Analyzing Actigraphy Data to Study the Efficacy of Dynamic Arm Support for Duchenne Muscular Dystrophy

by

Mahmoud Elkhadrawi

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This thesis was presented

by

Mahmoud Elkhadrawi

It was defended on

November 6, 2020

and approved by

Zhi-Hong Mao, Ph.D., Professor, Department of Electrical And Computer Engineering

Roxanna Bendixen, Ph.D., Professor, Department of Occupational Therapy

Ervin Sejdic, Ph.D., Professor, Department of Electrical And Computer Engineering

Thesis Advisor: Murat Akcakaya, Ph.D., Department of Electrical And Computer Engineering

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Mahmoud Elkhadrawi, M.S.

University of Pittsburgh, 2020

Duchenne muscular dystrophy (DMD) is the most common form of muscular dystrophy and it is the most common fatal genetic disorder diagnosed in childhood. DMD almost always affects boys as it results from a genetic mutation in the X chromosome that programs proteins critical to muscle integrity. DMD affects approximately 1 in every 3,500 to 6000 male births in the US (about 20,000 new cases each year worldwide). Typically, boys with DMD lose their ability to walk between the ages of ten and fourteen. By the late teenage years as the muscles deteriorate, significant loss of strength in the upper body results in loss of arm function and independence in everyday tasks. In this study we investigate the usage of an Actively Actuated Device called KINOVA-O540 as an assistive technology by such individuals during activities of daily living. This study compared the usage of KINOVA-O540 and no-KINOVA-O540 usage through the participation of individuals with DMD during Performance of Upper Limb (PUL) tests. PUL tests represent the activities of daily living. Specifically, three dimensional actigraphy data (accelerometer data) were used for this comparison. We have developed a feature selection and support vector machine (SVM)-based classification algorithm to identify when the KINOVA-O540 device is used based on the recorded actigraphy. Moreover, we showed how the selected features that separate the KINOVA-O540 usage from other data change as the success rate changes in PUL tasks. As the features that separate KINOVA-O540 from no-KINOVA-O540 usage are not optimized to identify task success, we then modified the feature selection and classification algorithm to separate the success from no-success in PUL tasks based on the recorded actigraphy. We showed that such an algorithm based on actigraphy is more successful in classifying between success and no-success when KINOVA-O540 device is used. This is a significant outcome as it shows that KINOVA-O540 can be used together with actigraphy to identify how successful DMD patients are during activities of daily living.

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Preface

This work was made possible thanks to the help of my advisor Dr. Murat Akcakaya, and our collaborators Dr. Roxanna Bendixen, Amy Hartman and Sarah McKendry, so I would like to give special thanks to them. I also thank my school INSA Lyon for giving me the opportunity to study in the US in the University of Pittsburgh. I thank also my family, whose support attributed heavily in my success and this work. I would like to also thank the committee members for accepting to attend my thesis defense.

1.0 Introduction

1.1 What is DMD

Duchenne Muscular Dystrophy (DMD) is the most common form of muscular dystrophy in early childhood [24]. It is a genetic disorder linked to the X-chromosome, thus it mainly affects males, with a frequency of 1 in 3600-6000 live male births[7] [10]. This mutation affects the dystrophin gene (essentially deletions), a gene that encodes the dystrophin protein that supports muscle fiber strength and helps prevent muscle fiber injury, and whose absence leads to muscle loss and deterioration including skeletal, cardiac, and pulmonary muscles causing the loss of the ability to walk by the age of 13 years [19] [8] [14]. The dystrophin protein exists also in the brain, and its absence might lead to non-progressive cognitive dysfunction impacting digit span, story recall, and comprehension[28] [13]. This disease is still currently incurable, therefore most of the effort is is aimed to treat the symptoms. For example by the use of corticosteroids to reduce the deterioration of muscle strength and function[21], and psychosocial care to provide coping mechanisms to live with such disease, and clinical management like rehabilitative interventions and the use of assistive devices (wheelchair, arm supports, exoskeletons etc.) [8] [4].

1.2 Assistive Devices

In the late stages of DMD, patients start to lose ambulation as their muscles deteriorate. Therefore, they rely on the use of Assistive Devices(ADs) to perform essential daily life activities. The use of ADs for lower limbs to help with ambulation like electric wheelchairs are established and reliable, however development of ADs for upper limbs are a lot more difficult [11], but they are becoming progressively important as life expectancy for DMD patients is inclining [27] [16] (patients living up to 30 and 40 years old) and such devices can significantly improve their quality of life [11].

1.3 Dynamic Arm Supports

In this study we'll be focusing on a dynamic arm support device which is an upper limb AD. Prior research on dynamic arm supports is limited. However studies have shown that their usage was essential for many daily life activities [32] [9]. Dynamic arm support devices can be categorized in 4 main categories [33]: **(i)** non-actuated devices, which are devices that are operated by the user's energy, that don't store potential energy nor need external energy input to function **(ii)** passively actuated devices that store potential energy allowing less energy input from the user and they don't need an external source of energy to operate, **(iii)** actively actuated devices, powered by electricity and also can store potential energy thus require minimal energy input from the user, **(iv)** or devices using the functional electrical stimulation principle. These devices can be further divided into **(a)** exoskeletons, which are devices that align with the users joint, following their movements, thus allowing better control of each joint, **(b)** end-effectors, which are devices that are attached to a single point on the user's body, making the joints follow a movement without controlling each joint individually. For this work, we'll be using an actively actuated end-effector device called KINOVO O540 (that will be referenced as KINOVO in this thesis)

1.4 Actigraphy

Measuring the performance and effectiveness of dynamic arm support is not standardized and also lacking [2]. And in the literature, most of the assessment found was done through questionnaires or interviews [32] or various clinical tests like Motricity index test to assess upper limb and Fugl-Meyer Assessment to assess motor functioning etc. for patients with cerebral palsy, multiple sclerosis, and stroke. [2] Actigraphy is a way to measure human activity non-invasively , through the use of an accelerometer (typically triaxial accelerometers). Therefore, the use of an actigraph allows us to get quantifiable descriptions of the difference between movements through the recorded accelerometer data. Many methods involving the use of actigraphy have been developed to assess the performance of upper limb

activity, gait, cadence, and ambulatory activity for patients with impaired mobility and neurological disease, where significant correlations between accelerometry and the studied conditions' clinical tests have been found [3] [29] [12] [26]. And recently, the use of actigraphy in tandem with DMD population is gaining traction, which is used for example to quantify energy expenditure [17] [20] [25], and one study was able to show the sensitivity of accelerometry to the differences between daily life activities for the DMD population and a correlation between accelerometry and the current standards for the evaluation of upper extremity functions [31], thus showing its potential as an assessment tool for studies concerning DMD. However, its use is still limited for the study of DMD. Moreover, many studies have successfully shown that it is possible to use accelerometry in order to classify between different kinds of body movements and postures using various approaches and techniques, starting from basic threshold-based techniques to more advanced machine learning techniques like random forests, Naive Bayes, neural networks, decision trees coupled with AdaBoost, Support Vector Machines etc... [22] [15] [30] [5]. This gives us the necessary motivation of using machine learning techniques (here Support Vector Machines) combined with actigraphy for this study.

1.5 Contribution of This Study

Our study offers a novel way to explore the implications and benefits of the use of actively actuated devices, through linking actigraphy data with the use of KINOVA-O540, a dynamic arm support device. Participants were asked to perform a number of movements of the standardized Performance of Upper Limb test (PUL test) [23] while using and not using KINOVA-O540, and their movements were captured by an actigraph (The ActiGraph GT9X Link) under the supervision of clinical experts or remotely. Moreover, a score indicating success or failure was assigned to each movement for each participant. From the actigraphy data, multiple statistical and inherent signal features were extracted. By using Support Vector Machines (SVM) and a feature selection algorithm (Forward Sequential Selection), we analyzed the separability between the usage of KINOVA-O540 and no KINOVA-O540 usage,

and then we tried to understand the relationship between the features that were chosen as the best features permitting that separation and the evolution of movements success while using KINOVA-O540 and not using KINOVA-O540 through their values. Furthermore, we analyzed the separability between the successful movements and the unsuccessful ones and compared the separability of successful movements when both KINOVA-O540 and No-KINOVA-O540 actigraphy data are considered, and when only KINOVA-O540 actigraphy data is considered, and when only no-KINOVA-O540 actigraphy data is considered. Through this analysis, we aim to provide all stakeholders, including clinicians, manufacturers and researchers with a clearer insight about the use of the device.

2.0 Participants & Methods

2.1 Participants

Local and national disability-related resources (e.g., Muscular Dystrophy Assocoiation, Duchene Connect Registry, and University of Pittsburgh Medical Center's Children's Hospital) were used for identification and recruitment of participants. Inclusion criteria included: **(i)** participants need to be at least 14 years of age, **(ii)** participants have a diagnosis of DMD, **(iii)** participants use a power wheelchair for mobility, **(iv)** no medical or psychological diagnosis unrelated to DMD that would impact their participation in daily activities or routines. Data are collected through a procedure that is approved by the University of Pittsburgh's Institutional Review Board (IRB # STUDY19100339)

2.2 Data Collection & Materials

2.2.1 Data Collection Procedure

The design of this study was the following: **(i)** A first home visit, where the participants were first asked to perform the Performance of the Upper Limb test (PUL test) while seated on their wheelchair and wearing the wrist-worn actigraph (ActiGraph GT9X Link) on their dominant arm without the KINOVA-O540 dynamic arm support. The session was video recorded for labeling and score assessment, and it will be used as our No KINOVA-O540 usage data. After finishing the PUL test without the device, the KINOVA-O540 was installed on the wheelchair to be used for the same arm, the objective here was simply testing and training using the device and its remote control while doing the PUL test. **(ii)** A month-long trial and experimenting with the device, where the participants were encouraged to use it for daily life tasks to gain more experience with the device. Instructions were given to caregivers on how to temporarily remove and re-install the device in case of space limitations or travel.

(iii) After one month of trial, a second home visit was conducted to reperform the PUL test while using KINOVA-O540, with the actigraph on and while video recording. This is the data used as our KINOVA-O540 usage data.

2.2.2 KINOVA-O540 - An Actively Actuated Device

The KINOVA® Dynamic arm support O540, manufactured by KINOVA inc, was used throughout this study. This device is intended to be mounted on a power wheelchair. The device is designed to compensate for the weight of the arm so that the user can move his arm easily. However, it does not take over any arm function and the user must make the movements by himself (it is not a robotic arm). The user rests his arm on a brace. Using a handheld remote, the user can **(i)** control the amount of compensation force, **(ii)** control the tilt angle of the device to adjust working range **(iii)** use a brake command to lock the device movement horizontally or vertically **(iv)** use a rotation brake command to lock rotational movements of the main axis.

2.2.3 Performance of the Upper Limb Test

The PUL test [23] is a test designed to assess the motor performance of the upper limb for DMD patients. The test consists of 22 movements, divided into 3 levels aiming to capture the progression of weakness in DMD. These three levels are:

- **High level** from the proximal shoulder girdle
- **Mid level** at the elbow flexors and extensors
- **Distant level** at the wrist and hand

Each movement was assigned a 0 or 1 score, depending on if the participant finished the movement successfully or not.

2.2.4 Actigraphy

While performing the PUL test, each participant was asked to wear the ActiGraph GT9X Link (ActiGraph Corp, LLC, Pensacola, FL) on the wrist of the dominant arm, for which

the KINOVA-O540 was used. The actiGraph GT9X Link features a triaxial accelerometer, a magnetometer, and a gyroscope. Only the accelerometer data was used as previously discussed. The vector magnitude of the triaxial data was computed. The data was collected at a **frequency of 1 Hz**.

2.3 Data Analysis

Not all participants were able to complete every task of the 22 movements of the PUL test due to the different range of abilities and depending on the progression of the disease. The clinical researchers hypothesized that most of the tasks that involve shoulder flexion wouldn't be completed without the KINOVA-O540. Therefore, each PUL task was analyzed separately and only attempted tasks were used for the analysis. A score was assessed individually for each of them instead of giving a composite score.

2.3.1 Preprocessing and Labeling

The videos recorded had frame rates of 30fps, and the actigraphy data had a frequency of 1 Hz. In order to sync the video with the vector magnitude of the triaxial accelerometer accurately, a MATLAB tool was designed: it has three controls, pause, advance, and rewind (figure 1) Each PUL task was labeled individually. Two other clinical research assistant labeled the data independently. Then we checked for discrepancies and an agreement relating to the start and the end of each movement was reached before using the data for further analysis.

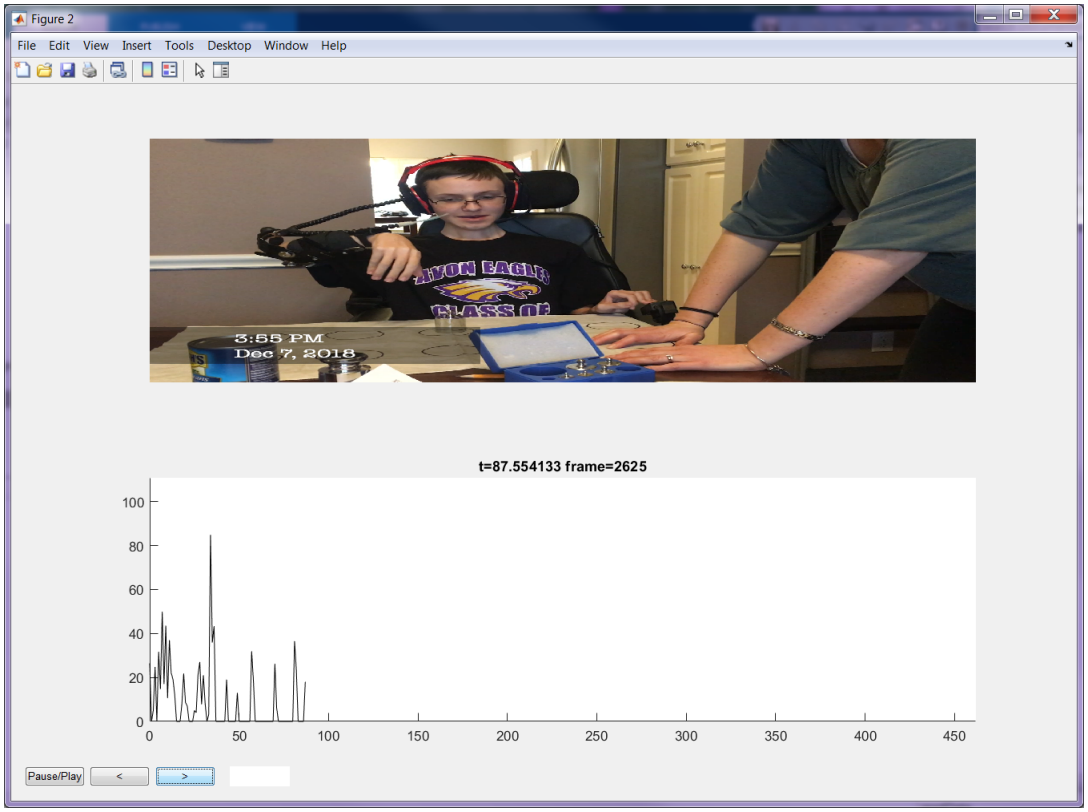

Figure 1: Syncing actigraphy and video for labeling

2.3.2 Movement Categorization

Each PUL task's actigraphy data from all the participants were given two labels **(1)** a label indicating either it was done using KINOVA-O540 or without KINOVA-O540, **(2)** a label indicating either it was successful(Score = 1) or not (Score = 0). Similar PUL tasks were grouped by three clinical experts in muscle function and assessment into seven movement categories as indicated in table 6 in appendix A. All samples were counted following their label (see Appendix B table 7). Some movements have unbalanced sample sizes of KINOVA-O540 usage. For example, movement B has more samples using KINOVA-O540, this is because many participants weren't able to attempt movements that require shoulder flexion, like raising the arm to shoulder height or stacking cans without the assistance of the device. Moreover, some movements have unbalanced success/failure samples like movement F, as

these require fine motor skills, that many of the participants weren't lacking, thus most attempts were successful. Also, some categories were lacking in samples for some or both labels. Therefore, only movement groupings D and E were used for all the analysis conducted in this study, as they had a balanced and a sufficient number of samples for both labels: device usage and success labels. Starting from here, movements D and E will be referenced to as category 1 and 2 respectively.

2.3.3 Formulating the Classification Problem

Using actigraphy data, we formulate two classification problems for: **(i)** identification of KINOVA-O540 usage, and **(ii)** separation between task success and failure. For both classification, we utilize support vector machine (SVM) and apply sequential forward feature selection. Both classifier will be created for each movement category. We then investigate how the changes in the Identified salient features for both classification problems affect the task success rate. We then compare KINOVA-O540 usage with no-KINOVA-O540 usage in terms of identification of task success when actigraphy is used. Figure 2 shows a summary of the study's approach. In the following sections, a description of the features extracted from our signal is presented, then we proceed with explaining SVM classifiers, sequential feature selection and success rate.

2.3.4 Feature Definitions

n order to use the above mentioned SVM classifiers, we extract the following features from the vector magnitude of the triaxial actigraphy data for each task: **(i)** Mean value across time, **(ii)** standard deviation across time, **(iii)** minimum value across time, **(iv)** maximum value across time, **(v)** median value across time, **(vi)** duration of the task completion(elapsed time), **(vii)** entropy, **(viii)** signal energy and **(iv)** normalized signal energy. Computation of the statistical features and task duration are trivial; therefore, below only the details of how the entropy, signal energy and normalized signal energy are computed.

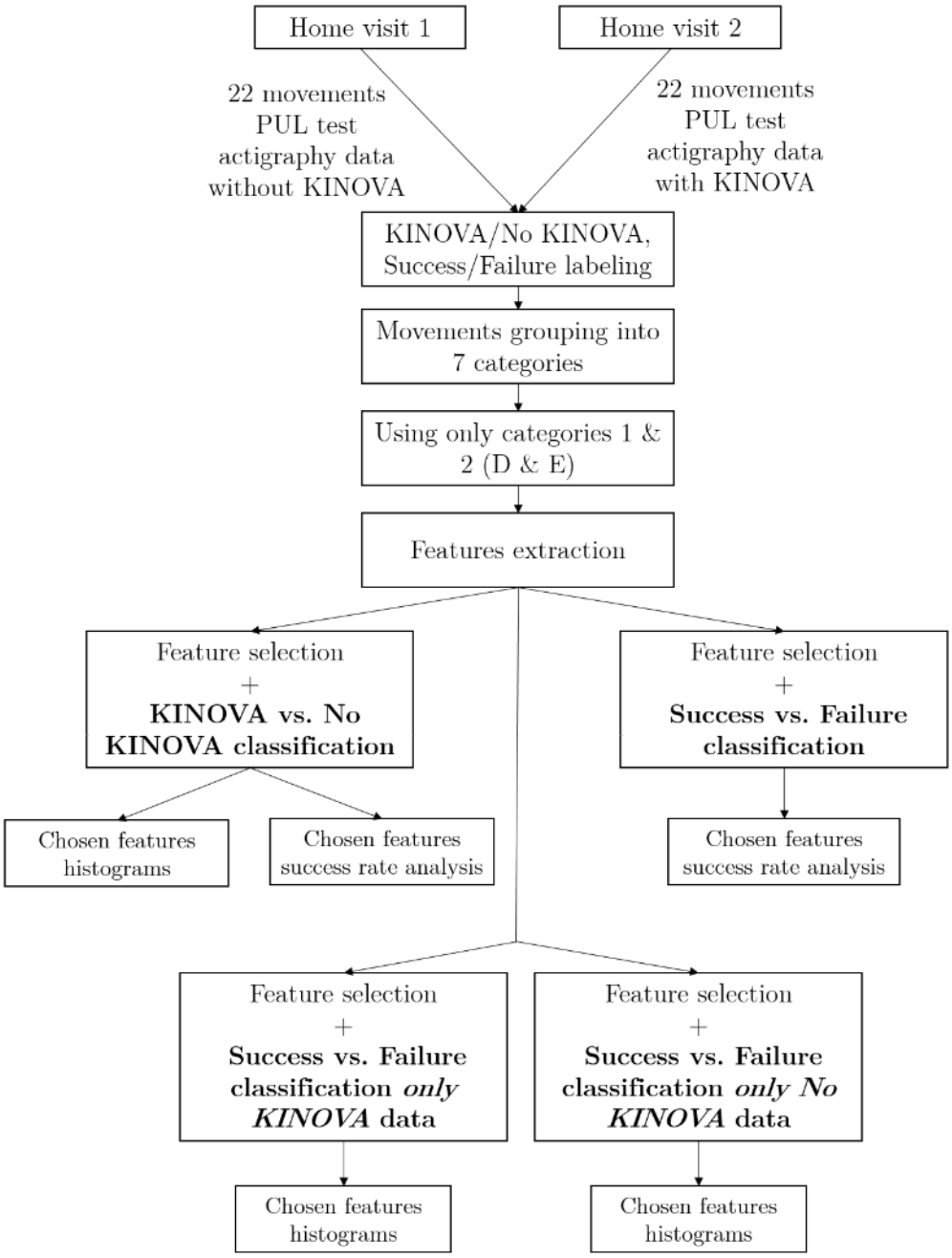

Figure 2: Summary of the study's approach

Entropy [18] [6] from an information theory sense, is a measurement of the amount of information/uncertainty in a signal, providing us a measure of the randomness of the signal. In order to compute it. First a distribution of the signal values $P(B)$ is obtained to get the frequency of occurrence (the probabilities) for each value of the signal, with B a random variable representing the the vector magnitude in the recorded actigraphy signal. Here we identify $P(B)$ through the computation of the normalized histogram of the vector magnitude values of the actigraphy signal for each task. Let b_i represent a bin value of the computed histogram, and $P_B(b_i)$ its probability, then entropy is defined as:

$$H(B) = -\sum_{i=1}^{N} P_B(b_i) log_2 \left(P_B(b_i)\right) \tag{2.1}$$

Where N is the number of bins in the histogram. With $I_B(b_i) = -log_2 \left(P_B(b_i)\right)$ know as self-information. We can observe that the "Entropy" is defined as the mean value of self-information. From the chosen of the self-information function, we observe that smaller probability $P(b_i)$ corresponds to higher self-information value, which means the more surprising/rare the value was. While a bigger probability yields a lower entropy value meaning the that the concerned value is highly expected and unsurprising. Therefore, if the normalized histogram of the vector magnitude values is closer to a uniform distribution, a higher entropy value is obtained. Because, we can see different values in the signal appearing with low rates, meaning lots of information is being captured. A low entropy means the values don't vary much in the signal showing how little unexpected information the signal contains. In our recorded actigraphy signals, low entropy corresponds to lower uncertainty with predictable task movements, while high entropy can be observed for unpredictable/uncontrolled movements which means lots of different accelerometer values were recorded to achieve a movement task. So a high entropy value for the actigraphy sample of a certain movement could be interpreted as that the concerned movement was abrupt and uncontrolled, while a low entropy value means a more controlled movement was captured.

Signal energy: Let the vector magnitude of the recorded signal be is x(i), with i = 1, 2, ..., n. Where 'n' is the length of the signal then the energy (E) is defined as:

$$E = \sum_{i=1}^{n} |x(i)|^2 \tag{2.2}$$

Normalized signal energy: Similarly, if the signal is x(i) with i = 1, 2, ..., n, then the normalized energy is defined as:

$$E_n = \frac{1}{n} \sum_{i=1}^{n} |x(i)|^2 \tag{2.3}$$

Similar to entropy, we expect higher energy in the actigraphy that correspond to more uncontrolled movements. Different than the signal energy, normalized energy considers also the task length.

2.3.5 Support Vector Machine Classifier (SVM)

SVM (support vector machine) is a supervised machine learning model for binary or multi-class classification. Provided a set of features associated with labeled data, the goal is to find the best hyperplane separating 2 categories from each other. This hyper-plane is the one that maximizes the margin between these 2 classes.

2.3.5.1 Linearly Separable Data - Hard Margin Here we start by a simple assumption that the two classes don't overlap and are linearly separable. This assumption won't work for all practical situations. Further modifications will be added and explained later in this section for the non linearly separable cases.

In our training data we have n samples, with features $x_i \in \mathbb{R}^d$ (d = number of features), and labels $y_i = \pm 1$ (indicating samples class: +1 for one category and -1 for the other), with $i = 1, 2, ..., n$, the hyper-plane is defined by the following affine function (visual representation in figure 3):

$$f(x, \beta, \beta_0) = \beta \cdot x + \beta_0 = 0 \; with \; \beta \in \mathbb{R}^d \; and \; \beta_0 \in \mathbb{R} \tag{2.4}$$

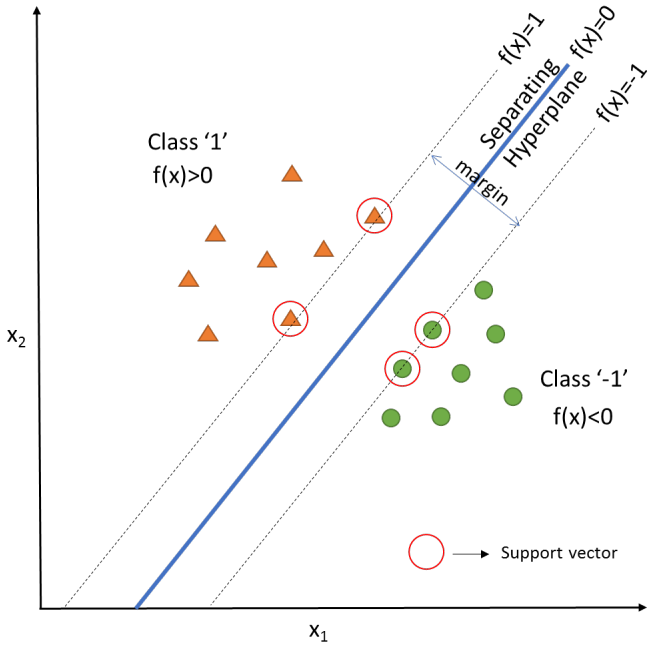

Figure 3: Separating hyperplane with support vectors

Our goal is to get:

$$\begin{aligned} f(x_i) = \beta \cdot x + \beta_0 \geq 1, \ \ when\ y_i = 1 \\ f(x_i) = \beta \cdot x + \beta_0 \leq -1, \ \ when\ y_i = -1 \\ Giving:\ y_i f(x_i) \geq 1\ for\ i = 1, 2, ..., n \end{aligned} \tag{2.5}$$

The distance l between a sample and the hyper-plane is $l = \frac{f(x)}{\|\beta\|}$. From our assumption that the training data is linearly separable, this means that for some samples, from equation 2.4 we will get $f(x) = \pm 1$ these samples are called support vectors (Figure 3), they are the closest samples to the hyper-plane from both categories, and they are the ones that decide the margin between the two classes, thus hyper-plane. The distance between the support vectors and the hyper-plane is $l = \frac{1}{\|\beta\|}$ which needs to be maximized. Thus we create the

following quadratic convex optimization problem whose primal formulation is:

$$\begin{aligned} &\min \frac{\|\beta\|^2}{2} \\ &\text{subject to: } y_i(\beta \cdot x_i + \beta_0) \geq 1, \text{ for } i = 1, 2, ..., n \end{aligned} \tag{2.6}$$

In order to solve this problem, it's easier to solve its Lagrangian dual problem. The primal's Lagrangian is:

$$L(\beta, \beta_0, \alpha) = \frac{1}{2}\beta \cdot \beta - \sum_{i=1}^{n} \alpha_i \left[y_i(\beta \cdot x_i - 1) \right] \tag{2.7}$$

By imposing stationarity:

$$\frac{\partial L}{\partial \beta} = \beta - \sum_{i=1}^{n} y_i \alpha_i x_i = 0$$

$$\frac{\partial L}{\partial \beta_0} = \sum_{i=1}^{n} y_i \alpha_i = 0$$

Thus obtaining:

$$\beta = \sum_{i=1}^{n} y_i \alpha_i x_i \tag{2.8}$$

$$\sum_{i=1}^{n} y_i \alpha_i = 0 \tag{2.9}$$

and from KKT conditions we know that:

$$\alpha_i \left[y_i(\beta \cdot x_i + \beta_0) - 1 \right] = 0 \tag{2.10}$$

$$\alpha_i \geq 0 \tag{2.11}$$

Then we substitute in the Lagrangian (2.7) to obtain the following dual optimization problem:

$$\begin{aligned} \max \quad & \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y_i y_j \alpha_i \alpha_j x_i \cdot x_j \\ \text{s.t.} \quad & \alpha_i \geq 0, \\ & \sum_{i=1}^{n} y_i \alpha_i = 0, \ i = 1, ..., n \end{aligned} \tag{2.12}$$

We then solve this maximization problem using a quadratic solver to obtain the values of α_i, to get the optimal value of β using (2.8). Then we can get the optimal β_0 from the primal constraints

$$\beta_0 = -\frac{\max_{y_i=-1}(\beta \cdot x_i) + \min_{y_i=1}(\beta \cdot x_i)}{2} \tag{2.13}$$

From the KKT conditions (2.10) (2.11), and knowing that the support vectors satisfy: $y_i(\beta \cdot x_i + \beta_0) - 1 = 0$, this means that the support vectors are the only active constraints in the Lagrangian formulation, meaning that the corresponding α_i satisfy $\alpha_i \geq 0$. While the alpha values of the rest of the points need to be zero. Hence showing that the support vectors are the only points that decide the separating hyperplane. Thus the optimal hyperplane can be expressed using the support vectors and the optimal values of β and β_0:

$$\begin{aligned} f(x, \beta, \beta_0) &= \beta \cdot x + \beta_0 \\ &= \sum_{i=1}^{n} y_i \alpha_i x_i \cdot x + \beta_0 \\ &= \sum_{i \in \text{ support vectors}} y_i \alpha_i x_i \cdot x + \beta_0 \end{aligned} \tag{2.14}$$

In order to use the obtained hyperplane for the classification of new unseen data, from our previously defined constraints on the two classes (2.5), $f(x)$ should be either positive or negative depending on which side of the hyperplane a sample resides. Thus we can use the sign of $f(x)$ as a decision function D(x) for classification:

$$D\left(x\right) = sign\left(f\left(x\right)\right) \tag{2.15}$$

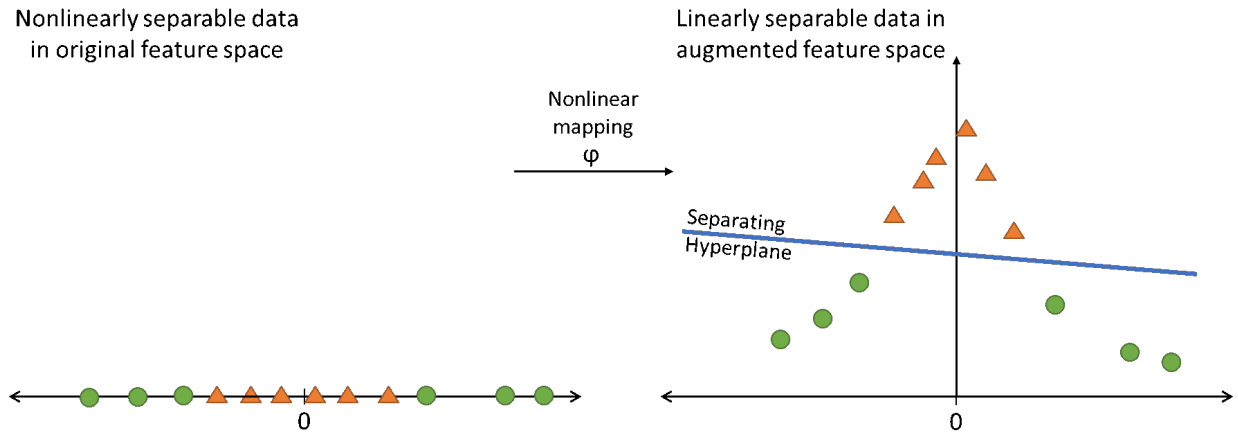

Figure 4: Finding a good nonlinear mapping

2.3.5.2 Kernel Trick In some cases, the data are not linearly separable, meaning that it can't be separated using an affine hyperplane. For example, imagine a 3-dimensional feature space, the data of one class can be clustered inside a circle, while all the area surrounding the circle contains the second class. In similar cases, an affine separating hyperplane (which corresponds to a line in the previous example) won't be compatible and a nonlinear transformation is needed. But in order to use the same approach derived for the linearly separable data, our goal is to find a nonlinear mapping that projects our features on a space where the data can be linearly separated as in figure 4. However, in order to achieve this, we need to find an explicit mapping that projects our data from the original feature space X, to the desired feature space F.

$$\phi : X \to F \tag{2.16}$$

$$f(x) = \beta \cdot \phi(x) + \beta_0 \tag{2.17}$$

However, this explicit mapping could result in a high computational cost and might be hard to find. Luckily, if we look again at equation (2.12), we can see that a sample 'x' is used

indirectly through an inner product

$$f(x) = \sum_{i=1}^{n} y_i \alpha_i \langle \phi(x_i) \cdot \phi(x) \rangle + \beta_0 \tag{2.18}$$

This means that we only need to know the inner product function associated with the target space (known as Kernel):

$$K(x, x_i) = \langle \phi(x) \cdot \phi(x_i) \rangle \tag{2.19}$$

for which the number of computations is not necessarily proportional to the number of dimensions in the desired feature space and allows us to map the data implicitly to the desired feature space while avoiding computational problems associated with finding the feature map ϕ , and reducing the computational cost.

$$f(x) = \sum_{i=1}^{n} y_i \alpha_i K(x, x_i) + \beta_0 \tag{2.20}$$

For this study, the Kernel that was used is the Radial Basis function(RBF) also know as Gaussian kernel.

$$K(x, x_i) = exp(-\frac{\|x - x_i\|^2}{2\sigma^2}) \tag{2.21}$$

with σ a free parameter that could be used for scaling the feature space. This approach improves the degrees of freedom. Nonetheless, the higher the feature map's dimensions and the more complex it is, this will result in a high number of support vectors which will create overfitting and generalization problems (the worst case is when all the data points are support vectors). To remedy that and account for eventual noisy data, we can improve our optimization function by leaving some room for intentional misclassification, thus improving our model generalization capability.

2.3.5.3 Soft Margin SVM As we discussed previously, in most cases, the data might not be separable because of overlapping. And using a very complex feature map might result in overfitting. So, we can use a soft margin to separate many but not all points into their correct class. One approach is to introduce a penalty parameter C and slack variables ξ_i:

$$\begin{aligned} \min\ & \frac{\|\beta\|^2}{2} + C\sum_{i=1}^{n}\xi_i \\ \text{s.t.}\ \ & y_i(\beta \cdot x_i + \beta_0) \geq 1 - \xi_i, \\ & \xi_i \geq 0,\ \text{for } i = 1, 2, ..., n \end{aligned} \tag{2.22}$$

The new Lagrangian is:

$$\begin{gathered} L(\beta, \beta_0, \xi, \mu, \alpha) = \frac{\|\beta\|^2}{2} + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\mu_i\xi_i - \sum_{i=1}^{n}\alpha_i\left(y_i(\beta \cdot x_i + \beta_0) - 1 + \xi_i\right) \\ \text{with } C, \xi, \alpha, \mu \in \mathbb{R} \text{ and } \alpha_i, \mu_i \geq 0 \end{gathered} \tag{2.23}$$

Stationarity gives:

$$\beta = \sum_{i=1}^{n}\alpha_i y_i x_i \tag{2.24}$$

$$\sum_{i=1}^{n}\alpha_i y_i = 0 \tag{2.25}$$

And KKT conditions give:

$$\alpha_i = C - \mu_i \tag{2.26}$$

From (2.23), (2.24) and (2.26) we get:

$$0 \leq \alpha_i \leq C \tag{2.27}$$

The penalty C is also called **box constraint** as it limits the value of α_i.
By substituting the values of the main variables in the primal formulation we get the following dual of the original optimization function:

$$\begin{aligned} \max\ & \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} y_i y_j \alpha_i \alpha_j x_i \cdot x_j \\ \text{s.t.}\ \ & 0 \leq \alpha_i \leq C, \\ & \sum_{i=1}^{n} y_i \alpha_i = 0,\ i = 1, ..., n \end{aligned} \tag{2.28}$$

If we want to use the Kernel trick we just replace the inner product:

$$\begin{aligned} \max \quad & \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \\ \text{s.t.} \quad & 0 \leq \alpha_i \leq C, \\ & \sum_{i=1}^{n} y_i \alpha_i = 0, \ i = 1, ..., n \end{aligned} \tag{2.29}$$

We can create even more degrees by giving giving different box constraint values for each class $C_{i \in certain\ class}$. This extra degree of freedom is very useful if the training data is not balanced as it could allow us to give different weights for each class, so we can give the class of the data that has a lower number of samples higher weights thus sometimes improving prediction accuracy. This will be used in some of this study's results as some of the movements have unbalanced samples as mentioned previously.

2.3.6 Sequential Feature Selection

From all the features defined previously, features were used for the SVM classification. For each classifier created for each movement task, only a subset of the features was selected using a sequential feature selection algorithm, which is a family of greedy search algorithms that aim to reduce the dimensions of the feature space from a d-dimensional space to a lower k-dimensional space ($d > k$). The goal is to remove irrelevant features or noise to reduce generalization error of the classifier model, which is the SVM model in our case. The selected features will be further studied to analyze and how they affect the performances of each movement task category. In this study, we are going to use **Sequential Forward Selection (SFS)** of exponential complexity [1], which is a variant of sequential feature selection algorithms. The method comprises of :

- **An objective function** that measure the classification error of an SVM model trained on a candidate subset of features. The objective function used here is the misclassification rate, which is the number of misclassified samples.

- **A sequential search algorithm** which adds or removes features from a candidate subset depending on the value of the objective function. As we are using Sequential Forward Selection, we will start with an empty set, then we will be adding one new feature at a time, as long as this addition reduces the misclassification rate. So, we will start with one feature that gives the lowest misclassification rate, then we will add second one from the rest of the set of features creating multiple candidate subsets, while choosing the combination that gets lowest misclassification rate. We will continue adding features one by one creating multiple candidate subsets, until there is no improvement in the classification or until we've added all of them or until we have reached a predefined maximum number k of features.
- **A performance function** which is the SVM classifier in our case, which will give us a measure of the chosen features by calculating the accuracy, the sensitivity and the specificity.

During each step of the search algorithm and for each candidate subset of features, an SVM model is trained on the candidate subset using a 5-fold cross-validation, where the data is divided into 5 batches, each batch will be used once as a testing set while the others are used as training sets, which gives us 5 SVM models and 5 objective function values. The final value used is the mean of the 5 obtained values. The cross-validation procedure for each candidate subset is repeated 100 Monte-Carlo repetitions and the mean value of all the computed objective function values is taken and then compared to the objective function values of other candidate subsets that went through the same procedure, finally the subset having the lowest objective function value is chosen. These 100 repetitions are done to reduce any bias while creating training and testing sets ensuring the generalization of the models created using the available features. Following feature selection, we'll use the chosen subset of features to train final SVM classifiers for our 2 classification problems, with results obtained using a 5-fold cross validation, to check the performance of the SVM classifiers.

2.3.7 Success Rate

Let $f_X(a)$ be the function representing success rate of $'X'$ which corresponds to a given feature, x_i corresponds to the value of that feature for a given sample, with $i = 1, ..., n$, with 'n' corresponding to total number of samples of a specific studied group(e.g. only KINOVA-O540 users), and 'a' corresponds to a specific value of 'X':

$$f_X(a) = \frac{\sum_{i \in \textit{Successful movement}} I(x_i \leq a)}{\sum_{i=1}^{n} I(x_i \leq a)} \tag{2.30}$$

The goal is to analyze how movement success evolves from the usage or absence of KINOVA-O540, through the metrics defined by the chosen features.

3.0 Results and Discussion

A total number of 12 participants participated in the KINOVA O540 dynamic arm support device trial while wearing the actigraph. Two participants did not have data for the PUL test with the device and 1 participant did not have actigraphy data for the PUL test without the device. Therefore in total, we have data on 9 participants using KINOVA-O540 for categories 1 & 2, 10 participants not using KINOVA-O540 for category 1 and 11 participants not using KINOVA-O540 for category 2. Below we demonstrate the results for the two actigraphy-based classification problems: (i) KINOVA-O540 vs No-KINOVA-O540, and (ii) Task success vs. failure in each of the two movement categories 1 & 2. The success vs. failure is further divided in 3 categories: (a) Success vs. failure for both KINOVA-O540 and No KINOVA-O540 actigraphy data, (b) Success vs. failure for only KINOVA-O540 actigraphy data, (c) Success vs. failure for only No KINOVA-O540 actigraphy data.

3.1 KINOVA-O540 Vs. No-KINOVA-O540 Classification

KINOVA-O540 vs No-KINOVA-O540 classification accuracies, specificities and sensitivities are listed for both movement categories in Table 1. Table 1 also lists the subset of features for each movement category that is most informative about this classification. We observe from this table that for both movement categories the KINOVA-O540 usage is very accurately separable from No-KINOVA-O540 usage through actigraphy. Moreover, for both movement categories mean value, standard deviation and normalized energy are the most informative features. The distribution/histograms of these feature are presented in Figure 5. We observe in Figure 5 that for both movement categories, the distributions of the feature values when KINOVA-O540 is used are highly separable from the distributions of the feature values when KINOVA-O540 is not used. This separability in the histogram domain supports the good classification performance we obtained in the separation between KINOVA-O540 and No-KINOVA-O540 cases.

Table 1: KINOVA-O540 vs No-KINOVA-O540 classification performance and the list of selected features. Here Sensitivity indicated the accuracy of correctly identifying O540 usage.

		SVM classifier performance using chosen features		
Movement category	**Subset of features chosen by sequential forward selection**	**Accuracy**	**Sensitivity**	**Specificity**
1	Mean, Std, Normalized energy	87.88%	82.76%	91.89%
2	Mean, Std, Max, Normalized energy	88.89%	91.30%	87.10%

Moreover, in Figure 5, we further observe that recording larger values for the actigraphy features when KINOVA-O540 is not used has higher probability compared to the cases when KINOVA-O540 is used. We believe this is because when KINOVA-O540 is used the PUL tasks are completed through more controlled movements and with less effort the participants were able to complete the tasks. Finally, we investigate the change in the task success rate as a function of the values of the selected features that are most informative about KINOVA-O540 vs No-KINOVA-O540 separation. The results of this investigation are presented in Figure 6. In Figure 6, for both movement categories, we observe that similar success rates are achieved for lower values of the selected features when the O540 is used which supports our claim that when the O540 is used tasks are completed with less effort by the participants. If these selected subsets of features are used for task success vs failure classification, the classification performance is poor. The features are informative about task success, but they fail to identify task failure, see Table 2. This is because the features investigated here are chosen for O540 vs No-O540 separation and they are not optimized to identify task success. Therefore, our next results focus on the classification between task success and failure and the corresponding feature selection.

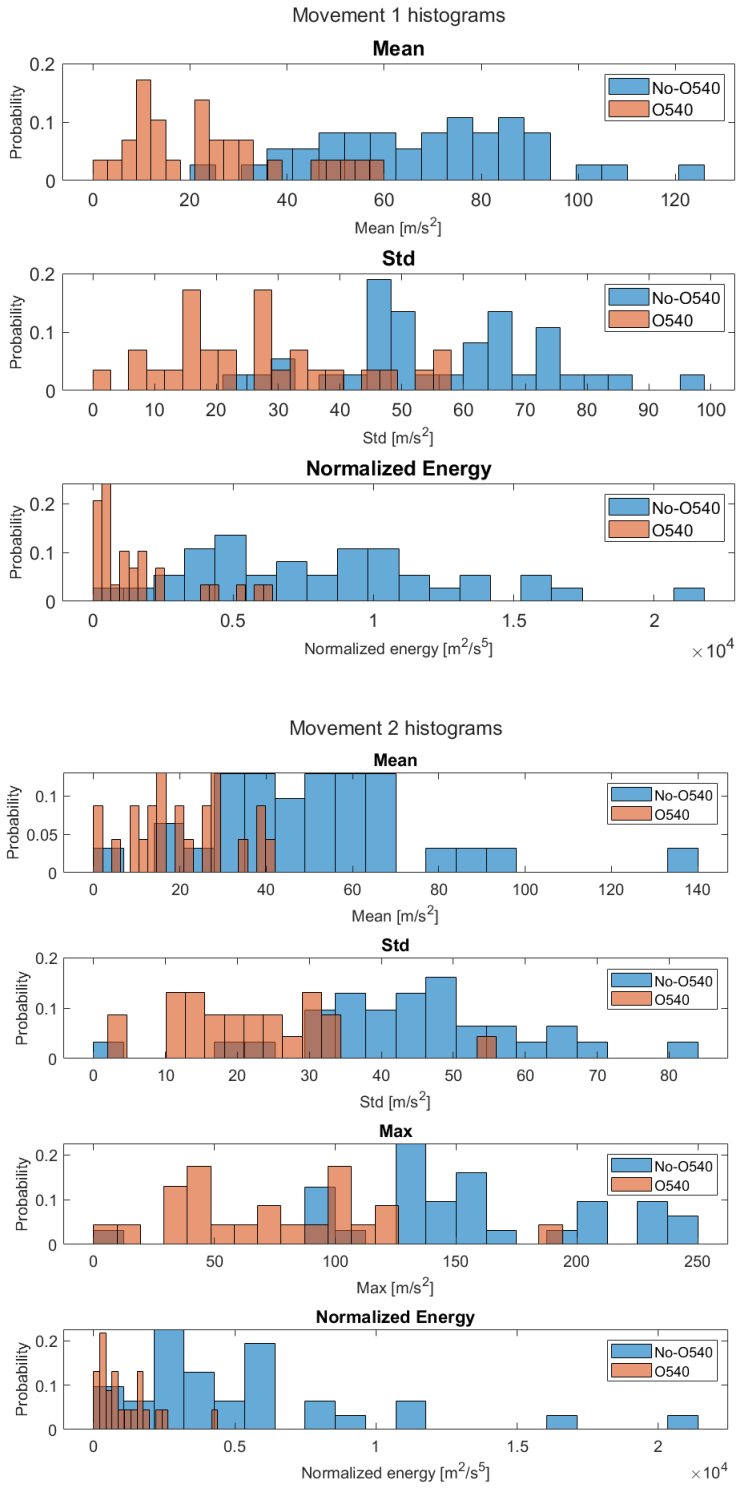

Figure 5: Movement 1 & 2 selected features histograms of KINOVA-O540 Vs No KINOVA-O540 classification

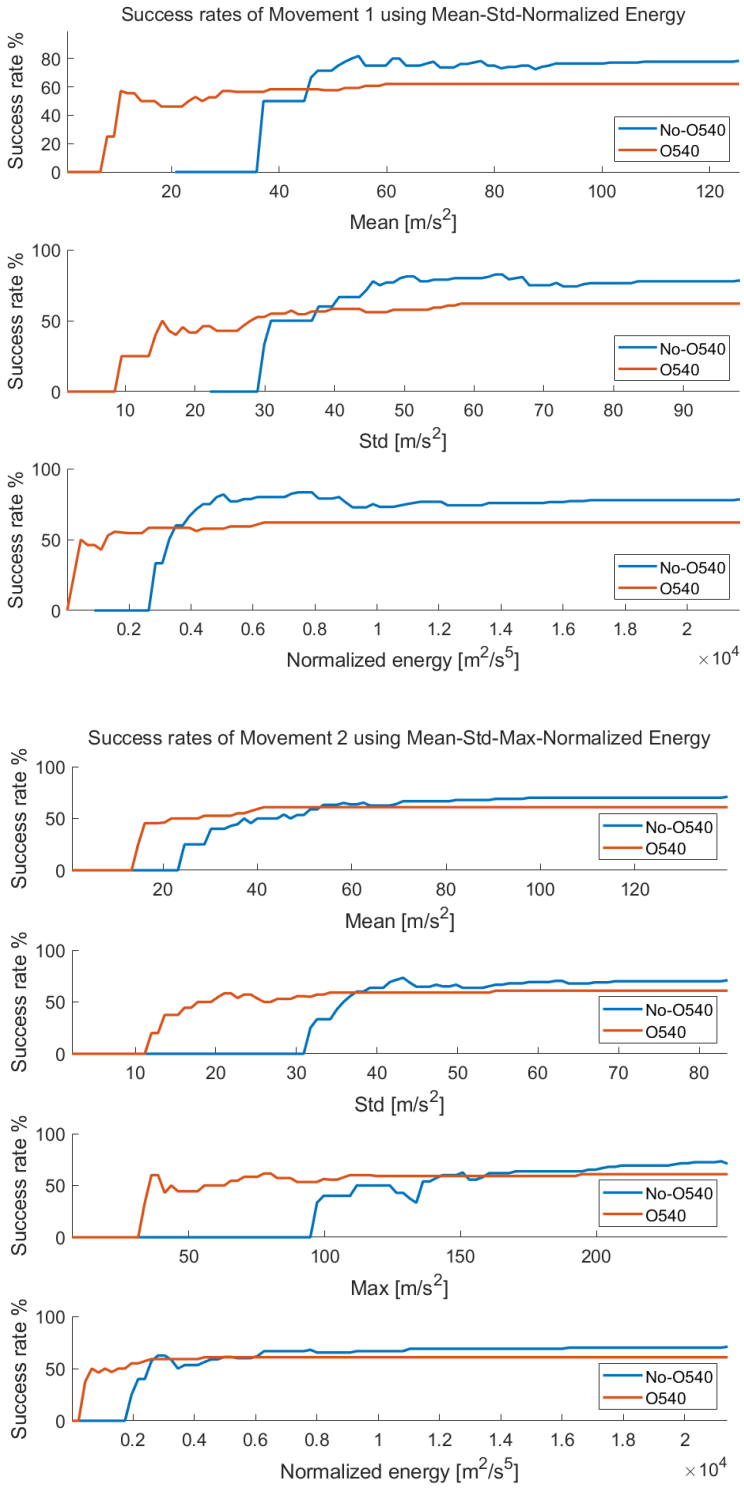

Figure 6: Movement 1 & 2 success rates of selected features from KINOVA-O540 vs. No KINOVA-O540 classification

Table 2: Task success vs failure classification performance when features that are most informative about KINOVA-O540 usage are used for the classification. Sensitivity indicates correctly identifying successful movements

		SVM classifier performance using chosen features		
Movement category	**Subset of features chosen by sequential forward selection**	**Accuracy**	**Sensitivity**	**Specificity**
1	Mean, Std, Normalized energy	71.21%	100%	0%
2	Mean, Std, Max, Normalized energy	69.17%	100%	0%

3.2 Success Vs. Failure Classification

Next, as described in the Methods Section, we formulated a classification problem, to separate the actigraphy data corresponding to the task success from task failure. The classification performance results are presented in Tables 3, 4 and 5. The results in Tables 3, 4 and 5 correspond to the classification performance when both KINOVA-O540 and No-KINOVA-O540 actigraphy data are used, when only KINOVA-O540 data are used and when only No-KINOVA-O540 actigraphy data are used, respectively.

Table 3: Task success vs failure classification performance and the list of selected features when both KINOVA-O540 and No-KINOVA-O540 actigraphy data are used. Sensitivity indicates the accuracy of correct identification of task success.

		SVM classifier performance using chosen features		
Movement category	**Subset of features chosen by sequential forward selection**	**Accuracy**	**Sensitivity**	**Specificity**
1	Normalized energy, Time	72.73%	72.34%	73.68%
2	Median	70.37%	75%	61.11%

Table 4: Task success vs failure classification performance and selected features when only KINOVA-O540 actigraphy data are used. Sensitivity indicates the accuracy of correctly identifying task success.

		SVM classifier performance using chosen features		
Movement category	**Subset of features chosen by sequential forward selection**	**Accuracy**	**Sensitivity**	**Specificity**
1	Entropy, Time	82.76%	88.89%	72.73%
2	Mean, Min, Median, Energy	82.61%	92.86%	66.67%

Table 5: Task success vs failure classification performance and selected features when only No-KINOVA-O540 actigraphy data are used. Sensitivity indicates the accuracy of correctly identifying task success.

		SVM classifier performance using chosen features		
Movement category	**Subset of features chosen by sequential forward selection**	**Accuracy**	**Sensitivity**	**Specificity**
1	Energy, Normalized energy, Time	45.95%	44.83%	50%
2	Std	51.61%	50%	55.56%

From Table 3, we observe that when both KINOVA and No-KINOVA-O540 data are used for classification, the task success vs failure classification accuracies, specificities and sensitivities are around 70% for both movement categories with lower than 70% specificity for movement category 2. Moreover, normalized energy, median and task time are selected as the most informative features for this classification problem. In Figure 7, we demonstrate the task success rate as a function of the selected feature values. For movement 1, higher success rates are achieved with lower task time and lower normalized energy when KINOVA-O540 is used and for movement 2 when KINOVA-O540 is used with lower median higher success rate could be achieved. For movement category 1, lower normalized energy and short elapsed time could indicate that KINOVA-O540 users tend to complete a task successfully while using lower amount of energy, in contrast to the higher energy for non-KINOVA-O540 users. On the other hand, for movement category 2, the recorded acceleration values for non-KINOVA-O540 users were higher potentially indicating more abrupt and uncontrolled movements by non-KINOVA-O540 users

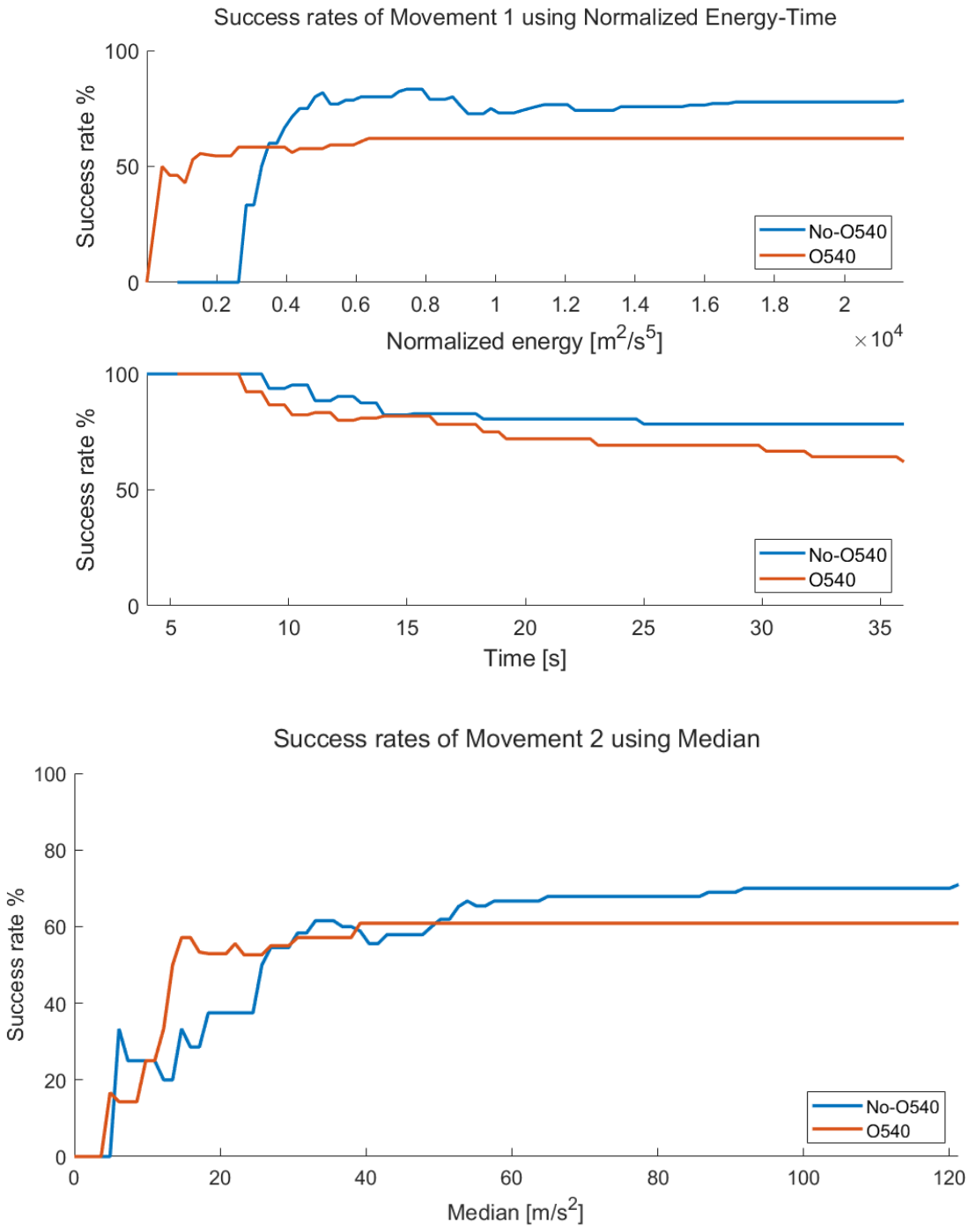

Figure 7: Movement 1 & 2 success rates for selected features of success vs failure classification of both KINOVA-O540 and No-KINOVA actigraphy data

Finally, we investigate the task success vs failure classification performance when only KINOVA-O540 or No-KINOVA-O540 actigraphy data are used and the classification results together with the selected features are presented in Tables 4 and 5, respectively. Comparing tables 4 and 5, we observe that when KINOVA-O540 is used task success classification performance is significantly higher than when KINOVA-O540 is not used. Moreover, Figures 3.2 and 3.2 demonstrate the distribution of the features selected to be most informative about task success vs failure classification. Comparing these two figures, we can identify that score the distributions of the features for failed samples and successful samples are more separable from each other when KINOVA-O540 is used. This higher separability for KINOVA-O540 case also supports our classification results for which when KINOVA-O540 is used actigraphy is more informative about task success identification. These results indicate that when KINOVA-O540 is used, actigraphy could be successfully used to identify if the PUL tasks are successfully completed.

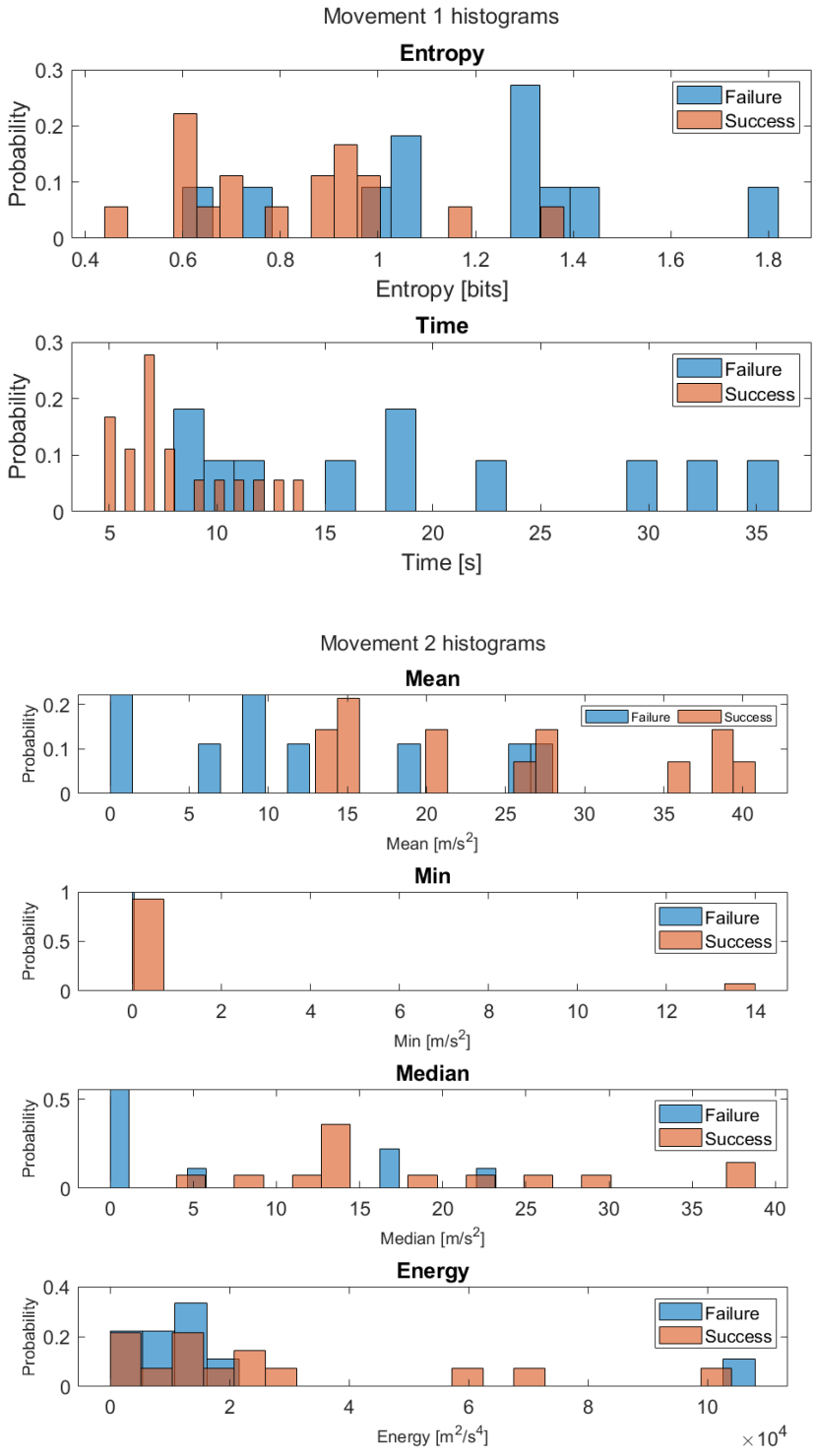

Figure 8: Movement 1 & 2 selected features histograms of success vs failure classification of only KINOVA-O540 actigraphy data

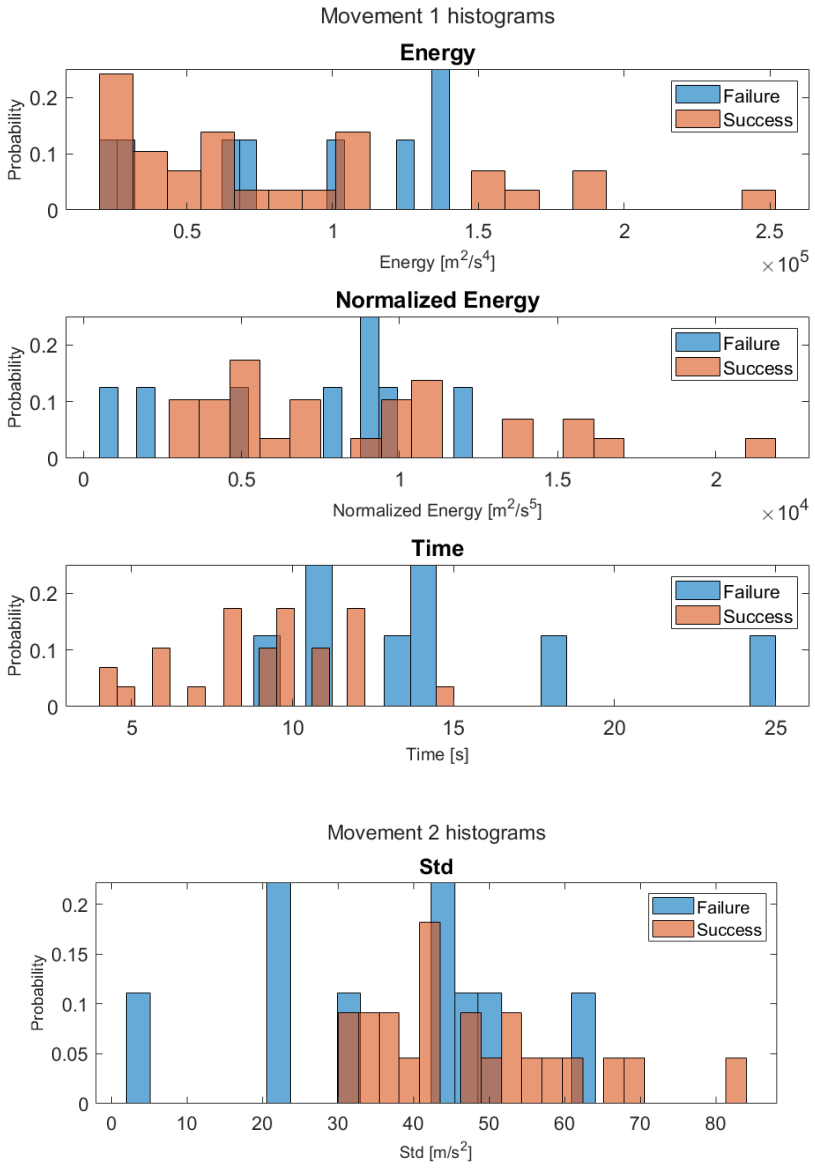

Figure 9: Movement 1 & 2 selected features histograms of success vs failure classification of only No-KINOVA-O540 actigraphy data

4.0 Conclusions and Future Directions

This study presents a novel method to remotely study dynamic arm supports for the Duchenne Muscular Dystrophy (DMD) population. Such a remote study is essential for this population as DMD is a rare disease, and the proposed approach is a step towards facilitating access to clinicians' assessment by remote monitoring. In our approach, we combined standardized testing with actigraphy data that is labeled through recorded videos, and then we applied machine learning and feature selection, specifically support vector machines (SVMs) and sequential forward feature selection. Our analysis with SVM showed that it is possible to detect with high accuracy the usage or no-usage of the KINOVA-O540, the dynamic arm support device that is utilized in this study. We argue that this was possible because of the smooth non-abrupt movements achieved when KINOVA-O540 was used. When KINOVA-O540 was not used, movements recorded through actigraphy had high variability due to different range of abilities of the participants. Such a distinction between KINOVA-O540 and No-KINOVA-O540 cases allowed the detection of a distinctive patterns within the actigraphy data. In future applications, this classification method could be used for remote monitoring of the usage of KINOVA-O540 for daily life tasks, permitting better planning for treatment. Furthermore, we analyzed how the standardized test task performance was impacted by the use or absence of KINOVA-O540. We showed through the selected features that when KINOVA-O540 is used, there was an improvement in energy expenditure and movement control. Finally, we showed that classification between success or failure of tasks that are defined by the standardized PUL test is more accurate if only KINOVA-O540 actigraphy data was considered, compared to using both KINOVA-O540 and No-KINOVA-O540 data together or just using No-KINOVA-O540 data. We argue that the low task success vs failure classification performance for No-KINOVA-O540 case could be explained by the irregular patterns in the actigraphy data due to the varying abilities of the participants. The main limitation of this study was the number of samples available for each movement category which prevented further analyses of the differences of performance among different movement types. Such a limitation might impact the generalization

ability of our classifiers across different movements and across more participants. However, we believe that our approach is a novel application of machine learning for the analysis of actigraphy data recorded from DMD population. In summary, the work presented in this thesis is an initial step towards remote monitoring of KINOVA-O540 or a similar dynamic arm support device usage and identification of task success when such devices are used by the participant during activities of daily living. Such a remote monitoring could then be used to investigate the long-term effect of such dynamic arm support devices.

Appendix A Movement Categorization

Below find how PUL tasks were categorized into seven movement categories

Table 6: Movement categorization

Movement grouping	**Commonalities in items**	**Item number and description on the PUL**
A	Require shoulder flexion at shoulder height or above	1. Shoulder abduction with arms above head 2. Raise both arms to shoulder height 3. Shoulder flexion to shoulder height (no weight)
B	Require lifting weight off of table	4. Shoulder flexion to shoulder height (500g) 5. Shoulder flexion above shoulder height (500g) 6. Shoulder flexion above shoulder height (1kg) 13. Stack 3 soup cans at midline 14. Stack 5 soup cans at midline
C	Requires primarily elbow/shoulder movement without weights	7. Hands to mouth 8. Hands from lap to table
D	Moving weight on table	9.Move 100g weight on table 10. Move 500g weight on table 11. Move 1kg weight on table 12. Lift heavy can diagonally on table
E	Requires use of two hands together	15. Remove lid from container 16. Tearing paper 18. Push on light
F	Fine motor tasks	17. Trace a path on a paper using a pencil 20. Pick up coins on tabletop 21. Place finger sequentially on numbers on a diagram 22. Pick up 10g weight using a finger pinch
G	Wrist movement only	19. Supination (move wrist to face palm up)

Appendix B Movements Count

Below are the number of samples existing for each of the 5 movements categories. Score 0 = Failure , Score 1 = Success

Table 7: Movements count

	Without KINOVA-O540	**With KINOVA-O540**	**Score 0**	**Score 1**	**Score 0 Without KINOVA-O540**	**Score 1 Without KINOVA-O540**	**Score 0 With KINOVA-O540**	**Score 1 With KINOVA-O540**
mov A	6	5	2	9	1	5	1	4
mov B	5	11	8	8	4	1	4	7
mov C	12	13	5	20	0	12	5	8
mov D	37	29	19	47	8	29	11	18
mov E	31	23	18	36	9	22	9	14
mov F	43	34	1	76	0	43	1	33
mov G	11	8	3	16	1	10	2	6

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