Feature Extraction and Analysis for Body Sensor Networks

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***Abstract*—Wireless body sensor networks are networks composed of nodes placed on different parts of the human body. These nodes are able to communicate in a wireless manner and transmit data from sensors mounted on them to a base unit or a computer that analyzes the data received. Wireless body sensor networks make on-body and mobile health-care monitoring possible; such systems can integrate information from different sources, and can initiate actions or trigger alarms when needed.**

In this project we investigate a collaborative signal processing scheme for physical movement monitoring with motion sensors. The signal processing consists of preprocessing, feature extraction and classification. We define a measure on feature significance as well as features' correlations. Because these nodes have a limited amount of battery power, we extract features to characterize the data. We develop a metric to rank each feature by its significance with respect to a particular movement class. We validate our metric by analyzing the accuracy of classification when using a subset of features selected by our metric. Using the characteristics of the best features we find from the rankings, we develop new features to improve the system accuracy and then assess their effectiveness.

I. Introduction

AS health care costs constantly increase due to, among other things, an ever increasing elderly population, there also increases a demand for reasonably priced technologies that aid in the assistance of these elderly patients. Assisted living is an area in which we believe that the elderly population would benefit from the use of information and communication technology (ICT), more specifically for those who live at home. Human physical movement monitoring systems, generally referred to as Body Sensor Networks (BSN) such as the one employed in this system, make it possible to evaluate the quality of life, as well as ensure the safety of the elderly. Advances in technology have made possible the creation of small wireless sensor motes that join a number of different technologies onto small units that can be worn on the human body. These platforms are able to measure physical attributes such as acceleration, momentum, and temperature, perform a limited amount of online computation, and have the ability to communicate with a base station within a short range. The use of body sensor networks for monitoring purposes increases the amount of privacy for patients being monitored because the system is decentralized. Such devices make it possible for the elderly to maintain their independence by living in the comfort of their own home while also being able to live at ease knowing that in the case of an illness or accident, emergency services would be contacted.

There are a couple of obstacles that must be addressed before ICT-based systems such as ours become widely accepted and used. Among others, there are concerns such as the ease of use, cost, durability, maintenance, and the consumer's amount of privacy. One of the most essential problems to be solved is the fact that these motes have a limited amount of power so complex computations cannot be performed onboard. In this paper we propose a system that is able to monitor the movements of human subjects as well as predict the need for medical attention. We also pay close attention to the challenge of making a system that uses robust features in order to perform simple equations that are not heavy on energy usage. In this paper we present a system overview, discuss the usage of metrics to measure the quality of our features, discuss and analyze our existing features, and then introduce, analyze, and compare our two new features to the existing features. We also present an improved metric, as well as, three significant, robust features for usage in our system.

II. Related Works

Many recent studies into the monitoring of human movement using similar systems have involved processing and analyzing the raw data after transmitting it to a computer or base station [1], [2], [3]. This data processing is performed offline after the data is recorded and sent to a processing unit rather than onboard the wearable system units themselves [1], [4]. These offline systems prove to be very accurate, but require a great deal of computational power. We propose a system that performs signal processing onboard the wireless motes worn on human subjects similar to the system in [5].

The use of feature selection in body sensor networks is proposed in [6] to reduce the number of sensors as well as save power. Because these motes have limited memory and power resources, the main goals in this study are to create more robust features and also to develop simple algorithms for processing and classification.

III. System Overview

We propose a system composed of on-body motion sensors and a gateway system allowing it to connect to a base station (i.e. a laptop, cell phone, or PDA) for monitoring purposes. Processing units on the motes are responsible for filtering and segmenting the data and extracting pre-programmed features from the data. Processing and global classification in this proposed system will take place on the motes as well. This system uses Telos-B motes developed at the University of California, Berkeley and our system set up is similar to that mentioned in [7].

For our current experiments we use three motion sensors and attach them to our subject's ankle, waist, and wrist. In the future we plan to do everything onboard the motes; however, at this time we are sending the raw data collected from the motes for offline processing because it is faster for testing new algorithms. The motes that record our subjects' movement data each have an accelerometer, as well as, a gyroscope onboard. The accelerometer records data along the x, y, and z-axes, while the gyroscope records data along the x and y axes.

There are three main steps we take in classifying our movements: filtering and segmenting, extracting features from the data, and classification.

A. Filtering and Segmenting

Each of the three on-body sensors gives us three readings of data from the accelerometer and two from the gyroscope. We must segment this data and split it into periods containing each of the specific movements. In order to do this, we must assume that a movement starts and ends with the subject at rest. Currently, our segmentation is being done offline to avoid any unnecessary complexity; however, we plan to have this done online in the future.

B. Feature Extraction

Because the motes themselves have a limited amount of battery power to be used for computing, we must extract only a portion of our data to be processed. Feature extraction is one of the most important steps in this system because better, more significant features improve the accuracy of classification. Features we have developed so far are as follows: mean value, start-to-end amplitude, standard deviation, peak-to-peak amplitude, root mean square (RMS), morphology, inter quartile range (IQR), peak-to-peak width/length(x). We are currently calculating these features also offline in MATLAB.

C. Classification

We use a k-nearest-neighbor (k-NN) algorithm to classify each of the eight movements as target classes that we established for testing purposes. These movements are: forward leg raise, forward knee raise, reverse ankle raise, stand to sit to stand (from a low cushioned chair), stand to sit to stand (from a normal fold-up chair), kneeling, jumping, and sitting to lying on a bed. We recorded the movements of seven different subjects with ages ranging between 20 and 60 years old performing each of these eight tasks to use for our data. When the subjects perform each movement for testing, we have them do the same movement ten times in a row. The collected data is then segmented into separate periods of activity. With the data from our seven different subjects, we specify a training set of 10 and a testing set of 60 for each of the eight movements.

IV. Feature Significance Metrics

We first use a metric in order to rank each of the features for classification. A metric assigns the significance value for a certain movement class. Those features ranked with the best rankings are the most significant features. Metrics used in [1] are σ_1, the standard deviation of the data for a specific feature, and $\frac{\sigma_1}{d_{1,2}}$, the standard deviation of the data divided by the distance from the mean of the existing class to the mean of the closest class. We are able to compare these metrics by analyzing the accuracy of classification by using each metric and taking the first one, two, three, etc. features in the existing ranked list of features and then taking the mean of these values (see Figure 1).

σ_1	$\frac{\sigma_1}{d_{1,2}}$	$\frac{3\sigma_1+3\sigma_2}{d_{1,2}}$
86.7%	89.5%	88.4%

Figure 1. Metric Accuracies

After analyzing the existing metrics, we are able to create a new metric. We tried to improve on the second metric mentioned and produced the following metric: $\frac{3\sigma_1+3\sigma_2}{d_{1,2}}$. In addition to the standard deviation of the data for the specific feature and the measure of distance to the closest class, we also consider the standard deviation of the closest movement class so as to prevent any overlaps in data. It is known that approximately 99.7% of a population of data lies within three standard deviations of the population's mean. Therefore, if the quantity, $3\sigma_1 + 3\sigma_2$ as a distance, is larger than the distance to the closest class it can be assumed that the two movement classes in question do not overlap.

The third and final metric, $\frac{3\sigma_1+3\sigma_2}{d_{1,2}}$, has a slightly lower accuracy than the second, however, this loss in accuracy is negligible. We think it will perform the best for our purposes because this metric takes into account the nearest class and considers scenarios in which there might be overlapping classes while losing only a negligible amount of accuracy. Overlapping classes should not receive higher rankings because if there are values for each class overlapping in the same area, there is a level of uncertainty and the accuracy of classification is lower. As can be seen in figure 2, the second metric would produce the same value for both scenarios. The values for σ_1 and the distance between the classes are equal. However, if the third metric is used, the value for σ_2 is used and different values are produced for each scenario—with and without overlaps. This proves that the third metric is best for our data.

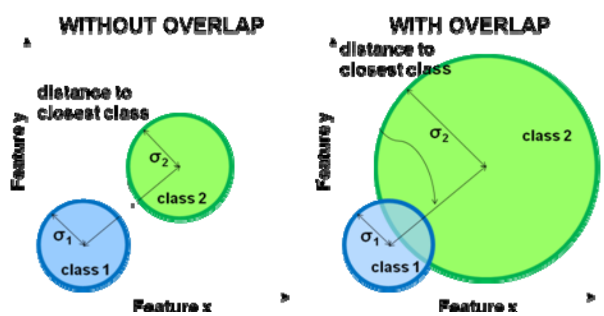

Figure 2. Overlapping and Non-Overlapping Movement Class Scenarios

V. Feature Analysis

We calculate our own features for extraction from the raw data. Originally, we calculated a total of six features in order to perform the classification. These features are as follows:

- **Mean value:** This is the mean value of the data points for a recorded movement. Because the data recorded contains both positive and negative values across the x-axis, the mean value is often close to zero; therefore, it is not a very significant feature in our study.

- **Start-to-end amplitude:** The Start-to-end amplitude is a measure of the total amplitude from the starting point value to the ending point value of the signal recorded. This measurement also seems to be problematic because our test subjects are instructed to start their movements and end their movements at rest. This means that both values would be similar, giving a start-to-end amplitude value of zero.
- **Standard deviation:** Standard deviation is a measure of the overall spread of our data values along the x-axis. When we put this feature through our metric to test its effectiveness in classifying movements, it ranked very high compared to the others. The dispersion of our data proves to be an important characteristic when calculating features.
- **Peak-to-peak amplitude:** This measurement of amplitude calculates the total length, or range, from the greatest positive value to the greatest negative value along the y-axis of our data. Peak-to-peak amplitude is also a measurement dealing with the spread of our data and also did well in comparison to the other features.
- **Root mean square (RMS):** The calculation of root mean square is also called the quadratic mean and is the measure of the magnitude of a varying quantity. The RMS feature's results were not very significant for our purposes.
- **Morphology:** This feature's calculation is a measurement of the shape and form of the data's distribution. We select ten evenly distributed points along the x-axis from the start to the end of each movement segment and take the sum of the rectangular areas under each point. "The distance between two morphological features is defined as the area between two morphologies."[8] Although this feature does not directly relate to the dispersion of our data, it appears to be a significant feature for classifying our data.

We use our metric to analyze these features, creating a ranking system to help distinguish what makes a good or bad feature. Using the metric, we rank all of the features for each movement and are able to compare their performances.

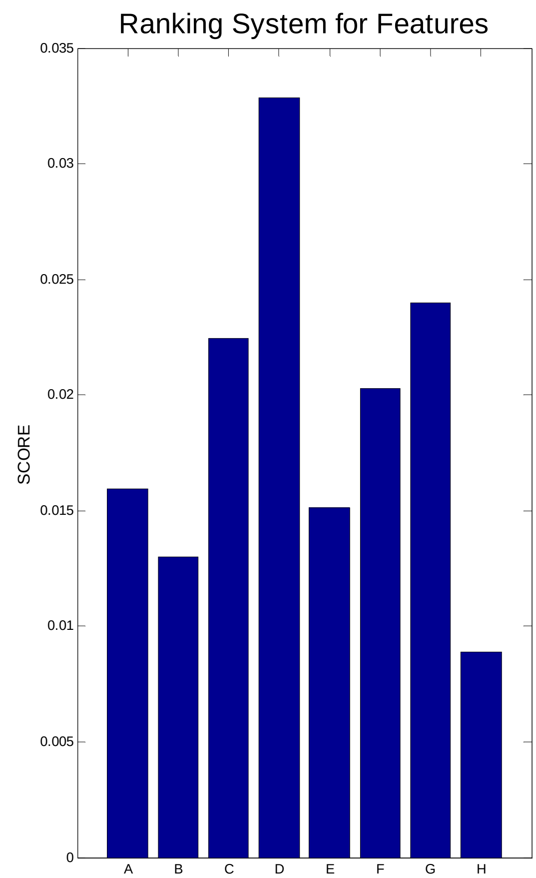

Figure 3. Feature Significance

Legend

A. Mean Value	E. RMS
B. Start-to-end Amplitude	F. Morphology
C. Standard Deviation	G. IQR
D. Peak-to-peak Amplitude	H. Peak-to-peak width/length(x)

From figure 3, one can see that standard deviation, peak-to-peak amplitude, and morphology rank higher than the others. Standard deviation and peak-to-peak amplitude are both related to the general distribution of data along the y-axis. Evidently, features based on the spread of our data tell a lot about the data and do remarkably well in distinguishing between movements.

Given that this is a body sensor network and our collected data is a numerical presentation of the movements of human subjects, we must keep in mind what exactly we are measuring when generating features. When a feature is significant it can be said that the feature values differ considerably from one movement to the other, therefore increasing the accuracy of the classifier.

An explanation for the significance of features based on the dispersion of the data along the y-axis could be because the y-axis is a measurement of a mote's acceleration in the x, y or z directions or the momentum in the x or y direction. These features consider the values along the y-axis that measure the magnitude of the actions of the subjects rather than the time taken to perform each activity. If this is true, we can assume that because these features are so significant, the magnitudes of each of the eight movements and their calculated values for standard deviation and peak-to-peak amplitude are distinct.

Our morphology feature measures the shape and form of our data. Because this feature is significant, one can assume that the morphology feature values for each of the eight movements must be quite different. Also, because it was ranked using the metric, there are minimal overlaps in the feature data for each of the movements. The morphology feature is similar to the other significant features because the distribution of the data is also taken into account when calculating the value for morphology. Although the ten evenly distributed values are taken from along the x-axis, their y-values are instrumental in calculating the areas underneath the curve (or above if the value is negative). The significance of this feature supports the assumption that the shape and form of the data for each of the eight different movements are very different.

VI. Feature Creation

Taking into account the characteristics of the original significant features, we were able to calculate our own and compare their performances. The following are the features that we produced:

- **IQR (Interquartile Range):** Noting the significance of the two features relating to the overall spread of the data points, we decided to develop another similar feature. We took the IQR which can be defined as the middle 50% of the data which lies between the first and third quartiles and measures the statistical dispersion of a data set. As can be seen in the graph, this feature, as expected, also ranked very high among the others.
- $\frac{peak\text{-}to\text{-}peak\ width}{length(x)}$**:** Keeping in mind the significance of the morphology feature that concentrates on the form and shape of data with respect to the x-axis, we propose a feature that takes into account the spread along the x-axis. This feature takes the width between the maximum positive and maximum negative points of the distribution and divides this value by the total period of activity. The reasoning for this feature is that there is a common proportion between each of the movements involving a specific portion of the wave of data (length between the highest peak to the lowest peak) with the total length of data recorded. This means that if from one subject performed a movement in a longer or shorter time than another, the proportion would still stay constant because both lengths would increase an equal amount. There may, in fact, be a case where this proportion holds true, however, this feature did not rank very well compared to the others.

Of each of the three features we created, IQR proves to be the most significant because of its connection with the dispersion of the data along the y-axis.

VIII. Conclusion

After all of our analysis, we were able to create a new, improved metric, discover the characteristics that make features more significant than others, and as a result, create a new significant feature. With our new metric, $\frac{3\sigma_1+3\sigma_2}{d_{1,2}}$, we are able to take into account scenarios in which there might be overlapping movement classes. This improves our ability to rank the features for significance. Using this metric, we are able to rank features for significance to determine what about a feature makes it significant. In doing so, we gathered that features dealing with the distribution or spread of the data as well as the shape or form of the data perform much better than the others. Finally, using this analysis of our existing features, we created a new significant feature, calculating the IQR of the data values. There is much future work to be done on this project. We have a total of four significant features that each yield considerably high accuracy classification, however, using our existing analysis we believe that we can find more. Once enough significant features are identified, the system will be one step closer to performing classification onboard the motes.

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