Activity Segmentation Using Wearable Sensors for DVT/PE Risk Detection

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***Abstract*—Using a wearable electromyography (EMG) and an accelerometer sensor, classification of subject activity state (*i.e.*, walking, sitting, standing, or ankle circles) enables detection of prolonged "negative" activity states in which the calf muscles do not facilitate blood flow return via the deep veins of the leg. By employing machine learning classification on a multi-sensor wearable device, we are able to classify human subject state between "positive" and "negative" activities, and among each activity state, with greater than 95% accuracy. Some negative activity states cannot be accurately discriminated due to their similar presentation from an accelerometer (*i.e.*, standing *vs.* sitting); however, it is desirable to separate these states to better inform the risk of developing a Deep Vein Thrombosis (DVT). Augmentation with a wearable EMG sensor improves separability of these activities by 30%.**

***Keywords*-Wearable Sensors, Classification Algorithms, Biomedical Computing**

I. Introduction

Deep Vein Thrombosis (DVT) is a condition occurring when a clot forms in the deep veins of the leg. This condition impacts between 300,000 and 900,000 people per year in the United States, and is the country's leading cause of maternal death [1]. Studies have shown that 10%-30% of patients suffer mortality after developing a venous thromboembolism [2]. In the majority of these cases, the cause of death is a Pulmonary Embolism (PE) caused by the displacement of a DVT. Most clinically significant PEs originate as venous thromboembolisms in the lower extremities or pelvis [3]. In addition to short term risks, risk of recurrence within 4 years for patients with unprovoked DVT is nearly 20% [4].

It is this long term risk that makes DVT a dangerous condition. Clinical detection of DVT is difficult because venous thrombi can be clinically silent, and many of the symptoms of venous thrombosis are also associated with nonthrombotic disorders [5]. Risk factors for DVT reflect the underlying pathophysiologic mechanisms of venous thromboembolism, with 70 to 96 percent of patients presenting at least one risk factor. Strong risk factors for DVT are orthopedic surgery, pregnancy, chemotherapy, and immobility [6]. Incidence rates vary drastically across patient populations. For elderly populations (age $>=$ 80), incidence rates are about 1 per 100, while for younger populations (age $<$ 80) the rates are less than 2 per 1000.

Determination of risk based on only one physiologic indicator is both insensitive and nonspecific [5]. The American Association of Family Physicians provides practitioners with clinical diagnostic algorithms that are widely accepted as the best method of providing prompt and accurate diagnosis in the field. The process of diagnosis combines both a physical examination and blood tests, both of which require a direct intervention by a trained physician.

Because a patient can be at risk for several years, it would be impractical for providers to continuously perform these diagnostic procedures without severely impacting the patient's quality of life. Automatic activity classification allows for continuous monitoring of a patient without the direct supervision of a medical practitioner. Because of the high correlation between calf muscle activity and venous blood velocity [7], it is possible that calf muscle activity could be used to directly assess DVT risk.

The most direct method of monitoring muscle activity is using electromyography (EMG). EMG measures the electrical activity of a muscle in response to nervous stimulation. Alternatively, using an accelerometer to measure the motion of the leg, and indirectly measure calf muscle activity, leverages a large amount of existing research and provides a robust data collection workflow [8], [9], [10], [11] . Accelerometers are a common method of monitoring patient activity; mainstream devices such as the Apple Watch already provide basic activity monitoring with feedback. In this paper, we explore the ability of both EMG sensors and accelerometers to accurately measure patient activity, and examine the effectiveness of each sensor in correctly measuring and classifying activity. Effective monitoring could allow for more accurate DVT risk determination, enabling practitioners and patients to make more informed decisions on how best to prevent thrombus formation.

II. Background

In 1856 Rudolf Virchow described the three factors: venous stasis, activation of blood coagulation, and vein damage, that are critically important in the development of venous thrombosis. These factors have come to be known as the Virchow Triad. Venous stasis can be caused by anything that slows or obstructs the flow of venous blood, and can result in an increase in blood viscosity and the formation of microthrombi.

While the formation and dissolution of microthrombi is a normal process; in the presence of increased stasis, procoagulation factors, or endothelial injury, the thrombi that form may grow and propagate in the vein [12]. Thrombi usually form behind valve cusps, at venous branch points (many of which begin in the calf), or where the flow is otherwise disturbed [12]. The process of thrombosis is usually characterized by cascading activation of enzymes that magnify the effect of the initial trigger event. This process causes platelets to adhere more readily, and provokes an inflammatory response within the vein.

For patients with low mobility, or those who are confined to bed rest, risk of thrombus formation is very high. Sitting or lying for long periods can cause blood to leave the lower extremities [13], [14]. This reduced outflow can affect autonomic tone and cause vascular dysfunction. Even in healthy adults, being seated for as little as 4 hours can reduce lower leg blood velocity by 13% [14].

The calf muscle plays an important role in the movement of blood from the leg. The so called calf muscle pump can push as much as 70% of the blood out of the calf during plantar flexion by generating a pressure gradient both proximally and superficially [15]. The American Association of Colleges of Pharmacy guidelines for the prevention of DVT include frequent calf muscle contractions for travelers who are taking flights longer than 8 hours [16] and most airlines recommend performing some sort of foot or leg exercises to improve circulation in the confined space of modern cabins. Study of the effect of active foot and ankle movements on lower extremity blood velocity has shown an increase in mean velocity over both no activity and passive movements [17], [18].

III. Related Work

For patients recovering from major surgery or who are otherwise relatively constrained in their mobility and are therefore at risk of DVT, traditional types of activities on which classifiers from the literature are trained may be impossible. Properly measuring factors such as time spent in bed, compliance with provider recommended therapeutic exercises, and overall mobility are crucial to determining patient risk.

Extensive work has been done on the subject of activity classification using data from a tri-axis accelerometer. Yang et al. used a wrist mounted sensor to segment activity of subjects performing a wide variety of activities and was able to achieve an accuracy of 96% [8]. Khan et al. and Mathie et al. were also able to achieve accuracy above 90% with sensors mounted on the chest and waist respectively [9], [11]. In other cases, such as Allen et al., a single waist mounted sensor was able to achieve 91.4% accuracy for classification of Lying but only 79.2% and 77.3% for Sitting and Standing respectively [10].

As with [10], the classification accuracy of Sitting and Standing consistently lags behind the accuracy of other activities for single sensor studies. Berninger et al. used a single hip mounted accelerometer to classify Standing, Sitting, and Walking. In the free living portion of their study the accuracy for Sitting and Standing were 72.6% and 87.1% respectively, compared to 96.8% for Walking [19]. Khan et al. demonstrated average accuracies for a single chest mounted accelerometer of 95% for Lying, but only 63% and 74% for Standing and Sitting respectively [9]. Some studies, such as [20] avoided the differentiation of Sitting versus Standing altogether by lumping them into a single activity. For Sitting and Standing, the results for single sensor studies not only lag behind detection of other activities, but also the accuracies for Sitting and Standing in multi-sensor studies such as [8], which achieved accuracies of 98% and 100% for Sitting and Standing respectively.

The use of EMG sensing for the measurement of muscle activity is accepted as a standard practice. Tomaszewski et al. demonstrated that EMG signals were able to be used to accurately classify hand gripping activities with an accuracy of greater than 80% [21]. The success of this EMG based system on classifying fine motor activity implies that such a system may assist a single accelerometer based system in better classifying low mobility activities performed by patients. The addition of an EMG sensor could also improve the system's ability to reject activity noise, improving classification accuracy during unstructured activity [22]. Roy et al. demonstrated that combining an accelerometer and EMG sensors can allow for classification of patient activity, but required the use of several EMG sensors to obtain accurate results [23]. Multiple sensors can be uncomfortable for the patient and make monitoring more intrusive. By utilizing only one EMG sensor the proposed system could be used more effectively in the treatment environment, but may reduce classification accuracy without additional sensor data.

While the existing work in this field has obtained highly accurate results for traditional activities, the problem of classification for low mobility activities presents challenges not accounted for in these works. It is therefore important to test specific activities that are more relevant to the patient population at risk of DVT. In this paper we outline a new set of activities that better represent the available range of motion for patients with low mobility. Evaluating the effectiveness of a multiple sensor system on low mobility activities is the major goal of this work.

IV. Approach

A. *Study participants*

Study participants were 17 healthy undergraduate and graduate student volunteers from the Drexel Wireless Systems Laboratory. Participants represented the demographics of the laboratory, and were randomly distributed in gender, age, and height. None of the participants had limited range of motion. Because the study sought to characterize sub-classifications of low mobility activities without the requirement that the participants themselves had reduced mobility, this population was suitable. This study was approved by and conducted in accordance with the Drexel Institutional Review Board protocol number 1703005276.

B. Structured Exercise regimens

Exercises were chosen from literature relating to both traditional accelerometer based activity classification and DVT prevention. For accelerometer based activity classification, the exercises that appeared most often in literature were Walking, Standing, and Sitting [24], [10], [8], [11]. The DVT prevention exercises selected were designed to activate the calf muscle and therefore increase blood flow in the lower leg [13]. The Tap and Twist and Ankle Circles were performed Sitting, while the Foot Pumps were performed standing up. All of these DVT prevention exercises were designed to be able to be performed by patients with low mobility. For ease of working with the data, each activity was assigned a number. Activities that were specifically referenced in literature as beneficial in reducing DVT risk were labeled as a Positive activity, while the activities that increased DVT risk were labeled as a Negative activity. These activity labels are shown in Table I, along with the subclass to which they belong. Additionally, the average magnitude of EMG signal is included for each activity to demonstrate the correlation between calf muscle activation and activity type.

Number	Activity	Average EMG Magnitude (V)	Classification
1	Walking	1.18	Positive
2	Sitting	0.54	Negative
3	Standing	0.60	Negative
4	Tap and Twist	0.74	Positive
5	Ankle Circles	0.84	Positive
6	Foot Pumps	1.07	Positive

Table I: Activity labels with their respective classifications. Based on the average EMG magnitude it is clear that positive activities have a higher level of calf muscle activity than negative activities.

For each exercise, the participant was given a verbal description as well as a demonstration of the exercise. Exercises were performed continuously for 2 minutes in the case of the first three, and in 30 second sets for those that remained. These shorter sets for more fatiguing exercises were designed to ensure exercise performance was consistent. At the end of each set, the participant was given the opportunity to take a break if they felt their ability to perform the exercise correctly was degrading.

C. Unstructured Exercise regimens

To determine robustness of the classifier in situations where data is collected over longer periods of time, participants were asked to spend one hour working at a standing desk. During this time, the participant was allowed to stand or sit at whatever interval they chose, noting only the time period that represented the transition. The participants were asked to perform some mental task to distract them from the activity they were performing.

D. Data collection

Data was collected using the x-IMU device from X-IO Technologies. This device has a 12-bit accelerometer with selectable range of up to $\pm 8g$, and an 8 channel 12-bit digital to analog converter. The EMG sensor used was the MyoWare Muscle Sensor, which was connected to the analog input of the x-IMU device. This sensor is able to measure muscle activity using two adhesive pads placed on the skin. The sensor was placed by the researchers for each participant, with the reference electrode placed on the shin, and the middle and end electrode placed at the center of the medial head of the gastrocnemius muscle as shown in Figure 1.

Figure 1: Image used to guide placement of the EMG sensor. Anatomic variation can result in slight variations in the ideal placement of the sensor which caused differences in the magnitude of the resulting signal. Feature selection was used to reduce the effects of this variation.

For each exercise, after being given verbal instructions, the participant was told to start the exercise. Shortly after the participant began to perform the exercise correctly (at the discretion of the investigator but without further instruction) the start time of the exercise was recorded. After 2 minutes, the labeling of the exercise was stopped and the participant was told to stop performing the exercise after a small period time. The goal of this procedure was to remove a margin at the beginning and end of each exercise to ensure that the activity labeling was as accurate as possible. Figure 2 illustrates the result of this procedure for a dataset, where the red color represents the excluded margin and the green color represents data that included. This labeled data was used as the ground truth for classification.

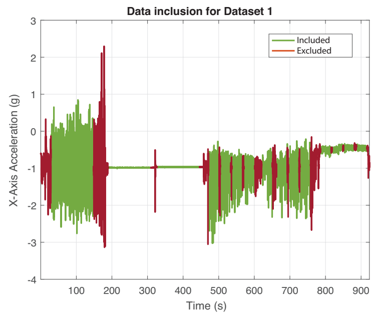

Figure 2: Accelerometer data for a trial showing the effect of the data collection methodology. Excluding transition periods between activities reduced the noise level and improved classifier performance.

Data collection was performed at a rate of 64 Hz for both data streams, and the data was saved to a storage device for later analysis.

E. EMG Descriptors

The EMG data feature descriptor was generated using a rolling window of 6.5 seconds with a 90% overlap [25]. All windows containing more than one activity were removed. The feature vector was $3(n-416)$ to account for the window size. The feature vector for a given window w_n is defined as shown in Equation 1 where var is the variance of the signal.

$$w_n = [E_n, \mu_{E_n}, var(E_n), \varphi^0, \varphi^1, \varphi^2, Q_1(E_n)] \quad (1)$$

where E_n is the EMG envelope defined by $E_n = \sum_{n=1}^{N} |e_n|$ for the raw EMG data e_n, N denotes the length of the EMG signal and μ_{E_n} represents the average of the signal over the window.

The vector $[\varphi^0, \varphi^1, \varphi^2]$ represents the coefficients of a second-order auto regressive model fit to the data window. This model was chosen because of its effectiveness at separating activities in EMG signals over time domain features [26].

Q_1 represents the median of the first quartile of the window. This value was used instead of minimum to eliminate the influence of localized minima spikes and better characterize the lower bound of the signal. This feature was designed to increase separability of Standing and Sitting. The separability between the activity classes can be seen in Figure 3.

F. Accelerometer Descriptors

The feature descriptor for the accelerometer data was generated using the same window parameters as the EMG signal. For each descriptor, a 1 x 4 vector was generated for the signals $a_n = [a_x, a_y, a_x, |a|]$. The feature vector for the accelerometer signal was therefore defined for window w_n as shown in Equation 2 where $rms()$ is the root mean

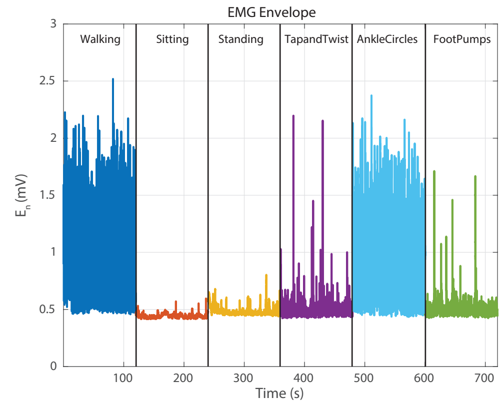

Figure 3: E_n for a trial, showing the activity labels. It is clear from the raw data the the amount of calf muscle activity varies drastically between certain activities but the EMG data alone is not enough to separate them with high granularity.

square value of the signal and μ_{a_n} represents the average of the signal over the window.

$$w_n = [\mu_{a_n}, rms(a_n), var(a_n)] \quad (2)$$

These features were chosen for their high efficiency to reduce classification latency.

G. Classifier

The classifier used in all testing was a single layer feed forward network. For all trials, the number of neurons was $n = 3(t)$ where t is the number of target classes, a formula that was determined to most effectively balance training data requirements and accuracy based on testing. Training and testing for the structured data was done using a leave-one-out methodology [27], and the results obtained by summing all of the resulting confusion matrices. For the unstructured data, the classifier was trained on all of the structured training data and tested using the long term data that was collected from a separate set of participants. While personalizing the trained model for each participant may have improved accuracy, the additional challenges of training such a system the end use environment would make this approach much less practical.

V. Results

Data collection for the study was performed over the course of a week. Fourteen participants each spent approximately 20 minutes performing the exercises. All data was verified to be without sensor malfunction, with any irregular data such as a sensor flat-line being cause for the removal of a dataset. In six cases, issues with EMG pad connection caused the dataset to be be thrown out. For each trial, unlabeled data was removed leaving exactly 1,118 labeled windows for each activity.

A. Individual Sensor Collection

On their own, each sensor measures fundamentally different aspects of the process of locomotion. As such it is important to understand the strengths and weaknesses of each on the model's ability to describe an abstract set of activities via each feature set independently. Using the same subset of the dataset to train and test, three separate networks were trained to classify all activities.

1) Accelerometer: The accelerometer alone achieved 85.8% ($\sigma = 0.128$) accuracy in the classification of the 6 activities as shown in Figure 4a. As was shown in the existing work, Sitting and Standing were frequently mistaken for each other, resulting in an accuracy for activities 2 and 3 of 61.1% ($\sigma = 0.522$) and 59.3% ($\sigma = 0.335$) respectively. This lagged behind the other activities by an average of 25%. Higher sigma values for both of these classes were caused by trials in which accuracy for these activities was 0%. These anomalies occurred when the classifier converged on a solution that was unable to separate activities 2 and 3 despite relatively high accuracy for the remaining classes. We observed 100% classification accuracy between Positive and Negative activities. The results for the accelerometer alone are shown in Figure 4a.

In the unstructured data, the results were similar. For Sitting the classifier achieved an accuracy of 58.7%, and for standing the accuracy was 18.6%. Again, all of the misclassified windows were put misclassified within the set of the two activities.

For Standing and Sitting, the accelerometer has a difficult job. There was little variance in the signal (variance of 0.000015 and 0.000011 respectively) resulting in no obvious features that would differentiate the raw signal of the two classes. It is understandable that this is the major source of error for the sensor, however this did not effect the accuracy of the Positive and Negative classification because both activities were within the same class.

2) EMG: The results of classification using only the EMG is shown in Figure 4b. In the case of almost all classes, errors were widely distributed across several activities. Activities 1, 4, and 6 all achieved more than 80% accuracy, with an overall accuracy of 74.8% ($\sigma = 0.03$). Standing had the highest degree of misclassification overall with an accuracy of 23.8% ($\sigma = 0.10$), with misclassification spread across all other classes relatively evenly, but Sitting was able to maintain a high accuracy. For the EMG sensor alone, the accuracy of Sitting and Standing lagged behind the other activities by 19.4%.

For the unstructured data, the classifier was only able to achieve an accuracy of 95.0% for Sitting and 22.8% for standing. Unlike the classifier that used only the accelerometer data, this classifier spread the classifications more evenly across all activities.

Where the accelerometer was able to maintain high accuracy across the Positive and Negative classes with an accuracy of 94%. The EMG was more widely distributed, subclass accuracy for the EMG was high for Positive exercises but very low for Negative ones with an accuracy of 98.0% ($\sigma = 0.008$) and 58.6% ($\sigma = 0.10$) respectively.

B. Combined Classification

The combined feature descriptor was a concatenation of both the Accelerometer and EMG features. This classifier showed high accuracy for all activities, with an overall accuracy of 97.7% ($\sigma = 0.128$) as shown in Figure 4c. For both Standing and Sitting, which have accuracies of 93.2% and 93.7% respectively, the majority of the misclassification (3.1% overall) was within these two exercises. We observed 99.99% classification accuracy between Positive and Negative activities. The results for the combined classifier are shown in Figure 4c.

For the unstructured data the classifier was able to achieve an accuracy of 62.1% for Sitting and 93.5% for Standing. This is a 40% increase in accuracy over the classifier that was trained on the accelerometer features alone, but the accuracy of Sitting is notably lower than the classifier trained on the EMG data.

VI. Conclusion and Future Work

The improvement between the classifier using the accelerometer features alone and the combined classifier was primarily in the separability between Sitting and Standing. While the classifier trained on the accelerometer features was able to classify with high accuracy most activities, the combined classifier was 30% more accurate at separating Sitting and Standing. As demonstrated in Figure 3, there was a noticeable increase in calf muscle activity for Standing over Sitting. When standing the patient is constantly making subconscious adjustments to posture to maintain balance. The EMG sensor also benefited the classification of the other activities and enabled an increase classification accuracy in the combined classifier of 11% overall.

Surprisingly the classifier trained on the EMG data alone also had poor performance when separating Sitting and Standing. While it improved significantly the accuracy of Standing, the accuracy of Sitting actually decreased. Whereas in the combined classifier adding the EMG data seemed to allow better information about the calf muscle's activity, on its own the EMG envelope data was insufficient for accurate classification.

There are several factors related to the EMG sensor itself that could have contributed to this performance. Across the dataset, there was sufficient variation in signal magnitude (due to sensor placement and anatomical variations) to cause clipping in 6 of the datasets which resulted in an artificially low maximum signal magnitude. This clipping did not have a significant impact on classifier accuracy most likely because the EMG descriptors chosen focused more heavily on the second order shape of the signal and variance levels.

(a) Accelerometer confusion matrix

(b) EMG confusion matrix

(c) Confusion matrix combining the accelerometer and EMG sensors

Figure 4: Confusion matrices for classifiers based on the accelerometer alone (left), the EMG sensor alone (center), and combined (right)

Additionally, the activities affected most by the clipping were those that had high levels of accelerometer activity and were therefore more easily separated. The Myoware Muscle sensor has a fixed gain; a more robust sensor may be able to prevent this issue.

Overall the addition of an EMG to a single ankle mounted accelerometer for the classification of activities has been shown in this paper to improve separability of Sitting and Standing, two activities whose accuracies lagged behind in other work, by 30%. In addition, the combination of an accelerometer and an EMG sensor is able to classify low mobility activities with an accuracy above 90% for both short and long duration. The system showed robustness to variations between participants and could provide vital data to practitioners concerned with a patient's compliance in a treatment plan deigned to prevent future clot formation.

A. *Future Work*

The results provided in the paper demonstrate that in a lab setting the classifier is robust and able to accurately classify activities. Further investigation is required to determine whether the classifier is able to perform with the same accuracy for patients with limited mobility. Several factors including skin condition and interaction with hospital equipment may interfere with the ability for the EMG sensor to gather accurate data. The use of a knitted sensor such as [28] may improve data accuracy in these situations while also improving the overall comfort of the device.

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