they were asked to repeat the same series of swallows in the chin-tuck head position. The unit for measuring viscosity was centipoise (cP), where 1 cP corresponds to the viscosity of water. Nectar-thick apple juice with a viscosity of 150cP is considered as mildly thick, while honey-thick apple juice with a viscosity of 400cP is considered as moderately thick. All bolus stimuli were served chilled (3-5C) in separate cups, which approximately one bolus per cup. Since there are difference between the sexes regarding comfortable bolus size [170], bolus volume was not measured, but participants were instructed to consume a comfortable amount of bolus volume. Saved data were preprocessed as is described in section 5.2.2.

6.2.2 Network constructions

Connectivity networks were constructed with time-frequency based phase synchrony measures, applied to data filtered in several frequency bands of interest: Delta (< 4Hz), Theta (4 - 7Hz), Alpha (8 - 15Hz), Beta (16 - 31Hz), and Gamma (> 32Hz). Time-frequency based phase synchrony measure is described in section 5.2.4.

6.2.3 Network measures

For analysis of the differences between two networks, it is important that they have the same number of connections. Therefore, in this study, the threshold is chosen such that the connectivity networks have the same density of connections. From the formed networks, we calculated network measures (i.e., clustering coefficient, characteristic path length, and small-worldness). In addition, the network measures were compared between swallowings of fluids of different viscosities, as well as swallowing between in head positions. Thresholding of the weighted networks and network measures used in this study are described in details in the section 5.2.5.

6.2.4 Data analysis

For all statistical analysis we used SAS® version 9.3 (SAS Institute, Inc., Cary, North Carolina). We fit a series of linear mixed models with each of the network parameters as the dependent variable; head position, viscosity, and gender, both individually and simultaneously, as fixed effect factors of interest; and a subject random effect to account for multiple measurements from the same set of participants. Appropriately constructed means contrasts were used to obtain pairwise differences. We used false discovery rate methodology to adjust the p-values for multiplicity correction. Finally, we repeated the entire analysis five times, once for each of the 5 bandwidths.

6.3 RESULTS

Results of the network measures are presented as a mean value \pm standard deviation, as the function of percent of network connections. For analyzing the pairwise comparison among various swallowing conditions, we considered in neutral head position: 245 water (thin liquid) swallows, 233 nectar-thick liquid swallows, and 228 honey-thick liquid swallows, while in the chin-tuck head position, we analyzed: 229 water swallows, 216 nectar swallows, and 217 honey swallows.



Figure 15: The value of mean clustering coefficient, C, for different threshold percentages and for different frequency bands, of three liquid viscosities swallows, in the 5 EEG frequency bands.

Figure 15 contains five figures. Each figure summarizes the mean value for the clustering coefficient as a function of connection densities (i.e., from 5% to 100%) in each of the five EEG frequency bands. Each colored line indicates a different bolus viscosity. Pairwise comparison between nectar-thick and honey-thick swallows did not exhibit significant differences in *Gamma* frequency band for the viscosity dependence, nor for the multivariable dependence of network parameters on head position, viscosity or sex (p > 0.05). However, nectar-thick swallows had a significantly higher clustering coefficient than did water swallows in the *Delta* (5% - 65%), *Theta* (15% - 90%), *Alpha* (5% - 90%), *Beta* (5%, 20% - 45%, 55%), and *Gamma* (20% - 35%) ranges (p < 0.0167) for the viscosity dependence alone as well as for multivariable dependence (p < 0.05). Also, honey-thick swallows had a significantly higher clustering coefficient than water swallows in all five frequency ranges for the viscosity dependence alone (*Delta* (5% - 25%), *Theta* (10%, 15%), *Alpha* (10%, 15%), *Beta* (5% - 15%), 40% - 85%), and *Gamma* (5% - 20%, 35% - 75%)) and for the multivariable dependence (*Delta* (5% - 25%), *Theta* (10%, 15%), *Alpha* (10%, 15%), *Beta* (5% - 15%, 40% - 85%), and *Gamma* (10% - 20%, 40% - 75%)) (p < 0.05). Furthermore, honey-thick swallows had a significantly higher clustering coefficient than nectar-thick swallows in the *Delta* (40% - 75%), *Theta* (25% - 60%), *Alpha* (25% - 75%), and *Beta* (25%, 30%) ranges for the viscosity dependence alone, and in *Delta* (40% - 70%), *Theta* (45%), and *Alpha* (25% - 75%) ranges for multivariable dependence (p < 0.05).

Figure 16 contains five figures. Each figure summarizes the mean value for the characteristic path length as a function of connection densities (i.e., from 5% to 100%) in one of the five EEG frequency bands. Each colored line indicates a different bolus viscosity. Pairwise comparison between nectar-thick and honey-thick swallows did not exhibit significant differences in *Beta* and *Gamma* frequency bands for viscosity dependence, nor for multivariable dependence of network parameters on head position, viscosity and sex (p > 0.05). However, water swallows had a significantly higher characteristic path length than nectar-thick swallows in *Delta* (20% - 40%), *Theta* (15% - 50%), *Alpha* (20% - 50%), *Beta* (35% - 50%), and *Gamma* (40% - 50%) ranges for the viscosity dependence alone, and in *Delta* (20%), *Theta* (20% - 50%), *Alpha* (20% - 50%), *Beta* (35% - 55%), and *Gamma* (40% - 50%) ranges for the multivariable dependence (p > 0.05). Also, water swallows had a significantly higher characteristic path length than honey-thick swallows in all five frequency ranges for the viscosity dependence alone (*Delta* (5% - 25%, 35% - 75%), *Theta* (10%, 15%, 30% -50%), *Alpha* (5% - 15%, 35% - 70%), *Beta* (15%, 20%, 30% - 60%), and *Gamma* (20%, 25%, 40% - 55%)) and for the multivariable dependence (*Delta* (5% - 25%, 35% - 75%),



Figure 16: The value of mean characteristic path length, L, for different threshold percentages and for different frequency bands, of three liquid viscosities swallows, in the 5 EEG frequency bands.

Theta (10%, 15%, 30% - 50%), Alpha (5% - 20%, 30% - 70%), Beta (15%, 20%, 30% - 60%), and Gamma (20%, 25%, 40% - 55%)) (p < 0.05). Furthermore, nectar-thick swallows had a significantly higher characteristic path length than honey-thick swallows in *Delta* (30% - 45%), Theta (20% - 25%), and Alpha (20% - 25%) ranges for the viscosity dependence alone, and in the *Delta* (30%), Theta (20% - 25%), and Alpha (20% - 25%) ranges for the multivariable dependence (p < 0.05).

Figure 17 contains five figures. Each figure summarizes the mean value for the smallworldness as a function of connection densities (i.e., from 5% to 100%) in one of the five EEG frequency bands. Each colored line indicates a different bolus viscosity. Pairwise compari-



Figure 17: The value of mean small-worldness, S, for different threshold percentages and for different frequency bands, of three liquid viscosities swallows, in the 5 EEG frequency bands.

 25%, 50% - 85%), Alpha (5% - 20%, 70% - 80%), Beta (5% - 80%), and Gamma (5% - 65%)) (p < 0.05). Furthermore, honey-thick swallows had a significantly higher small-worldness than nectar-thick swallows in the Delta (20% - 55%) range for the viscosity dependence alone, and in the Delta (30% - 40%) range for the multivariable dependence (p < 0.05).

Furthermore, we compared features extracted from the different head positions. Smallworldness did not show statistical difference between two head positions (p > 0.05). Also, the characteristic path length and clustering coefficients exhibited no significant difference between swallowing in neutral and chin-tuck head positions in *Delta* and *Theta* frequency ranges (p > 0.05). However, swallowing in chin-tuck head position had higher clustering coefficient than did swallowing in neutral head position in the *Alpha* (25% - 85%), *Beta* (5%, 10%, 20% - 90%), and *Gamma* (5%, 10%, 25%, 30%, 50% -80%) frequency ranges for the head position dependence alone, and in *Alpha* (5%, 25% - 85%), *Beta* (5%, 10%, 20% - 90%), and *Gamma* (5%, 10%, 25%, 30%, 50% -80%) (p < 0.05). Also, swallowing in chin-tuck head position had smaller characteristic path length than swallowing in neutral head position in the *Alpha* (10\$ - 20%, 45% - 55%, 70%), *Beta* (10%, 70% - 80%), and *Gamma* (5%, 10%, 75%) frequency ranges for the head position dependence alone, and in *Alpha* (10% - 20%, 45% - 55%, 70%), *Beta* (10%, 70% - 80%), and *Gamma* (10%, 75%) (p < 0.05).

6.4 DISCUSSION

Our hypothesis, that swallowing with various fluid viscosities has small world properties in the neutral and chin-tuck head position, was supported by our results. Our other hypothesis that the brain network is different among swallowing of various fluid viscosities, as well as between swallowing in the neutral and chin-tuck head positions, were also supported by our results. It has been reported that the *Delta*, *Theta*, and *Alpha* frequency bands exhibit changes in activation during sensory stimulation [223–225]. Swallowing is a complex process that involves different types of sensory stimulation such as smell, taste, temperature, and touch in the oral areas. Stimuli that are used in the study are characterized by different viscosities (i.e., water, nectar-thick, and honey-thick) and different tastes (i.e., water and apple juice) that affect the sensory receptors responsible for touch and the sensory receptors responsible for taste. In the previous studies, changes in the *Theta* [133,138,226], *Delta* [226], and *Alpha* [134] frequency bands during these sensory components of the swallowing were reported. Thus, changes in these three frequency bands (*Delta*, *Theta*, and *Alpha*) could be attributed to the evoked sensation that stimuli from the study produced.

Besides activation during sensory stimulation, it has been reported that the *Alpha* frequency band is also associated with the inhibition control [215–217]. Our results showed a higher clustering coefficient in the *Alpha* frequency band than for the swallowing in the chin-tuck head position. Swallowing in the chin-tuck position exhibits changes in the pharyngeal dimensions, owing to an unnatural execution of performing a swallow [220]. As a consequence, swallowing in the chin-tuck position exhibit reduced muscular recruitment in the pharyngeal dimensions when compared with swallowing in neutral head position [?]. Therefore, we can attribute changes in the alpha frequency band to the inhibition which is responsible for the reduced muscular recruitment in chin-tuck head position.

Studies that investigated cortico-muscular synchronization suggested that the *Beta* EEG frequency band is correlated to attention during certain sensorimotor tasks [227–229]. Even though consuming the thicker liquids and using the chin-tuck postural technique are considered comfortable therapeutic techniques for a patient, swallowing under these conditions is not natural. Thus, these swallows will require more of the subject's attention and a higher awareness of the swallowing task. Therefore, changes in the *Beta* EEG frequency band during swallowing of thicker liquids and swallowing in the chin-tuck head position could be attributed to the reallocation of cognitive resources towards these otherwise relatively automatic sensorimotor motor tasks.

A number of studies reported activation of the Gamma EEG frequency band during different muscular recruitment demands [55, 218, 219]. During swallowing, the tongue imparts pressure on the hard palate to propel the bolus [230, 231]. When swallowing thicker liquids, studies have shown, increased submental muscles activity, which was associated with a higher pressure on the palate during oral propulsion [232]. Also, changes in the pharyngeal dimensions during swallowing in the chin-tuck head position are associated with changes in the muscle recruitment involved in swallowing [55, 164]. Therefore, changes in the *Gamma* frequency band during the swallowing of thicker fluids and swallowing in the chin-tuck position could be attributed to changes in the muscle recruitment during these two therapeutic techniques.

Significant differences for the small-world parameter have been found among swallowing of various viscosities in the *Delta*, *Theta*, and *Alpha*. This means that the evoked sensations during swallowing of thicker liquids will have an important role in providing better communication between brain neurons. Also, significant differences for the small-world parameter have been found between swallowing in the normal and chin-tuck positions in the *Alpha*, *Beta*, and *Gamma* frequency bands. These results indicate that central nervous system resource reallocation, as well as changes in muscle recruitment, will be involved in providing better communication among the brain regions for swallowing in the chin-tuck position.

Studies showed that small-world properties correspond to easier communication between neighboring nodes as well as a more efficient communication between far apart regions [202, 203]. A greater small-world parameter for both the swallowing of thicker liquids and for swallowing in the chin-tuck position indicates that there is the possibility that a greater functional connectivity in the brain network during these therapeutic techniques contributes to better swallowing safety with the some dysphagic patients. However, The specific physiologic abnormalities that are ameliorated or facilitated by these techniques are still not clearly understood. Therefore, in order to understand how greater neural organization contributes to the better swallowing control during these therapeutic techniques, similar study should be performed on those patients that benefit from these techniques.

A limitation of our study is that the volume of the boluses was not controlled. Thus, there is a possibility that bolus volume, which has been shown to influence peripheral kinematics, could affect the brain networks. Also, the order of consumed stimuli in this study was specified and not randomized which also could have influenced our result. Another limitation is that swallowing components responsible for sensation such as: taste, bolus size, shape, and speed of motion of the liquids being processed were not strictly controlled even though they can possibly influence results of the measurements. EEG signals are very sensitive to the artifacts. Chin-tuck head posture most likely would introduce artifacts that are due to head movement. Even though we used ICA for artifacts removal, it is possible that some of the unwanted components were not removed after applying ICA algorithm. Therefore, future investigations should include measurement of the bolus size, randomizing the order of the administered stimuli, as well as investigate separately swallowing components that evoke sensation.

6.5 CONCLUSION

In this study we have investigated differences in the brain network between swallowing of various fluid viscosities in the neutral and chin-tuck head positions. Swallowing EEG signals were collected from 55 healthy adults who performed five water swallows, five nectar-thick apple juice swallows, and five honey-thick apple juice swallows, in both the neutral and chin-tuck head positions. Our results showed differences in the brain networks between swallowing of different stimuli for all frequency bands of interest (i.e., *Delta*, *Theta*, *Alpha*, *Beta*, and *Gamma*). Also, our results demonstrated difference between swallowing in the neutral and chin-tuck head positions for the *Alpha*, *Beta*, and *Gamma* frequency bands. Additionally, we showed that the functional brain network has small-world properties during swallowing.

7.0 INFLUENCE OF ATTENTION AND BOLUS VOLUME ON BRAIN ORGANIZATION DURING SWALLOWING

This chapter was excerpted partly or in entirety from the following submitted journal article: Jestrović, I., Coyle, J.L., Perera S., Sejdić, E., "Influence of attention and bolus volume on brain organization during swallowing," Brain Structure and Function, submitted in March, 2016. This article is currently under review with Brain Structure and Function.

7.1 MOTIVATION

In order to provide better rehabilitation for dysphagia patients, it is important to understand events that can influence swallowing physiology. Studies have shown that patients who have altered attention or impaired cognitive functions due to brain damage caused by stroke often manifest changes in their swallowing function [102,103]. This means that increased cognitive demands can influence swallowing activity and potentially lead to compromised swallowing safety. For example, Brodsky et al. [233] reported significantly longer reaction time during the anticipatory swallowing stage in the case of swallowing elicited by an auditory stimulus. The longer reaction time may be explained by the compromised neurological system's need for more time to process information. In addition, one previous study has shown that additional cognitive demands can influence swallowing safety in dysphagic patients [234]. These findings suggest that swallowing physiology, and consequently swallowing safety as reflected by airway protection, could be compromised when employing higher cognitive demands during swallowing tasks. Even though previous studies have provided evidence of changes in the swallowing physiology under conditions of additional cognitive demand such as those imposed by external distractions, much remains to be understood regrading how additional cognitive demands influence brain activity during swallowing. Therefore, it is germane to the investigation of neurogenic dysphagia and the effects of behavioral treatment of dysphagia, in which patients must perform volitional augmentation of oropharyngeal activities, to investigate the effects of external distraction on brain activity during swallowing.

In this study, we hypothesize that the brain network is different between no-distraction swallowing and swallowing with distraction. Brain damage induced by neurological disorders responsible for impaired cognitive function may involve the brain regions involved in swallowing control. Characterizing the brain networks during swallowing with distraction could potentially explain the reason for higher risk of aspiration within some groups of dysphagic patients [235, 236]. Also, these findings could potentially lead to the development of better rehabilitation strategies for dysphagia patients who also have altered attention or impaired cognitive function resulting from neurological disorders.

7.2 METHODOLOGY

7.2.1 Data acquisition from participants

Data was collected from 15 healthy male subjects, aged from 18 to 35. All participants provided informed consent, and also information about age, height, and weight. Setup of the data collection process is described in the section 5.2.1. The protocol was approved by the Institutional Review Board at the University of Pittsburgh.

After setting up all devices, participants were asked to consume ten 1ml water swallows, ten 5ml water swallows, and ten 10ml water swallows. Then, participants were asked to do the same thing, but this time while they watching a video which occupies their attention and involves cognitive demands. All stimuli were served chilled (3-5C) in separate cups, and participants were instructed to consume stimuli in their selfselected time base between each swallow. Saved data were preprocessed as is described in section 5.2.2.

7.2.2 Network constructions

Connectivity networks were constructed using time-frequency based phase synchrony measure, applied to data filtered in several frequency bands of interest: Delta (< 4Hz), Theta (4–7Hz), Alpha (8–15Hz), Beta (16–31Hz), and Gamma (> 32Hz). Time-frequency based phase synchrony measure is described in the section 5.2.4.

7.2.3 Network measures

We used the Brain Connectivity Toolbox (BCT) [207] running in MATLAB to calculate each of the discussed network measures:

• The *clustering coefficient* describes the ratio between the number of existing edges between the nearest neighbor of the node and the maximum number of possible edges [208]. In the case of the weighted network, the clustering coefficient is calculated as:

$$C_i = \frac{1}{S_i(D_i - 1)} \sum_{j,k} \frac{w_{ij} + w_{ik}}{2} a_{ij} a_{ik} a_{jk},$$
(7.1)

Where the parameter $S_i(D_i - 1)$ normalizes the clustering coefficient to be in the range $0 < C_i^W < 1$. a_{ij}, a_{ik} , and a_{jk} all have a value of one in a case of connection between two nodes. The mean clustering coefficient is defined as:

$$C = \frac{1}{N} \sum_{j=1}^{N} C_j.$$
 (7.2)

• The characteristic path length is the average shortest path length that connects every pair of nodes. [210, 211]. The characteristic path length contains information about connection strength between node i and node j [207], and is defined as as:

$$L_{i} = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} d_{i,j},$$
(7.3)

Furthermore, the mean characteristic path length is equal to:

$$L = \frac{1}{N} \sum_{i \in N} L_i. \tag{7.4}$$

• The *small-worldness* describes the optimal organization in the network that would provide the most efficient communication between nodes [213]. The small-world network should satisfy two conditions:

$$\gamma = \frac{C}{C_{random}} \gg 1, \tag{7.5}$$

where γ is the normalized clustering coefficient, and

$$\lambda = \frac{L}{L_{random}} \approx 1, \tag{7.6}$$

where λ is the normalized characteristic path length. C_{random} is the mean clustering coefficient of the random network, and L_{random} is mean characteristic path length of the random network. C_{random} and L_{random} are calculated as the average mean clustering coefficient and average mean characteristic path length from from the 100 random networks generated using the Markov-chain algorithm [77,214]. Finally, we can say that a network has small-world properties if its ratio:

$$S = \frac{C/C_{random}}{L/L_{random}} \tag{7.7}$$

is higher than one (S > 1).

7.2.4 Data analysis

To examine differences in swallowing brain networks based on volume (1/5/10 ml) and task (neutral/distraction), we fit a series of linear mixed models with each network characteristic as the dependent variable (i.e. volume, task and volume by task interaction) as fixed effects of interest, and a participant random effect to account for multiple measurements from the same participant. We appropriately constructed means contrasts to make pairwise comparisons between different volumes for a given task, and between different tasks for a given volume. Next, to examine whether participant age was associated with network characteristics, we fit another set of linear mixed models stratified by task and volume. We used each network characteristic as the dependent variable, and we used age as the fixed-effect independent variable, and a participant random effect to account for multiple trials of the same participant. We used SAS® version 9.3 (SAS Institute, Inc., Cary, North Carolina) for all statistical analysis.

7.3 RESULTS

We analyzed 900 swallows of various volumes in the no-distraction condition and during the distraction. Results of the network measures are presented with the mean values (\pm standard deviation) of the network measure on the vertical axis, and the frequency bands on the horizontal axis. Results are presented in colored bars that are paired based on bolus volume (blue = 1mL, red = 5mL, green = 10mL) and experimental conditions (left bar = no-distraction condition, right bar = distraction condition). Black dots on the plots represent statistically significant differences between no-distraction condition swallowing and swallowing with distraction within the frequency bands of interest.

7.3.1 Distraction effects on brain networks

Figure 18 summarizes the mean value of the clustering coefficient for various bolus volumes consumed during the two different states. No-distraction swallowing of all bolus sizes (1 ml, 5 ml, and 10 ml) exhibited a higher clustering coefficient than swallowing with distraction in the *Theta*, *Alpha*, and *Beta* frequency bands (p < 0.03). Also, 10 ml no-distraction swallowing had a higher clustering coefficient than 10 ml swallowing with distraction in the *Gamma* frequency band (p < 0.01).

Figure 19 summarizes the mean value for characteristic path length for various bolus volumes consumed during the two different states. The no-distraction swallowing showed significantly higher characteristic path length than did swallowing with distraction during 5 ml swallowing within the *Delta*, *Theta*, and *Beta* frequency bands (p > 0.02). Also, the no-distraction swallowing showed higher characteristic path length than did swallowing with distraction during 10 ml swallowing within all frequency bands of interest.

Figure 20 summarizes the mean value for the small-world parameter for various bolus volumes consumed during the two different states. Swallowing with distraction for the all bolus volumes (1 ml, 5 ml, and 10 ml) showed a higher small-world parameter than did no-distraction swallowing in the *Beta* frequency band (p < 0.03). In the *Delta* frequency band, 5 ml swallowing with distraction had a higher small-world parameter than did 5 ml no-



Figure 18: The value of mean clustering coefficient, C, for different bolus volumes and for different frequency bands. The black dots show whether there is significant statistical difference between no-distraction swallowing and swallowing with distraction.

distraction swallowing (p < 0.01). Also, in the Alpha frequency band 10 ml swallowing with distraction had a higher small-world parameter than did the 10 ml no-distraction swallowing (p < 0.01).

7.3.2 Volume effects on brain networks

In the *Beta* frequency band during no-distraction swallowing, 1 ml swallowing showed a higher clustering coefficient than did the 5 ml swallowing (p = 0.04). During swallowing with distraction, 1 ml swallowing showed a higher clustering coefficient than did the 5 ml swallowing within all frequency bands of interest (p < 0.05). Also, during swallowing with distraction, 1 ml swallowing showed a higher characteristic path length than did 5 ml swallowing within the *Delta*, *Theta*, and *Alpha* frequency bands (p < 0.05).



Figure 19: The value of mean characteristic path length, L, for different bolus volumes and for different frequency bands. The black dots show whether there is significant statistical difference between no-distraction swallowing and swallowing with distraction.

The 1 ml swallowing with distraction showed a higher clustering coefficient than did the 10 ml swallowing with distraction within all frequency bands of interest, while the 1 ml no-distraction swallowing had a lower clustering coefficient than did the 10 ml no-distraction swallowing (p < 0.05). The 1 ml no-distraction swallowing showed a lower characteristic path length than did 10 ml no-distraction swallowing within the *Beta* and *Gamma* frequency bands (p < 0.01). The 1 ml swallowing with distraction showed a higher characteristic path length than did 10 ml no-distraction swallowing within the *Theta* and *Alpha* frequency bands (p < 0.01). Furthermore, in the *Gamma* frequency band during the no-distraction swallowing and the swallowing with distraction, the 1 ml swallowing showed a higher small-world parameter than did 10 ml swallowing with distraction in the *Theta* frequency band (p = 0.02).



Figure 20: The value of mean small-worldness, S, for different bolus volumes and for different frequency bands. The black dots show whether there is significant statistical difference between no-distraction swallowing and swallowing with distraction.

During no-distraction swallowing, 5 ml swallowing had a lower clustering coefficient and characteristic path length than did 10 ml swallowing within the *Alpha*, *Beta*, and *Gamma* frequency bands (p < 0.05). Also, during no-distraction 5 ml swallowing had a lower small world parameter than did the 10 ml swallowing within the *Theta* and *Gamma* frequency bands (p < 0.01).

7.3.3 Age effects on brain network

Lastly, we investigated age dependence on the swallowing characteristics during both nodistraction swallowing and swallowing with distraction. Results did not depend on the subject's age in any of the frequency bands of interest for both swallowing conditions.

7.4 DISCUSSION

Our hypothesis, that the brain network is different for no-distraction swallowing compared with the brain network constructed during swallowing with distraction, was supported by our results. The significant statistical differences between no-distraction swallowing and swallowing with distraction are described for each frequency band of interest:

- Delta and Theta: Our results showed differences in the Delta and Theta frequency bands between no-distraction swallowing and swallowing with distraction for the clustering coefficient and characteristic path length. Changes in the lower EEG frequencies (i.e. Delta and Theta) have been previously reported as important in the process of selective attention to both auditory and visual stimuli [237]. Also, one EEG study combined with fMRI confirmed that sensory cortices such as the auditory and visual cortices are associated with the activation of the *Delta* and *Theta* EEG frequency bands [238]. This means that changes in the *Delta* and *Theta* frequency bands (i.e., higher clustering coefficient, higher characteristic path length, and lower small-worldness for no-distraction swallowing in comparison with swallowing with distraction) can be attributed to the changes in the sensory cortices produced by auditory and visual stimulation during swallowing with distraction task. Furthermore, our results also showed changes in the *Delta* and Theta frequency bands between the swallowing of various bolus volumes. Previous studies have shown that the *Delta* and *Theta* frequency bands are activated during sensory stimulation [226]. The swallowing process involves different types of the sensory stimulation such as smell, taste, and touch in the oral areas, all of which have been shown to lead to subsequent alterations in swallowing motor activation patterns [239]. The various bolus volumes used in this study differently affected sensory receptors responsible for touch, kinesthesia, and proprioception in the oral cavity. Therefore, changes in the Delta and Theta frequency bands between swallowing of the various bolus volumes may be attributable to the effects of altered afferent activity entering the swallowing brain networks caused by variations in bolus volume.
- Alpha: The Alpha frequency band is the most dominant EEG component for the conscious person. Studies showed that the activity of the Alpha frequency band is less

prominent when visual stimulation is present [240]. Furthermore, previous studies have reported differences in the Alpha waveforms between attended and unattended stimuli [241, 242]. Our results are in agreement with these finding by showing significant differences between no-distraction swallowing and swallowing with distraction for the characteristic path length and the small-world parameter in the Alpha frequency band. Thus, we can attribute these statistical differences to the different attentional demands of the no-distraction and distraction conditions while swallowing. In addition, our results showed significant statistical differences in the Alpha frequency band between swallowing of various bolus volumes. Studies have shown that EEG waveforms also exhibit changes in the Alpha frequency band during sensory stimulation [134, 137]. Therefore, changes between swallowing of different bolus volumes can be attributed to the changes in the activation of the sensory, kinesthetic, and proprioceptive receptors and pathways introduced by the variously-sized stimuli employed.

- Beta: Several previous studies have suggested that the Beta EEG frequency band is directly related to attention during sensorimotor tasks [227, 228, 243–245]. Our results demonstrated changes in the Beta frequency band between no-distraction swallowing and swallowing with distraction for the small-world parameter. Swallowing is a complex process that involves activation of a number of sensory receptors, as well as muscle activity in both the head and neck. Therefore, changes in the Beta EEG frequency band during swallowing with the distraction could be attributed to the reallocation of cognitive sources during this task [227, 228].
- Gamma: A number of studies reported changes in the Gamma EEG frequency band during various motor activities and muscle recruitment [55, 218, 219]. Brodsky et. al [246] showed that consumption of stimuli during distraction may alter swallowing activity. Naturally, altered swallowing neural activity may also cause changes in the muscular recruitment involved in performing the swallowing act [247]. Therefore, changes in the Gamma EEG frequency band during swallowing with the distraction could be attributed to motor changes introduced by compromised attention. In addition, we found significant differences in the Gamma frequency band between the swallowing of the various bolus volumes. Alteration of bolus volume influences the kinematics of oral and pha-

ryngeal activity, the upper esophageal sphincter opening, and hyolaryngeal excursion during swallowing, all of which are motor events [248–250]. Therefore changes in the *Gamma* frequency band can be attributed to the changes motor activity in response to manipulation of bolus volume that various bolus volumes produce.

Limitations of the present study: A limitation of this study is that the order of consumed stimuli was specified (i.e., 1 ml first, 5 ml second, 10 ml third), as well as the order of conditions (i.e. no-distraction swallowing first, then swallowing with the distraction). In order to overcome this limitation, future studies could randomize the order of the various manipulations of swallowing conditions. Furthermore, future studies could also investigate the influence of distraction on the swallowing of the different stimuli (i.e. nectar-thick apple juice, or solid food).

7.5 CONCLUSION

In this study we investigated the differences between the brain networks formed during swallowing of three bolus volumes in a no-distraction condition and during distraction. Swallowing EEG signals were collected from fifteen healthy male adults aged 18 to 35. Each participant performed ten 1 ml swallows, ten 5 ml swallows, and ten 10 ml swallows in both conditions. Our results showed a difference between no-distraction swallowing and swallowing with distraction in all frequency bands of interest (i.e., *Delta*, *Theta*, *Alpha*, *Beta*, and *Gamma*). In addition, our results showed differences in the swallowing of boluses of various volumes in all frequency bands of interest.

8.0 FAST WINDOWED FOURIER TRANSFORM

This chapter was excerpted partly or in entirety from the following submitted journal article: Jestrović, I., Coyle, J.L., Sejdić, E., A fast algorithm for vertex-frequency representations of signals on graphs, Signal Processing, submitted in December, 2015. This article is currently under review with Signal Processing.

8.1 MOTIVATION

In spectral graph analysis, vertex-frequency distributions of the signal on the graph could give important information about structural properties of the graph. In classical signal processing, the windowed Fourier transform is one of the most commonly used tools for extracting time-frequency information from signals [251]. However, the windowed Fourier transform has the limitation of a fixed window size that can result in poor time-frequency resolution. The S-transform originates from the windowed Fourier transform with a window size that is dependent on frequency, which overcomes limitations of the fixed window of the windowed Fourier transform method. In one of the previous studies, following the notation from classical signal processing and adopting it for signals on graphs, Shuman et al. [107] developed the for the extraction of the vertex-frequency content from signals on graphs. As WGFT also has the limitation of fixed window size, it would be straightforward to implement the graph S-transform (GST) using the algorithm for WGFT and change the size of the windowed function for different frequencies, as we have shown in the next section. However, algorithms for the WGFT and the GST have the drawback of high computation complexity, which results in long computation times for larger graphs. This means that potential applications which would use the WGFT or the graph S-transform would be impractical.

In order to overcome computational burdens, the WGFT and GST could be computed by operating on the Fourier spectrum of the signal and the Fourier spectrum of the window function. Previously, this approach has been used in classical signal processing for calculating more efficiently windowed Fourier transform and S-transform of a one-dimensional signal [165]. In classical signal processing, this fast algorithm resulted in a significantly lower computational time than the original approach. Therefore, taking advantage of operating with the signal and window spectra, the fast WGFT and GST could significantly decrease computation complexity and overall computation time.

This study presents fast algorithms for calculating WGFT and GST; therefore these new techniques are referred to as the fast windowed graph Fourier transform (FWGFT) and the fast graph S-transform (FGST), respectively. The proposed schemes were tested using synthetic test signals on graphs and then using an example of the real signal on a graph. Performances are compared between the FWGFT and WGFT algorithms, as well as between the FGST and GST methods. Results have shown significant computational improvements for the fast algorithms. These proposed algorithms could be useful for many applications that use the signal processing on graph analysis, specifically for biomedical data.

8.2 THE PROPOSED SCHEME

8.2.1 Classical signal processing case

In order to overcome computational burdens, we can calculate the windowed Fourier transform and S-transform by operating on the Fourier spectrum of the signal on the graph as well as the window function on the graph. Previously this approach has been used in classical signal processing for calculating the windowed Fourier transform of a one-dimensional signal [165]. In the classical case of the one-dimensional signal, the windowed Fourier transform and the S-transform can be calculated by performing the inverse Fourier transform from the " α domain". The α domain is defined as the Fourier transform of the windowed Fourier domain or the S-transform defined in (B.1) and (B.3) in the B section. This domain can mathematically be presented as:

$$\alpha(f',f) = \int_{-\infty}^{\infty} WFT(\tau,f)e^{-j2\pi f'\tau}du,$$
(8.1)

where the f' axis is produced by taking the Fourier transform along the τ axis of the timefrequency domain. The α domain could also be expressed as a representation of the Fourier transform of the original signal, shifted by one sample and multiplied by the Fourier transform of the windowed function:

$$\begin{aligned} \alpha(f',f) &= \int_{-\infty}^{\infty} WFT(\tau,f) e^{-jf'\tau} du \\ &= \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} x(t) [w(t-\tau),\sigma] e^{-j2\pi ft} dt \right\} e^{-j2\pi f'\tau} d\tau \\ &= \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt [W(f,\sigma) e^{-j2\pi f'\tau}] \\ &= W(f,\sigma) \int_{-\infty}^{\infty} x(t) e^{-j2\pi (f+f')t} dt \\ &= X(f'+f) \cdot W(f',\sigma) \end{aligned}$$
(8.2)

where σ will determine the size of the window function. Finally, the windowed Fourier transform and the S-transform can be recovered by applying the inverse Fourier transform on each row from the matrix which represents the α domain:

$$FWFT(\tau, f) = \int_{-\infty}^{\infty} \alpha(f', f) e^{j2\pi f'\tau} df', \qquad (8.3)$$

In the case of the windowed Fourier Transform, σ will be fixed, while for the S-transform, σ will change over various frequencies.

8.2.2 Fast windowed graph Fourier transform and fast graph S-transform

In order to adopt the algorithm from Section 8.2.1 to calculate the WGFT and the GST, we first define the α domain as a graph Fourier transform of the WGFT. The α domain can be represent as multiplication of the shifted graph signal spectrum and spectrum of the window function:

$$\begin{aligned} \alpha(\lambda_{l},\lambda_{l'}) &= \sum_{n=1}^{N} \left\{ \sum_{n=1}^{N} x(n) [T_{n}w(n,\delta)] \mathcal{X}_{l}^{*}(n) \right\} X_{l'}^{*}(n) \\ &= \sum_{n=1}^{N} x(n) \mathcal{X}_{l'}^{*}(n) \sum_{n=1}^{N} [T_{n}w(n,\delta)] \mathcal{X}_{l}^{*}(n) \\ &= \sum_{n=1}^{N} x(n) \mathcal{X}_{l'}^{*}(n) \sum_{n=1}^{N} \mathcal{X}_{l}^{*}(n) \sum_{l=0}^{N-1} \hat{w}(\lambda_{l},\delta) \mathcal{X}_{l}^{*}(n) \mathcal{X}_{l}(n) \\ &= \sum_{n=1}^{N} x(n) \mathcal{X}_{l}^{*}(n) \mathcal{X}_{l'}^{*}(n) \sum_{n=1}^{N} w(n,\delta) \mathcal{X}_{l}^{*}(n) \\ &= \hat{w}(\lambda_{l},\delta) \sum_{n=1}^{N} x(n) \mathcal{X}_{l}^{*}(n) \mathcal{X}_{l'}^{*}(n) \\ &= \hat{w}(\lambda_{l},\delta) \hat{x}(\lambda_{l},\lambda_{l'}), \end{aligned}$$
(8.4)

where $\hat{x}(\lambda_l, \lambda_{l'}) = \sum_{n=1}^{N} x(n) \mathcal{X}_l^*(n) \mathcal{X}_{l'}^*(n)$. The $\lambda_{l'}$ axis is produced by taking the Fourier transform along the vertices of the graph from the vertex frequency representation. Parameter δ will determine size of the window function. In the case $\delta = C$ is a constant, the window function $w(n, \delta)$ is fixed, and will be used for calculating FWGFT. In that case, the Fourier transform of the window function is defined as a heat kernel $\hat{w}(\lambda_l, \delta) = Ce^{-k\lambda_l}$, where C is chosen such that $||\hat{w}||_2 = 1$. For calculating the FGST, the parameter $\delta = l'$ (l' = 0, 1, ..., N-1), the window size will be frequency dependent and the window function is defined in the vertex domain as $w(n, l) = e^{-\frac{n^2\lambda_l^2}{2}}$. That means, in the case of the FWGFT, the size of the window function will be the same across all frequencies, while for the FGST, the window size will tend to be more narrow for higher frequencies.

$$\alpha(\lambda_l, \lambda_{l'}) = \hat{w}(\lambda_l, \delta) \hat{x}(\lambda_l, \lambda_{l'}), \qquad (8.5)$$

Thus, the vertex-frequency domain can be recovered by taking the inverse Fourier transform of each row from the matrix which represents the α domain of the signal on the graph:

$$FSG(n,\lambda_l) = \sum_{l'=0}^{N-1} \alpha(\lambda_l,\lambda_{l'}) \mathcal{X}_{l'}(n)$$
(8.6)

where n refers to the node, and k is the signal frequency which for the signal on the graph is the eigenvalue λ_l of the Laplacian.

Moreover, the signal x(n) can be recovered from the fast windowed graph Fourier representation using the expression:

$$x(n) = \sum_{l=0}^{N-1} \mathcal{X}_{l}(n) \sum_{n=1}^{N} FSG(n, \lambda_{l}).$$
(8.7)

8.2.2.1 Algorithm for calculating FWGFT and FGST The algorithm for calculating FWGFT and FGST is defined through the following steps:

(1) Calculate $N \times N$ matrix which represents:

$$\hat{x}(\lambda_l, \lambda_{l'}) = \sum_{n=1}^{N} x(n) \mathcal{X}_l^*(n) \mathcal{X}_{l'}^*(n).$$
(8.8)

This step has $O(N^3)$ computational complexity. Alternative way for calculating $\hat{x}(\lambda_l, \lambda_{l'})$ is using matrix calculus as:

$$\hat{X}(\lambda_l, \lambda_{l'}) = \hat{x}(\lambda_l, \lambda_{l'}) = (X * \mathcal{X}'_l) \cdot \mathcal{X}_l,$$
(8.9)

where the "*" sign represents element-by-element multiplication of the two matrices, and "·" sign represents standard matrix multiplication. The variable X is $N \times N$ matrix formed such that each row of the matrix is the signal x(n), and \mathcal{X}_l is also $N \times N$ that represents a given set of eigenvectors. (2) Form a matrix where each row is the Fourier transform of the window function \hat{w} .

$$\hat{W}(\lambda_{l},\delta) =
= \begin{vmatrix} \hat{w}(\lambda_{0},\delta_{0}) & \hat{w}(\lambda_{1},\delta_{0}) & \cdots & \hat{w}(\lambda_{l-1},\delta_{0}) \\ \hat{w}(\lambda_{0},\delta_{1}) & \hat{w}(\lambda_{1},\delta_{1}) & \cdots & \hat{w}(\lambda_{l-1},\delta_{1}) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{w}(\lambda_{0},\delta_{l'-1}) & \hat{w}(\lambda_{1},\delta_{l'-1}) & \cdots & \hat{w}(\lambda_{l-1},\delta_{l'-1}) \end{vmatrix}$$
(8.10)

In the case of FWGFT, parameter δ is constant, and $\hat{w}(\lambda_l, \delta)$ will be directly defined and each row in the $\hat{W}(\lambda_l, \delta)$ matrix will be the same. Therefore, this step will not influence computational complexity of the algorithm. However, if we calculate FGST, parameter δ is equal l', therefore, $\hat{w}(\lambda_l, \delta) = \hat{w}(\lambda_l, l')$ is defined as the Fourier transform of the window function that is dependent on frequency $(w(n, l') = \frac{|\lambda_{l'}|}{\sqrt{2\pi}}e^{-\frac{n^2\lambda_{l'}^2}{2}})$. That means that each row of the $\hat{W}(\lambda_l, l')$ matrix will be calculated by obtaining the Fourier transform of the window function that corresponds to the particular frequency point. Thus, in the case of FGST, this step will have $O(N^3)$ computational complexity.

(3) Calculate the α domain representation by multiplying each row of the $\hat{X}(\lambda_{l'}, \lambda_l)$ matrix with the appropriate window function:

$$\alpha(\lambda_{l'}, \lambda_l) = \hat{X}(\lambda_{l'}, \lambda_l) * \hat{W}(\lambda_{l'}, \delta), \qquad (8.11)$$

where the "*" sign represents element-by-element multiplication of the two matrices.

(4) Finally, the vertex-frequency content is calculated by doing the inverse Fourier transform using formula (B.5) for each row from the α(λ_{l'}, λ_l). According to the formula (B.5), the computational complexity of the inverse Fourier transform is O(N²). Thus, the computational complexity of this step will be O(N³).

In the algorithm described above, step (2) and step (4) do not affect the computational complexity. This means that the fast algorithm for calculating the vertex frequency representation will have a $O(2N^3)$ computational complexity in the case of FWGFT, and $O(3N^3)$ in the case of FGST. For the higher N, this computational complexity is a significant improvement in comparison with the original algorithm which has a $O(N^4)$ computational complexity.

8.3 PERFORMANCE EVALUATION OF VERTEX-FREQUENCY ALGORITHMS

In order to evaluate the performance of the fast WGFT and the fast graph S-transform, we generated examples of the graphs where we know the expected frequency. For that purpose we used examples of the time series as path graphs, where each time point represents nodes on the graph, and time samples are signals on the graph. Weights of the edges between nodes are equal to one. We considered a sampled sinusoidal signal that contains one frequency for the entire duration of the signal (s_1) , a signal that contains different frequencies during different time points (s_2) , and a chirp signal (s_3) (see Figure 21). Signals s_1 , s_2 , and s_3 are defined as:

$$s_1(n) = \sin(60\pi n), \quad 0 \le n \le 200$$
(8.12)

$$s_2(n) = \begin{cases} \sin(150\pi n) & 0 \le n < 65\\ \sin(50\pi n) & 65 \le n < 135\\ \sin(100\pi n) & 135 \le n \le 200 \end{cases}$$
(8.13)

$$s_3(n) = \sin((10n + kn^2)\pi), \quad 0 \le n \le 200$$
 (8.14)

Next, we calculated the vertex-frequency representation of the graph examples using the FWGFT, FGST, WGFT, and FGST methods. Then, we normalized all representations to have the same energy and calculated the mean squared error (MSE) between FWGFT and WGFT, and between FGST and GST. The MSE between the vertex-frequency representations is calculated using the formula [252]:

$$MSE = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{l=1}^{N} (\hat{Y}_{i,\lambda_l} - Y_{i,\lambda_l})^2, \qquad (8.15)$$

where $\hat{Y}_{i,k}$ is the vertex-frequency representation calculated using WGFT, $Y_{i,k}$ is the vertexfrequency representation calculated using fast WGFT, and N is the number of nodes of the graph. We also calculated the MSE between the reconstructed and the original signal, as



Figure 21: Signals used for testing the algorithm.

well as the MSE between the reconstructed and the original signal contaminated with noise. The MSE between the reconstructed and the original signal is calculated as:

$$mse = \frac{1}{N} \sum_{n=1}^{N} (\hat{x}(n) - x(n))^2, \qquad (8.16)$$

where $\hat{x}(n)$ is the reconstructed signal, and x(n) is the original graph signal. Then we compared the required computation time between the fast algorithms and the slow algorithms. Finally, we checked the performance of the fast algorithm by applying it to the real brain network. The real brain network was formed using an electroencephalography (EEG) signal recorded during a swallowing activity.

Figure 22 shows the calculated vertex-frequency representation for each graph using FWGFT, WGFT, FGST, and GST. The heat kernel $\hat{w}(\lambda_l) = Ce^{-\tau\lambda_l}$ with the $\tau = 60$ is used as the spectral domain of the window function for calculating the FWGFT and WGFT, where the constant C is chosen such that $||w||_2 = 1$. For calculating FGST and GST, we used the window function $w(n, l) = \frac{|\lambda_l|}{\sqrt{2\pi}}e^{-\frac{n^2\lambda_l^2}{2}}$ defined in the vertex domain.



Figure 22: Vertex-frequency representation of the signals s_1 , s_2 , and s_3 using FWGFT, WGFT, FGST, and GST.

According to Figure 22, one may see that all methods produce the expected results. Results showed that the mean squared error (MSE) between the normalized representations of FWGFT and the normalized representations of WGFT, as well as between the normalized representations of FGST and the normalized representations of GST are less than 10^{-31} for the all signals used in testing $(s_1, s_2, \text{ and } s_3)$.

The MSE between the original and the signal reconstructed using FWGFT or WGFTfor all three test signals is significantly less than 10^{-29} , while for FGST and GST, it is slightly higher, but still it is less than 10^{-6} . The MSE between the original signal contaminated with the noise and the reconstructed signal did not change across the different levels of noise using any of the four algorithms (FWGFT, WGFT, FGST, and GST). This means that noise will have no effect on the reconstruction error for each vertex-frequency technique used in this study.

Figure 23 shows the computation time for the FWGFT versus WGFT and the computation time for the FGST versus GST. From these results, it is obvious that the computation time improved for the fast algorithms in comparison to the original algorithms. One may see from the graph containing 5000 nodes that the computation time for the WGFT and GST is around 40 minutes. Using this fast approach, computing vertex-frequency changes of the signal on the graph with 5000 nodes will take less than one minute.



Figure 23: The required time for computing WGFT versus FWGFT and GST versus FGST for the different graph sizes. Blue lines represent computation time for the original algorithms while red lines represent computation time for the fast algorithms.

8.3.1 Performance evaluation using real graph signals of the brain network

The proposed scheme was also tested on the example of a brain network formed from the EEG signals recorded during a swallowing activity. The data collection process, swallowing segmentation, and pre-processing steps are described in our previous study [205]. Weighted connectivity networks were formed using the time-frequency based phase synchrony measure (i.e., reduced interference Rihaczek distribution) proposed by Aviyente et al [99]. From the formed weighted connectivity networks, weak connections were removed by applying a threshold on the network. Then, in order to provide the signal on the graph, we formed a line graph [253] from the weighted connectivity network that corresponded to the synchronization

between signals from the EEG electrodes during swallowing. The process of forming the line graph is provided in Appendix A. With the new formed line graph, each vertex will represent one edge from the original graph. Vertices from the line graph will be connected if corresponding edges from original graph are connected to the same node.



Figure 24: Vertex-frequency representations of the sample signals representing the brain network formed with EEG signals recorded during swallowing using FWGFT, WGFT, FGST, and GST.

Figure 24 shows the calculated vertex-frequency representation for each graph using FWGFT, WGFT, FGST, and GST. The FWGFT and WGFT are calculated from the spectral domain of the window function. A heat kernel represents the spectral domain of the window function, and it is defined as $\hat{w}(\lambda_l) = Ce^{-\tau\lambda_l}$ with $\tau = 0.05$. When calculating the FGST and GST, we used the window function $w(n, l) = \frac{|\lambda_l|}{\sqrt{2\pi}}e^{\frac{n^2\lambda_l^2}{2}}$. In both cases the constant C is chosen such that $||w||_2 = 1$. Results showed that the MSE for the normalized vertex-frequency representation between the FWGFT and WGFT was less than 10^{-6} .

8.4 DISCUSSION

In this study, we have described the basic signal processing operations on graphs: the graph Fourier transform, translation on graphs, modulation on graphs, the WGFT, and the graph S-transform. We have also described algorithms for calculating the fast WGFT and the fast graph S-transform. We showed that FWGFT and FGST have a significantly lower computational complexity than WGFT and GST [107].

Figure 22 summarizes the vertex-frequency representations for the signals s_1 , s_2 , and s_3 on the path graph, and Figure 8 summarizes the vertex-frequency representation for an example of the real signal on the swallowing brain network formed using EEG signals. From Figure 22 it can be seen that all used methods produced results that would match a spectrogram from classical signal processing. As in classical signal processing, the *FWGFT* and *WGFT* have the limitation of a fixed window size. *FGST* and *GST* overcome the limitation of a fixed window by using a window size that is dependent on frequency. It is well known from classical signal processing that a wide window gives good frequency resolution but poor vertex resolution, while a narrow window trades improvements in frequency resolution for decreased quality of the vertex resolution. Such trends can be seen from Figure 8 in the signal on graph vertex-frequency representations using *FGST* and *GST*, where we have poor vertex resolution at the very low frequencies and poor frequency resolution at the very high frequencies. Therefore, just as in classical signal processing [254], we can say that *FGST* and *GST* provide a good concentration of the energy at lower frequencies, but poor concentration of the energy at higher frequencies.

Results of the MSE between the original and the reconstructed signal showed that FWGFT and WGFT show an almost perfect reconstruction of the signal. However, the FGST and GST exhibited higher MSE between the original and the reconstructed signal. This means that varying window size in the case of the FGST and GST affects the reconstruction formula. Our results also showed that the MSE between the original and the reconstructed signal contaminated with noise is approximately constant for various noise levels. This means that noise will have no effect on the reconstruction error when we use any of the methods of analysis for the vertex-frequency changes in the graph signal.
Finally, we showed significant computation time improvement in the algorithm for the FWGFT and FGST in comparison with the original WGFT and GST (see Figure 23). Also, from Figure 23 it can be seen that the computation time for the WGFT and GST is likewise good for smaller graphs. However, as the number of nodes increases, computation time progressively increases as well. Fast approaches could be applied in any application that is sensitive to time or memory, or on those applications which deal with large graphs.

Figure 24 summarizes the vertex-frequency representations of the brain network during healthy human swallowing activity. From the figure, it can be seen that the vertex-frequency representations of healthy swallowing have a distinctive pattern. Deeper investigation of brain network swallowing patterns could provide a way to recognize swallowing difficulties caused by neurological conditions and abnormal brain activities, and provide insight into contributions of the higher central nervous system mechanisms on swallowing physiology in healthy and pathological conditions. In the future, this approach could potentially lead to developing improved diagnostic and rehabilitation techniques for patients with swallowing difficulties.

8.5 CONCLUSION

In this study, we developed fast algorithms for the WGFT and the graph S-transform. The developed algorithms are referred to as the fast windowed graph Fourier transform and the fast graph S-transform. Performance of the fast algorithms are evaluated and compared with the standard WGFT and the graph S-transform algorithms using synthetic graph signals and a real graph signal. Results showed that the proposed approach significantly decreases the computation time for extracting vertex-frequency information from graph signals. We also showed that the inverse formula for the proposed algorithms provides almost perfect reconstruction. Additionally, we showed that the signal reconstruction is not affected by noise.

9.0 DIFFERENCES IN THE BRAIN NETWORK BETWEEN CONSECUTIVE SWALLOWS - OPTIMIZED WINDOWED FOURIER TRANSFORM

This chapter was excerpted partly or in entirety from the following submitted journal article: Jestrović, I., Coyle, J.L., Sejdić, E., "Differences in brain networks during consecutive swallows detected using an optimized vertex-frequency algorithm," IEEE Journal on Selected Topics in Signal Processing, Special Issue on Advanced Signal Processing in Brain Networks, submitted in November, 2015. This article is currently under review with IEEE Journal on Selected Topics in Signal Processing, Special Issue on Advanced Signal Processing in Brain Networks.

9.1 MOTIVATION

Consecutive swallows could significantly influence swallowing control for people who have impaired clearance of swallowed material from the throat or impaired muscles that are involved in swallowing control (i.e., due to fatigue in the muscles of the larynx involved in swallowing or due to residue in the pharynx [104–106, 166–168]). Therefore, understanding the differences in the brain networks between consecutive swallows could be very important for future investigations. Figure 25 shows the brain network of three healthy consecutive swallows. Even visually, we can notice that there is some difference in the brain network structure between each swallow. However, result did not show statistical differences for the clustering coefficient and characteristic path length of each node from the network between these three swallows. Thus, in order to understand the difference in the brain network between consecutive swallows, we need to use a different approach.



Figure 25: Brain network of four consecutive swallows.

Signal processing on graphs enables deeper insight into the structure of the graph, which provides more information about the topological properties of the graph than classical graph theory provides. In this case, the WGFT [107] could be useful in extracting information about the identity of the brain network for each swallow. In addition, with the WGFT, we will be able to see how the graph frequency changes among the vertices between consecutive swallows. However, the FWGFT has limitations regarding the fixed window size. Choosing too wide or too narrow window can result in poor resolution of the representation of the graph's frequency content. On the other hand, FGST suffers in some cases from bad energy concentration in the vertex-frequency representation. One way to optimize window size with the WGFT and the graph S-transform is to directly optimize energy concentration in order to minimize the spread of the energy beyond the edges of the signal components [255]. When applied to the swallowing brain network, the optimized algorithm could provide more reliable information about the differences in vertex-frequency representations of the swallowing brain network between consecutive swallows.

9.1.1 Effect of window size on windowed graph Fourier transform

In order to provide a better understanding of the effect of window size on the WGFT, we will consider a simple example of 3 graphs which contain 9 nodes and variously positioned edges (Figure 26). Connections between all nodes are equal to one. Values of the nodes represent samples of a signal on the graph. Depending on the values of nodes and the position of edges between them, we could draw approximate assumption regarding whether the frequency of the signal on graph is lower or higher.



Figure 26: A signal f on the path graph.

We will calculate the WGFT for all three graphs using equation B.9. As a window function we use a heat kernel $\hat{g}(\lambda_l) = Ce^{-\tau\lambda_l}$, where C is chosen such that $||g||_2 = 1$. Since the parameter τ can control the width of the window, we will calculate the WGFT for all three graphs using different values for τ . Figure 27 shows the shape of the window for the different values of τ that were used for calculating the vertex-frequency representation of the graph G1.

Figure 28 shows the vertex-frequency representation of all three graphs for different values of τ . According to the figure, we can tell that the results match with the intuition, but also the resolution of the representation is highly dependent on the window size. A wide window gives better vertex resolution but poor frequency resolution, and vice versa. Therefore finding an optimal window size is important for producing the most accurate result.



Figure 27: A kernel function of the graph G1 for the different values of τ .

9.2 THE PROPOSED SCHEME

For $\hat{w}(\lambda_l) = Ce^{-k\lambda_l}$, the window size depends on the parameter k (i.e., as k will tend to be more narrow). Consequently, improvement of the energy concentration with the graph S-transform could be accomplished by introducing a new parameter, p, into the window function. Thus, the new window function used in the graph S-transform would be defined as $w(\lambda_l) = \frac{|\lambda_l|^p}{\sqrt{2\pi}}e^{-\frac{n^2\lambda_l^{2p}}{2}}$, where parameter p will be optimized. In order to automatically calculate an optimal window size, concentration measure (CM) [256] was used.

CM is defined as:

$$CM(\tau) = \frac{1}{\sum_{n=1}^{N} \sum_{l=0}^{N-1} |S^{\tau} f(n, l)|}$$
(9.1)

where $S^{\tau}f(n,l)$ is the vertex-frequency representation and τ is the parameter that we want to optimize. In the case of FWGFT, τ will be k, while in the case of FGST, τ will be p. Optimal τ can be calculated as a vertex-invariant constant or as a vertex dependent parameter ($\tau(n)$). In the following subsections both algorithms are described.



Figure 28: Vertex-frequency representation of G1, G2, and G3 graphs, for different values of τ .

9.2.1 Algorithm for optimizing vertex-invariant τ

To calculate the optimal value for the parameter τ , we will have to calculate the vertexfrequency representation using different values of τ ($S^{\tau}f(i,l)$). In the next step, each calculated vertex-frequency representation will be normalized, in order to provide equal energy:

$$\overline{S^{\tau}f(n,l)} = \frac{S^{\tau}f(i,l)}{\sqrt{\sum_{n=1}^{N}\sum_{l=0}^{N-1}|S^{\tau}f(n,l)|^2}}.$$
(9.2)

Using equation (9.1), concentration measures will be calculated for each normalized vertexfrequency representation:

$$CM(\tau) = \frac{1}{\sum_{n=1}^{N} \sum_{l=0}^{N-1} |\overline{S^{\tau} f(n, l)}|}.$$
(9.3)

In addition, the optimal parameter τ , will be determined as:

$$\tau_{opt} = \max_{\tau} [CM(\tau)]. \tag{9.4}$$

9.2.2 Algorithm for optimizing vertex-dependent $\tau(n)$

In the first step, we will calculate the vertex-frequency representation of the signal using the formula described in the Section 8.2.2, and from that vertex-frequency representation we will calculate the energy, E. Then, the vertex-frequency representations will be calculated by using the different values of τ ($S^{\tau} f(i, l)$). Vertex-frequency representations will be normalized as:

$$\overline{S^{\tau}f(n,l)} = \sqrt{E} \frac{S^{\tau}f(n,l)}{\sqrt{\sum_{n=1}^{N} \sum_{l=0}^{N-1} |S^{\tau}f(n,l)|^2}}.$$
(9.5)

The concentration measure that corresponds to each vertex will be calculated as:

$$CM(n,\tau) = \frac{1}{\sum_{l=1}^{N} |\overline{S^{\tau}f(n,l)}|}.$$
(9.6)

Finally, the optimal $\tau(i)$ for the each vertex will be the maximized concentration measure:

$$\tau(n)_{opt} = \arg\max_{\tau} [CM(n,\tau)].$$
(9.7)

9.3 PERFORMANCE EVALUATION OF THE OPTIMIZED VERTEX-FREQUENCY ALGORITHMS

The algorithms were evaluated using the test graph signals, where the expected frequency was known. For a test signal, we used a time series as the path graph, where each time points represents nodes on the graph, and time samples are signals on the graph. The weights of the edges between nodes are equal to one. The test signals s_1 and s_2 are defined as (see Figure 29):

$$s_1(n) = \begin{cases} \cos(15\pi \ln((10n - 10.5)^2 + 1)) & 0 \le n < 100\\ \cos(15\pi \ln((10n - 10.5)^2 + 1)) + \cos(200\pi n) & 100 \le n < 180\\ \cos(15\pi \ln((10n - 10.5)^2 + 1)) & 180 \le n \le 200 \end{cases}$$
(9.8)

$$s_2(n) = \cos[40\pi(n-0.5)\arctan(21n-10.5) - 20\pi\ln((21n-10.5)^2 + 1)/21] + \sin(\pi(80n-kn^2))$$
(9.9)

Next, we calculated FWGFT, FGST, optimized FWGFT, and the optimized FGST. For



Figure 29: Signals used for testing the algorithm.

calculating optimized FWGFT as a value of τ , we used a range of values from 10 to 70 with increments of 1, while the τ parameter was equal to 35 for calculating the FWGFTdefined in (8.6). For calculating the optimized FGSTs, a range of p values from 0.01 to 1 with increments of 0.01 were used. Vertex-frequency representations for the test signals s_1 and s_2 are presented in Figures 30 and 31 respectively.



Figure 30: Vertex-frequency representations for the test signal s_1 .

The concentration measure algorithm showed that the optimal k value for calculating FWGFT for s_1 is equal to 25, while that for calculating FWGFT for s_2 , it is equal to 5. Also, the concentration measure algorithm showed that the optimal p value for calculating FGST for s_1 is equal to 0.57, while for calculating FGST for s_2 is equal to 0.79. Improvements in the representation of the optimized algorithm can be seen clearly in both Figures 30 and 31. The performance measure of each representation was calculated using the formula:

$$\Xi = \left(\sum_{n=0}^{N-1} \sum_{k=1}^{N} |\overline{S^{\tau} f(n,k)}|\right)^{-1}, \qquad (9.10)$$

where $|\overline{S^{\tau}f(n,k)}|$ is the normalized vertex-frequency representation. This performance formula is actually a concentration of the vertex-frequency representation. In addition, the



Figure 31: Vertex-frequency representations for the test signal s_2 .

performance measure is also estimated for the signals on graph contaminated with noise (SNR=10dB and SNR=20dB). The results of the performance measure for each vertex-frequency representation for both signals are shown in the Table 4. According to Table 4, the performance measure value does not show improvement for the optimized algorithms when it is used for the *FWGFT*. However, the *FGST* performance measure value is the highest for each representation that used vertex-invariant optimized window size. Table 4 also shows that with the higher level of noise, the performance measure value tends to be lower.

	Noise free		SNR=20dB		SNR=10dB	
	Ξ_{s1}	Ξ_{s2}	Ξ_{s1}	Ξ_{s2}	Ξ_{s1}	Ξ_{s2}
Standard WGFT	0.0096	0.0093	0.0071	0.0070	0.0063	0.0063
Vertex-invariant optimized $WGFT$	0.0097	0.0093	0.0073	0.0072	0.0064	0.0064
Vertex dependent optimized $WGFT$	0.0094	0.0093	0.0091	0.0090	0.0081	0.0081
Standard $FGST$	0.0086	0.0081	0.0071	0.0068	0.0065	0.0066
Vertex-invariant optimized $FGST$	0.0094	0.0089	0.0073	0.0070	0.0068	0.0068
Vertex dependent optimized $FGST$	0.0096	0.0088	0.0092	0.0086	0.0080	0.0077

Table 4: Performance measure for the considered vertex-frequency representations.

9.4 ANALYZING THE DIFFERENCES BETWEEN CONSECUTIVE SWALLOWS

9.4.1 Data acquisition

55 healthy people, between the ages of 18 and 25, participated in the data collection process. Data collection setup is described in detail in section 5.2.1. After setting-up devices for data acquisition, the participants were asked to perform five saliva swallows, five water swallows, five nectar-thick apple juice swallows (nectar-thick, Nestlé Health Care Inc., Florham Park, N.J.), and then five honey-thick apple juice swallows (honey-thick, Nestlé Health Care Inc., Florham Park, N.J.) The unit for measuring viscosity was the centipoise (cP), where 1 cP corresponds to the viscosity of water. The nectar-thick apple juice with a viscosity of 150cP is considered mildly thick, while the honey-thick apple juice with a viscosity of 400cP is considered moderately thick. The water, nectar, and honey were served chilled (3-5C) in separate cups. Since previous studies documented differences in comfortable bolus size between the sexes [170], the bolus size was not measured. However, participants were instructed to consume a bolus of comfortable amount of bolus volume.

9.4.2 Pre-processing steps; forming graphs and signals on graphs

The collected data were further pre-processed as is described in section 5.2.2. The weighted connectivity networks were formed using the time-frequency based phase synchrony measure described in section 5.2.4. The calculated swallowing brain networks were averaged across the conditions for first, second, third, forth, and fifth swallows. Depending on the density levels of connection, the brain networks will have different sparsity. Previous studies have shown that networks with more than 40% of the connection can be considered as too dense [212,213]. Thus, in the formed connectivity matrices we applied a threshold such that we keep 40% of the strongest connections in the network.

The most convenient way to provide signals on graphs is to form a line graph from the original graphs, which corresponds to the synchronization between signals from the EEG electrodes during swallowing [253]. With the newly formed line graphs, the weights of the edges from the original graph will correspond to the nodes of the line graph, while the new nodes will be connected if edges from the original graph that correspond to the vertices of the line graph are connected to the same node. All connections from the new line graph will have weights equal to one. Thus, we define an undirected, unweighted graph $G = \{\mathcal{V}, \mathcal{W}\}$, where \mathcal{V} is a set of vertices in the graph, and \mathcal{W} is the connectivity matrix of the graph.

9.4.3 Analysis of the differences between conditions

For forming vertex-frequency representations of the swallowing brain networks, we used vertex-invariant optimized FWGFT and vertex-invariant optimized FGST. In order to estimate the differences between vertex-frequency representations between consecutive swallows, the vertex-frequency representations were converted to the gray scale image. The difference between gray scale images that represent the vertex-frequency representations between consecutive swallows were estimated using structural similarity index [257]. The structural similarity index estimates similarity between two images, where the maximum similarity structural similarity index is equal to one.

9.4.4 Results

The vertex frequency representations were calculated using 252 saliva swallows, 245 water swallows, 233 nectar-thick liquid swallows, and 228 honey-thick liquid swallows. The results were presented as a vertex frequency representation of the line graph formed from the averaged swallowing brain networks for the first, second, third, forth, and fifth swallows of each saliva, water, nectar, and honey swallows.

Figure 32 summarizes FWGFT representation of the signals on graphs that correspond to the brain network during consecutive swallowing of various stimuli, while in Figure 33 summarizes the FGST representation of the signals on graphs that correspond to the brain network during consecutive swallowing of various stimuli. All vertex-frequency representations have the most dominant energy at the lower frequencies. Also, each representation shows the frequency burst, which is the most prominent around the 300th and around 700th node.

Table 5 summarizes the structural similarity index for the standard FWGFT and standard FGST between consecutive swallows among various viscosity fluids, while Table 6 summarizes the structural similarity index for the optimal FWGFT and optimal FGSTbetween consecutive swallows of fluids of the various viscosities. According to the tables, the mean structural similarity index between consecutive swallows tends to be lower for thicker liquids. Also, the values of structural similarity index between consecutive swallows for the standard and the optimal FWGFT are very similar, while the values of structural similarity index between consecutive swallows for the standard FGST are higher than values of structural similarity index between consecutive swallows for the optimal FGST.



Figure 32: The vertex frequency representation of the brain network during consecutive saliva, water, nectar, and honey swallows.

9.5 DISCUSSION

In this study, we have introduced an algorithm for optimizing the window size for calculating FWGFT and FGST. We have shown that the optimized window size provided a higher energy concentration for the vertex-frequency representation. In addition, we used this algorithm to investigate differences between signals on the brain networks for consecutive swallows.

From Figures 30 and 31 the improvement of the vertex-frequency representation of the algorithms with optimal window size can be seen. This improvement is confirmed by Table 4, where the results show a higher performance measure value for the algorithm with the



Figure 33: The vertex frequency representation of the brain network during consecutive saliva, water, nectar, and honey swallows.

optimized window size. Even though the optimized FWGFT and the optimized FGST have higher energy concentrations for the vertex-frequency representation, these optimized algorithms have a higher computational complexity in comparison with the standard FWGFTand FGST. A higher computational complexity resulted from the optimization procedure, which is necessary for the parameter tuning. However, in comparison with the WGFT and graph S-transform [107], the optimized FWGFT and the optimized FGST still exhibit a significantly lower computational complexity.

Our hypothesis, that the vertex-frequency information of the brain network is different between consecutive swallows, is supported by our results. Swallowing is a complex process, which involves the activation of many sensory receptors in the oral cavity, as well as the

	Standard FWGRFT				Standard FGST				
Swallows	Saliva	Water	Nectar	Honey	Saliva	Water	Nectar	Honey	
comparison									
1-2	0.6120	0.4627	0.4275	0.4362	0.5075	0.2776	0.2619	0.2331	
1-3	0.6350	0.4434	0.4597	0.4354	0.4937	0.2557	0.2746	0.2505	
1-4	0.5972	0.4193	0.4328	0.4205	0.5009	0.2435	0.2582	0.2235	
1-5	0.6555	0.4474	0.4022	0.4352	0.4982	0.2524	0.2512	0.2643	
2-3	0.6188	0.4341	0.4685	0.3958	0.5454	0.2387	0.2601	0.2245	
2-4	0.6146	0.3934	0.4149	0.4028	0.5937	0.2288	0.2271	0.2263	
2-5	0.6284	0.4402	0.3919	0.4280	0.5643	0.2381	0.2443	0.2514	
3-4	0.6113	0.3981	0.4579	0.3910	0.5565	0.2333	0.2697	0.2288	
3-5	0.6486	0.4264	0.4225	0.3901	0.5508	0.2537	0.2720	0.2263	
4-5	0.6238	0.4153	0.4080	0.4161	0.5747	0.2603	0.2490	0.2498	
mean	0.6245	0.4280	0.4286	0.4151	0.5386	0.2482	0.2568	0.2378	

Table 5: Structural similarity index for the standard FWGFT and standard FGST between consecutive swallows.

activation of several head and neck muscles. Previous studies have shown that changes in EEG wave forms during voluntary movement can be observed in the sensorimotor areas of the cortex. Consecutive swallows can cause neuromuscular fatigue, which can result in a reduced level of muscular force involved in performing this activity [258]. Therefore, the results can be attributed to the changes caused by the activation of the sensorimotor neurons due to neuromuscular fatigue.

Similarity between vertex frequency representation of the brain networks during consecutive swallows tends to be lower for the thicker liquids. Previous studies investigating brain activity during eating reported that different groups of neurons are activated due to various food viscosity, or due to the various food taste, or sometimes due to various viscosity and taste combinations [181]. It has also has been reported that some neurons are only activated by specific ranges of fluid viscosities [182]. This means that some neurons will have increased or decreased activity due to various viscosities. Also, studies have shown that consuming

	Optimal FWGRFT				Optimal <i>FGST</i>				
Swallows	Saliva	Water	Nectar	Honey	Saliva	Water	Nectar	Honey	
comparison									
1-2	0.6151	0.4502	0.4037	0.4000	0.0263	0.0375	0.0437	0.0338	
1-3	0.6358	0.4198	0.4478	0.4095	0.0704	0.0380	0.0426	0.0315	
1-4	0.6052	0.3978	0.3948	0.3964	0.0525	0.0425	0.0386	0.0250	
1-5	0.6554	0.4182	0.3882	0.3998	0.0879	0.0299	0.0324	0.0258	
2-3	0.6366	0.4016	0.4374	0.3787	0.0250	0.0391	0.0509	0.0273	
2-4	0.6427	0.3834	0.3890	0.3787	0.0323	0.0250	0.0412	0.0331	
2-5	0.6467	0.4055	0.3890	0.3787	0.0324	0.0444	0.0387	0.0245	
3-4	0.6426	0.3782	0.4412	0.3736	0.0474	0.0322	0.0388	0.0280	
3-5	0.6666	0.4111	0.4159	0.3619	0.0655	0.0378	0.0324	0.0196	
4-5	0.6590	0.4000	0.3938	0.4029	0.0504	0.0342	0.0320	0.0205	
mean	0.6406	0.4066	0.4093	0.3913	0.0491	0.0361	0.0392	0.0270	

Table 6: Structural similarity index for the optimal FWGFT and optimal FGST between consecutive swallows.

thicker liquids causes an increase in submental muscular activity [232], which increases the traction forces applied to the hyolaryngeal complex, this leading to airway closure during swallowing and opening of the upper esophageal sphincter. The changes in the muscle activity also cause a change in neural activity in the brain [55,218]. Increased or decreased neural activity cause changes in EEG waveforms, which will affect the weights of the connection in the swallowing brain network. The changes in the connection weights in the swallowing brain network will directly modulate signals on the line graphs that correspond to the swallowing brain network. Thus, the lower similarity between the vertex frequency representations during consecutive swallows of thicker liquids could be attributed to the changes in the neural responses that the higher viscosity fluids produce.

According to Table 5 and 6, the structural similarity index is much higher for the dry swallows (i.e., saliva swallows) as compared to the wet swallows (i.e., water, nectar-thick, and honey-thick). During swallowing, sensory receptors in the oral cavity capture information

about the bolus size, shape, temperature, smell, and taste. The captured information is sent to the sensorimotor cortex and a motor plan is produced by the swallowing central pattern generator in the brainstem [33]. In the case of saliva swallows, sensory information such as temperature, smell, and taste, are not captured. Thus, the neurons which are involved in processing this sensory information, will not be activated. Also, this study was conducted such that participants consumed wet stimuli from cups. Consumption of stimuli from cups involves additional head movements, which activate additional neurons responsible for motor activation. Thus, a higher structural similarity index between vertex-frequency for the consecutive swallows could be attributed to the reduced motor activity and sensory stimulation of the dry swallows.

Figures 32 and 33 show that the vertex-frequency representations of the swallowing brain networks mostly contain low frequency components. In addition, they display the frequency burst around the 300th and around the 700th node. In the line graph, the connections of the newly formed nodes depend on the position of the edges in the original graph. By applying thresholds on the brain networks, the low connections are dismissed, which disable the direct connection between some neighboring nodes in the line graph. This indirect connection results in more oscillations in the signal between neighboring nodes, resulting in higher frequency in the vertex-frequency representation. This means that the position of the weak connections and proper thresholding of the brain network can be very important for future studies, as it provides distinctive information about the brain network.

A limitation of this study is that the bolus size was not measured. There is a possibility that a non-uniform bolus size could affect the brain network in different sized subjects. Another limitation is that the order of consumed stimuli was the same for each participant (i.e., saliva first, water second, nectar-thick third, honey-thick forth). The order of consumed stimuli could also potentially influence the results of the formation of brain networks. Thus, future investigations should consider measuring of the bolus size and scaling bolus volume to a standard proportion of bolus volume to patient size, as well as randomizing the order of consumed stimuli.

9.6 CONCLUSION

In this study, we presented an algorithm, which provides a higher energy concentration of the FWGFT and FGST. The algorithm was based on the window size optimization, which uses the concentration measure. In order to optimize the window size with the graph Stransform, we introduced a new parameter, which controls the window size that corresponds to the each frequency point. The algorithm was tested using two synthetic signals. The results of the tests showed that the optimized FWGFT and the optimized FGST have a higher energy concentration than do FWGFT and FGST. In addition, we used the proposed algorithm to investigate differences between consecutive swallows by analyzing vertex-frequency information from the swallowing brain networks. For this analysis, we collected signals from 55 healthy people, who performed five saliva, five water, five nectar thick, and five honey thick swallows. We showed that there are differences in the vertexfrequency representations of the brain networks between consecutive swallows, which can be attributed to changes in activation of the sensorimotor neurons due to fatigue in the muscular force. Furthermore, we showed that differences between consecutive swallows are higher for the thicker liquids, which corresponds to changes in cortical activation due to various sensory stimuli.

10.0 SUMMARY

10.1 CONCLUSION

In this dissertation we investigated brain activity during swallowing using graph theory and the signal processing on graph approach applied to EEG recordings. To our knowledge, there is no previous study that investigated swallowing brain activity using this approach. Therefore, the purpose of presented studies were at first to check if, using this approach we, could gain some useful information about brain activity during swallowing, and second, to provide some insight into brain activity during swallowing. More precisely, we investigated how head position, bolus viscosity, attention, and consecutive swallows influence performance of the swallowing action in healthy people. I order to answer these questions, first we investigated the behavior of EEG signals during swallowing in order to choose the best methods for forming swallowing brain networks. Furthermore, we improved existing methods for analyzing vertex-frequency information from the signals on graphs, and we applied those improved algorithms in our analysis. Our results showed that there are differences between swallowing in the neutral and the chin-tuck head position, between swallowing of different stimuli, between normal swallowing and swallowing with distractions, and between consecutive swallows. Therefore, head position, fluid viscosity, attention, and consecutive swallows should be considered in future investigations concerning swallowing.

10.2 FUTURE DIRECTIONS

One of the most challenging problems inherent in the analysis of acquired central neural swallowing data is the difficulty in determining when each of the swallowing phases begins and ends, and whether the swallowing is healthy or unhealthy. Unlike the gold standards for investigation of brain activity (i.e., fMRI and PET), EEG is not sensitive to any nearby metal objects (e.g., implants), so it can be easily combined with other testing techniques that deploy instrumentation containing metal components, such as imaging technology (fiberoptic endoscopic evaluation of swallowing, videofluoroscopy (VFSS)). Concurrent imaging together with EEG sampling during swallowing could provide more information about swallowing that EEG alone cannot obtain (e.g. swallowing start and stop points), and that can be compared to the EEG signals, and could then be important for future developments in the field. Incorporting EEG together with a videofluoroscopic swallowing study [1, 259] could also provide chance to investigate the relationships between neural activity and the biomechanics of the oropharyngeal swallowing phases. In the case of dysphagia, aspiration often occurs during the pharyngeal phase. By performing a simultaneous recording on patients with both EEG and VFSS, a speech language pathologist can demarcate the swallowing phase segments' duration using the VFSS and correlate EEG signals to physiological events. Analysis of segmented signals would enable a better understanding of brain activation during each swallowing phase. Finally, single treatment modalities do not provide a complete set of information regarding the effects of treatment because treatments are often combined. However, individual treatment modalities are designed to address specific impairments in swallowing physiology and are then combined with other treatments that address other impairments. Understanding the effects of each component of a combined treatment program on the EEG signal will elucidate whether and how each modality may contribute to treatment-induced cerebral plasticity.

The ability to combine EEG with other techniques could be used for a number of different applications and may provide better insights into the swallowing function itself. For example, it could be beneficial to combine EEG with pharyngeal neuromuscular stimulation. Neuromuscular electrical stimulation activates muscles and peripheral motor nerves and may be able to recover normal swallowing control by strengthening the muscles that were weakened by a stroke or other neurological condition, though the evidence supporting its efficacy is mixed. A number of studies have shown the advantages of the neuromuscular electrical stimulation (NMES) as a safe and effective treatment that provides better swallowing function [260-263]. However, the majority of these studies were poorly controlled and tainted by design flaws that rendered their results equivocal at best. In a meta-analysis published by [264], 81 studies of NMES for dysphagia treatment were evaluated. 74 of these studies were rejected from the analysis due to the poor quality of their evidence, and the remaining 7 studies were significantly heterogeneous. Although a small but significant effect size was measured, the authors cautioned: "Because of the small number of studies and low methodological grading for these studies, caution should be taken in interpreting this finding." Hence, the use of EEG to monitor brain activity during neuromuscular electrical stimulation and other dysphagia treatments warrants significant further investigation to determine whether it may be a worthwhile addition to the treatment armamentarium. Further, EEG can also be combined with some other commonly used techniques for the screening and diagnosis of dysphagia, such as fiberoptic endoscopic evaluation, or with some techniques which are still under development, such as cervical auscultation. Combining EEG with other techniques could provide additional information about swallowing that may provide deeper insight into brain activity during swallowing.

Since the motor imagery of swallowing may evolve into an adjunct for dysphagia rehabilitation, it would be highly desirable to evaluate the efficacy of this approach in combination with EEG for future swallowing investigations. This could eventually lead to the development of advanced human-to-computer interface based applications. A previous study produced a 70.89% classification accuracy of swallowing-imagery detection using the dual-tree complex wavelet transform feature. Better accuracy could be achieved by employing more features, or perhaps using an alternative analysis technique such as graph theory or signal processing on graph. However, translation of this result to improved swallowing function in humans with dysphagia needs to be established in order to advance the clinical utility of this method.

APPENDIX A

LINE GRAPH

The line graph L(G) of the graph G, is an undirected binary graph, that represents the adjacencies between edges of G. The line graph is formed such that, to each vertex of the graph L(G) is attributed a value of the one edge from the graph G. Vertices of the graph L(G) are connected if edges from the graph G that corresponds to the vertices of L(G) are connected to the same node (Figure 34). Thus, the weights of the edges from the graph G will be parts of the signal of the graph L(G).



Figure 34: Forming of the line graph from the regular graph.

APPENDIX B

WINDOWED FOURIER TRANSFORM AND S-TRANSFORM

B.1 CLASSICAL SIGNAL PROCESSING CASE

The windowed Fourier transform in classical signal processing is a commonly used technique for extracting frequency information from one dimensional signals. Mathematically, the windowed Fourier transform of a function $x \in L^2(\mathbb{R})$ can be written as the inner product of the original signal and the windowed Fourier atom [265]:

$$WFT(\tau, f) := \langle x(t), w_{\tau, f}(t) \rangle = \int_{-\infty}^{\infty} x(t) w(t - \tau) e^{-j2\pi f t} dt,$$
(B.1)

where the classical windowed Fourier atoms are defined using notation for translation $((T_{\tau}f)(t) := f(t-\tau))$ and modulation $((M_f x)(t) := e^{-j2\pi ft})$ as:

$$w_{\tau,f}(t) := (M_f T_\tau w)(t) = w(t-\tau)e^{-j2\pi f t},$$
(B.2)

where w(t) is the fixed window function. The fixed window in the windowed Fourier transform is the limitation that can influence the resolution of the time-frequency signal representation. In order to overcome the limitations of the fixed window, the S-transform was defined as [266]:

$$ST(\tau, f) := \langle x(t), w_{\tau, f}(t) \rangle = \int_{-\infty}^{\infty} x(t) w(t - \tau, f) e^{-j2\pi f t} dt,$$
(B.3)

where the term $w_{\tau,f}(t) := (M_f T_\tau w)(t) = w(t - \tau, f)e^{-j2\pi ft}$ is the S atom. The window function, w, is also dependent on frequency, and can be represented with the function $\frac{|f|}{\sqrt{2\pi}}e^{-\frac{(\tau-t)^2f^2}{2}}$. This means that for the higher frequencies, the window size will be more narrow. Such a defined window should adjust the time-frequency resolution to provide better frequency resolution for the lower frequencies and better time resolution for the higher frequencies.

B.2 SIGNALS ON GRAPHS

The windowed Fourier transform and S-transform can be adapted for signals on graphs using the Laplacian matrix. The Laplacian matrix enables the adjustment of basic classical signal processing operations to graph signals [70,71]. The (unnormalized) graph Laplacian is defined as $\mathcal{L} := \mathbf{D} - \mathbf{W}$, where \mathbf{D} is a diagonal matrix containing the degree values of each node from the graph, and \mathbf{W} is the connectivity matrix of the graph. The graph Laplacian \mathcal{L} has a complete set of orthonormal eigenvectors $\{\mathcal{X}_l\}_{l=0,1,\dots,N-1}$, and real, nonnegative eigenvalues $\{\lambda_l\}_{l=0,1,\dots,N-1}$ that correspond to each eigenvector. We assume that nonnegative Laplacian eigenvalues are ordered as $0 < \lambda_0 \leq \lambda_1 \leq \lambda_2 \dots \leq \lambda_{N-1} := \lambda_{max}$. Eigenvectors corresponding to the lower eigenvalues have smooth oscillations, while eigenvectors that correspond to the higher eigenvalues have more rapid oscillations. Therefore, we can tell that in graph signal processing notation, the eigenvalue will correspond to the frequency of the graph signal.

Since in the classical signal processing the Fourier transform can be represented as the expansion of a signal in terms of the eigenfunctions, we can say that the graph Fourier transform of a signal on the vertices of a graph $x \in \mathbb{R}^N$ can be defined as the expansion of x in terms of the eigenfunctions of the graph Laplacian [267]:

$$\hat{x}(\lambda_l) := \langle x, \mathcal{X}_l \rangle = \sum_{n=1}^N x(n) \mathcal{X}_l^*(n).$$
(B.4)

The inverse graph Fourier transform is then given by:

$$x(n) = \sum_{l=1}^{N} \hat{x}(\lambda_l) \mathcal{X}_l(n).$$
(B.5)

Following basic signal processing on graph notation, translation and modulation on graphs can be defined as (derivation provided in [107]):

$$(T_i x)(n) := \sqrt{N} (x * \delta_i)(n) = \sqrt{N} \sum_{l=0}^{N-1} \hat{x}(\lambda_l) \mathcal{X}_l^*(i) \mathcal{X}_l(n),$$
(B.6)

$$(M_k x)(n) := \sqrt{N} x(n) \mathcal{X}_k(n).$$
(B.7)

Equipped with the above defined generalized notions of translation and modulation of signals on graphs, we can now define the windowed graph Fourier atom as [107]:

$$W_{i,k}(n) := (M_k T_i w)(n) = N \mathcal{X}_k(n) \sum_{l=0}^{N-1} \hat{w}(\lambda_l) \mathcal{X}_l^*(i) \mathcal{X}_l(n),$$
(B.8)

where \hat{w} is the Fourier transform of the window function. For calculating the windowed graph Fourier atoms, we will use a kernel function defined directly in the spectral domain as $\hat{w}(\lambda_l) = Ce^{-\tau\lambda_l}$, where C is chosen such that $||\hat{w}||_2 = 1$. In the case of the WGFT, the window size iz fixed, which means the τ parameter in the kernel function is arbitrarily chosen such that the vertex frequency representation has the most optimal resolution. However, if we want to define Fourier graph atoms for the S-transform, we will define a window function in the vertex domain as $w(n, l) = \frac{|\lambda_l|}{\sqrt{2\pi}} e^{\frac{n^2 \lambda_l^2}{2}}$.

Finally, the WGFT and GST of a function $x \in \mathbb{R}$ is defined as the inner product of the signal and the windowed graph Fourier atoms:

$$SG(i,k) := \langle x, W_{i,k} \rangle.$$
 (B.9)

Moreover, the signal f(n) can be recovered from the WGFT or GST representation using the expression [107]:

$$x(n) = \frac{1}{N||T_n g||_2^2} \sum_{i=1}^N \sum_{k=0}^{N-1} SG(i,k) W_{i,k}.$$
 (B.10)

WGFT or GST requires high computational complexity [107]. For the N number of nodes, the vertex-frequency representation will generate an $N \times N$ spectrum for Fourier graph atoms. Each of those $N \times N$ points will generate N additional iterations in order to calculate the translation of the signal. Those N^3 points in the next step will integrate with the N signal points. Therefore, the total computational complexity will have $O(N^4)$ operations. Such a high computational complexity requires too long computation time for larger graphs.

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