A Resource Optimized Physical Movement Monitoring Scheme for Environmental and on-Body Sensor Networks

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Abstract— **Perhaps the most significant challenge in design of on-body sensors is the wearability concern. This concern requires that the size of the nodes (sensors, processing units and batteries) be minimized. Therefore, the computation and communication executed in on-body nodes must be moderated significantly. In this paper, we propose a collaborative signal processing scheme for physical movement monitoring that utilizes on-body and environmental sensors. The environmental sensor nodes perform the bulk of the signal processing and provide feedback to the on-body sensor nodes. This is due to the fact that the environmental sensor nodes have access to more powerful processing units and an unlimited energy supply. The feedback simplifies the signal processing on the on-body nodes significantly. We achieve this by performing a hierarchical classification and introducing a probabilistic measure on likelihood of possible classes for the final level of classification on on-body sensor nodes. The experimental results show the effectiveness of our method. On average the classification accuracy is reduced by 3% while the computational complexity can be scaled down by one order of magnitude compared to a global and comprehensive classification scheme.**

I. Introduction

Continuation of Moore's law along with development of novel sensing devices have led to the introduction of a variety of COTS wireless sensor platforms. These platforms can measure physical attributes such as temperature and acceleration, perform limited local computation and storage, and communicate within a short range. Wireless sensor platforms enable ubiquitous presence of sensing, computing and communication capabilities and hence, enable a large number of application domains. In particular, they can be mounted on human body or clothing, or even be woven into the very fabric that we wear to realize various health monitoring applications. We take special interest in such systems, generally referred to as Body Sensor Networks (BSN), due to the unparalleled significance of their application domain and their very specific requirements and implications. Sensor platforms integrated into clothing provide the possibility of enhanced reliability of accident reporting and health monitoring. Such devices improve the independence of people needing living assistance.

Despite their immense potentials to impact both quality of life and economy for members of society, such health monitoring applications and their host BSNs are still developed in a very inefficient manner today. There is not enough known on generic methodologies to efficiently compose, setup and configure a BSN out of COTS products, and to efficiently develop and execute applications on a particular BSN.

In this paper, we investigate developing a collaborative signal processing for wearable and environmental sensors. The environmental sensors are less resource constrained and provide more flexibility in terms of platform design. This is due to the fact that the wearability is no longer a major concern, and the system may have access to unlimited source of energy and more powerful processing infrastructure. We take advantage of this by overloading signal processing on environmental sensor nodes. The environmental sensor nodes provide conditional information that will simplify the processing on on-body sensor nodes.

As to the target application, we employ human physical movement monitoring which may have several applications such as Gait analysis, rehabilitation, fall monitoring, etc. We implement our technique for this application and illustrate its effectiveness.

II. Related Work

Both of the measurement methods we are using for movement classifying, using a film type dynamic pressure sensor as an environmental sensor and using accelerometers and gyroscopes as wearable sensors, are widely studied. Combining these two, on the other hand, has not been so well investigated in the past.

Suutala et al. [1] used EMFi sensors in their pressure sensitive floor to identify people. In classification of foot step pattern they used a classification method called Distinction-Sensitive Learning Vector Quantification (DSLVQ), which includes automated feature selection during classification.

R. Headon and R. Curwen [2] and R. Orr and G. Abowd [3] used load cells placed on the corners of floor plates to measure the vertical component of ground reaction force (GRF) caused by the weight and the inertia forces of the body. In [3] features calculated from GRF were used for identifying people with a 1-NN classifier. In [2] the system was used in recognizing different primitive movements such as crouch, sit, or jump with Hidden Markov Models (HMMs) in classification. Load cells, however, are difficult to install, as they require space underneath a floor tile.

J. Mäntyjärvi et al. [4] used two sets of accelerometers placed on left and right side of the hip to recognize different types of movements like level walking or walking downstairs. In classification they used wavelet coefficients of principal- and independent components (PCA and ICA) of the signals as features and multilayer perception neural networks as classifiers. They discovered that using PCA and ICA prior to calculating the wavelet coefficients improved the classification accuracies considerably.

J. Lester et al [5] suggested using features extracted from multiple sensors each measuring different modalities to classify everyday activities. In their investigation the sensors are attached to a cellular phone. They were able to achieve good classification accuracies even when the data collected from a particular user was not included into training of the classifier. In classification they used a combination of simple static classifiers and Hidden Markov Models and a fairly large initial set (651) of features.

Paradiso et al. [6] combined a movement sensor and a floor sensor in Magic Carpet. The system allowed users to affect music with their movements. The pressure sensors were PVDF (polyvinylidine fluoride) sensors. The movement sensors used in the study were Doppler radars for measuring upper body kinematics (velocity, direction of motion, amount of motion). Accelerometers are now the most commonly used movement sensor.

Most prior studies have included fairly complex computation in extracting features and/or in running the classification. In our work, we have aimed to keep both the features we are using and the classification process simple so that both could be embedded on a simple modern microcontroller considering energy consumption and bandwidth limits. Our approach in distributing processing between environmental and on-body sensors also has not been investigated in this context, and for such platforms to the best of our knowledge.

III. System Architecture

Our system is composed of motion sensors, a piezo-electric based floor sensor, tiny processing units, and a gateway station. The most important components of our system are the processing units that can support various types of sensors. These blocks are responsible for reading from the sensors, executing preprocessing (filtering, segmentation, etc), feature extraction and local classification. Furthermore, they enable communications that will lead to global classification. Currently, we have been send out the raw data for off-line processing. The processing units that we utilize are Telos-B motes developed at University of California, Berkeley.

In this system, we utilize two classes of sensor nodes: The first class, referred to as on-body sensors, include the following sensors:

Accelerometers: We utilize MEMS type 3-axis accelerometers to measure the motion. They can also be used to measure vibration and acceleration due to gravity.

Gyroscopes: Gyroscope is a device for measuring or maintaining orientation, based on the principle of conservation of angular momentum. In addition to accelerometers, gyroscopes can be used for physical movement monitoring.

The second class, which we call environmental sensor nodes, mainly encompasses sensors that are mounted in the environment. In this particular application, we utilize film type pressure sensor manufactured from EMFi®-film [7].

Telos-B motes collect sensor readings from on-body and environmental sensors at the sampling rate of 40Hz and 300Hz respectively. A picture of our wearable sensor and floor sensor nodes is shown in Figure 1.

Figure 1. Our on-body and environmental sensor nodes

IV. Signal Processing

We propose the following framework for movement assessment and classification of physical activities. In particular, we are interested in classifying transition movements.

Given the goal of classifying movements based on subject motion, the functionality of our automated pattern recognition system is divided into three basic tasks: preprocessing and filtering, the description task which generates attributes of a movement using feature extraction techniques, and the classification task which classify this movement based on its attributes.

A. *Preprocessing*

From each on-body sensor node, we obtain three readings from the accelerometer and two from the gyroscope. The preprocessing step involves splitting this signal into periods of activity and idleness in order to classify the activity periods as particular movements. This can be accomplished by a threshold scheme that compares the base value of each sensor to the signal. For the results presented in this work, we used the signal recorded by our environmental sensor to automatically annotate the beginning and the end of each activity period. We then based on this, automatically selected a predefined time period from the on-body sensor data.

B. *Feature Selection and Extraction*

The feature selection is of paramount importance in pattern recognition and classification. High quality features can significantly enhance the accuracy of classification. By observing sensors readings from both on-body and environmental sensors, we have adopted the following feature set for each particular sensor:

Features used for floor sensors:

1. Period of activity
2. Minimum of difference signal
3. Maximum of difference signal
4. RMS power of difference signal
5. RMS power of original signal
6. Standard deviation of the signal
7. Peak-to-peak amplitude of the signal

Features used for on-body motion sensors (accelerometers and gyroscopes):

1. Period of the activity
2. Minimum of difference signal
3. Maximum of difference signal
4. RMS power of difference signal
5. RMS power of original signal
6. Standard deviation of the signal
7. Mean value of the signal
8. Peak-to-peak amplitude of the signal

Several other complex features have been proposed by other researchers, for example wavelet representations of principal components and independent components of signal samples [4] or features calculated from the frequency domain presentation of the signal [1,5]. These types of features, however, were excluded from our analysis due to their real-time computational complexity on our 8 or 16-bit microcontrollers with limited memory. All features currently selected can be implemented on our tiny and low-power processors.

Currently, we have implemented our features in MATLAB, and have preformed our analysis off-line.

C. *Feature Normalization*

We normalized all features by linear scaling to unit variance:

$$\tilde{x} = \frac{x-\mu}{\sigma} \qquad (1)$$

, where μ and σ are mean and standard deviation of the values of certain feature through all classes, respectively. [8]

D. *K-Nearest Neighbor Classifier*

We utilize the k-nearest-neighbor (k-NN) algorithm [9] to classify movements. Neural network classifiers are a data-driven option, which may better adapt to idiosyncratic motions over time, whereas k-NN provides scalability for distributed sensing platforms. We adopt a k-NN classifier due to 1) the simplicity of its implementation, 2) small training set requirement 3) small memory requirement, 4) its effectiveness.

V. PRELIMINARIES

Due to the extensive variation of morphologies from medical/biological sensors, potentially many features can be considered on data readings. However, in tightly resource constraint platforms such as on-body sensor networks, the processing may not be capable of calculating a comprehensive list of features. In this section, we first define a consistency and discriminance measures on features for each class of movements (that is a list of features that can be used to identify each particular movement effectively). Both of these measures are very simple to compute and can therefore be implemented in our hierarchical classifier, which we elaborate in the next section. In addition, we define a probabilistic measure on likelihood of possible classes after each classification step.

A. *Feature Consistency*

Feature consistency is a value of standard deviation of feature values within a single class. It is simply a measure to evaluate if a feature gets coherent values in the class and can therefore be used to describe that class. It does not consider if the feature has similar values in other classes.

B. *Feature Discriminance*

We also suggest taking into account a “discriminance” measure on the features. The value of discriminance can be defined as how well each feature can contribute to an accurate classification. Let us assume we want to detect a set of features. We adopt k-NN classification scheme, and assume data-points corresponding to movements are mapped onto classes.

A feature is “discriminative” if its value is consistent across repetition of each particular movement that is for class and its values in other classes differ from the values in certain class. Essentially, in classification, we attempt to measure the distance between a new movement and the center of the clusters or the training sets. Each movement in the training set can be represented by a vector of size k, where each component is a feature. The distance between two data-points can be defined as Euclidean distance between the two vectors. Therefore, the closer the points are with respect to each feature, the more likely they will be classified correctly.

In addition, within-class distance plays an important role in discriminating the target class. This can be essentially interpreted as how distance between the closest class to the target class with respect to a particular feature.

Hence, we seek to define the ratio of standard deviation divided by the distance from the closest class as the feature significance on each feature and across every movement. The smaller the ratio is, the more discriminative the feature is with respect to the particular movement. Therefore, in the case where there exist several features to be communicated with a central node, the system may choose the most significant features to minimize the communication cost. This may also occur due to the resource constraints or the time sensitivity in communications (i.e. the communication must be completed by a deadline). Minimizing the number of features will significantly improve the system performance both in terms of reducing the processing and communication overhead. In addition, the features detected and communicated simultaneously may introduce wireless collusion, and may affect system performance adversely.

VI. Problem Formulation

The objective of this study is to utilize environmental and on-body sensors in a manner that environmental sensors will simplify the processing on on-body sensors, and will improve the accuracy of classification. Therefore, we implement a hierarchical classifier as follows:

A preliminary classification is performed on environmental sensor nodes. Consequently, a set of classes, or movements, are conveyed to the on-body sensor nodes. These classes are selected based on maximum likelihood criteria, that is, the target movement is most likely one of the classes. We define a probabilistic measure on each possible target class based on how many of k points (where k-nearest neighbor classifier is used) belong to the target class. We further refine the probabilities by the distance of each data-point to the respective k nearest neighbors. In the next level of classification, the on-body sensor node only considers classes with high probabilities. This is done by considering only the significant features for the respective classes. This significantly simplifies the signal processing on-body sensor nodes.

In this technique, we do not take into consideration the correlation between features. That is two features might be significant; yet be highly correlated and provide redundant information. The feature ranking technique can take this into account, and remove the features that have highly correlated predecessors. For the sake of simplicity, however, we do not consider the correlation. Yet, this method can be easily implemented, and will further improve the performance of the system.

VII. Setup of Experiment

A. Test Subjects

Six normal volunteers, three males and three females with an average of thirty performed a set of given movements. The characteristics of the test subjects' vary notably which presumably leads to variance in the feature values.

B. Movements

We used eight different movements in the tests. In all movements, the subjects were stepping on the sensor with right leg. The movements were repeated for twenty times to create adequate amount of training and testing data. The movements were:

1. Normal walking by stepping once on the floor sensor with the right leg.
2. Stepping partly on the sensor, toe only.
3. Stepping partly on the sensor, heel only.
4. Changing the walking direction 90 degrees clockwise. Inner foot on the sensor.
5. Changing the walking direction 90 degrees counterclockwise. Outer foot on the sensor.
6. Stepping on the sensor and staying standing on it.
7. Stepping off the sensor in a backward direction.
8. Stepping off the sensor to forward direction.

The test subjects' only footwear were socks.

VIII. Experimental Results

We ran classification tests with our data set using several setups: We used features from the environmental sensor, the wearable sensor, as well as from both sensors together and compared the performance of each setup to our proposed method considering both classification accuracy and computational intensity.

We also compared the performance using four different feature sets for classification: We used all features, the best set of features selected with the Sequential Forward Floating Selection (SFFS) [9] method, the union of the most significant features for each class and the union of the most discriminative features for each class. For latter two, we chose the three most significant or discriminative features for each class.

Figure 2 shows (weighted) suggested classes provided by the environmental sensors to the on-body sensor for eight classes of movements over forty trials. Movements 2 and 3 are almost unanimously classified to correct classes, which means no further classification is necessarily on on-body sensor node.

Tables 1 and 2 show the classification accuracies and the relative computational complexities with different combinations of feature selection methods and sensors used.

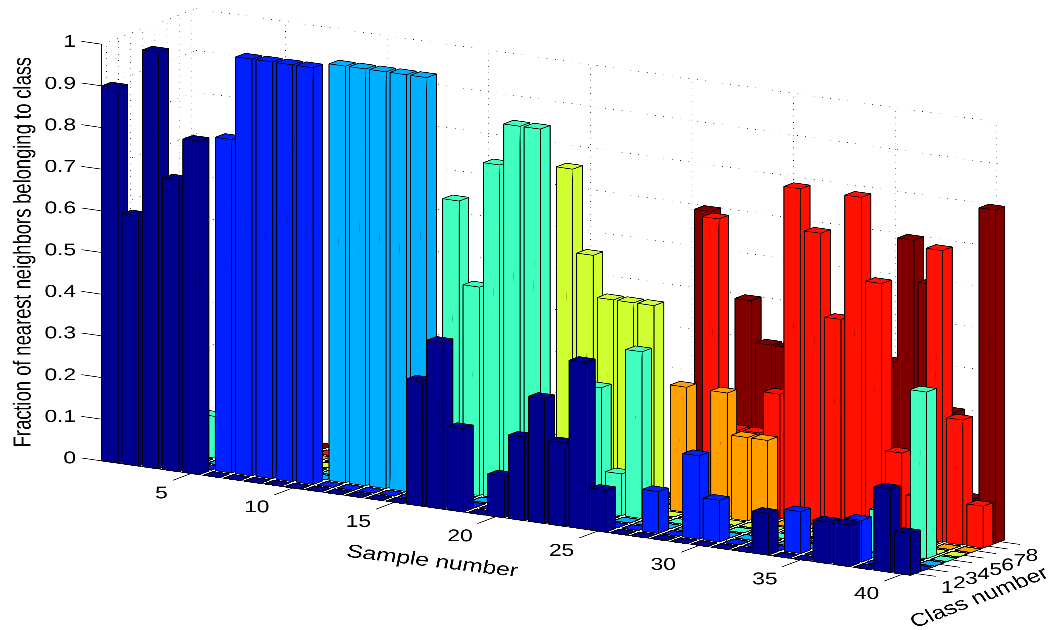

Figure 2. An example of distribution of classes suggested by the environmental sensor for our eight

Classification accuracy achieved when using only the environment sensor is fairly good, over 77%, and higher accuracy can be achieved when using only the on-body sensor and selecting the set of features according to their discriminance and consistency measures. Combining the data from the two sensors, however, further improves the accuracy considerably.

The best classification accuracy, more than 94%, is achieved when using the SFFS optimized set of features from both sensors. This method is, however, relatively computationally intensive for the on-body sensor since it involves, in our experiment setup, computation of eight features, receiving values of six features from the environment sensor, and classification into all eight classes with 10-NN classifier.

It should be noted at Table 1 that the SFFS feature set optimization algorithm used 1-NN classification to find the optimal set of features, while we are using 10 nearest neighbors in classification. We are using 10-NN so our proposed method can suggest more than one possible class to use in the next phase.

When testing the classification with our proposed method and SFFS optimized feature set, we optimized the feature set for all classes beforehand and not separately for each combination of classes that the first classification phase suggests separately.

Running the SFFS algorithm for each combination of classes separately is not feasible and is practically impossible to do in real-time with constrained computational resources due to the computational complexity of the method. Using a lookup table for selecting the features, though possible, is impractical with even a moderate number of classes because the number of different combinations increases exponentially. Our feature selection method, the union of the most discriminative features, provides a good set of features for classifying between certain set of classes with relatively low computational complexity.

In Table 2, the relative computational complexity is presented as a number of features used for classification run at the on-body sensor times the number of classes (relative to the number of training points for which the distances are calculated) in the classification. The communication complexity is the number features, which is expressed in terms of "information units", communicated between two levels of classification. All the numbers reported are the average across the trials and different movements.

The smallest communication and computational complexity is achieved when using our proposed two-phase classification scheme and for each combination of possible classes received from the environment sensor, taking the union of the most discriminative features for each class. This method also provides fairly good classification accuracy, 86%, in our experiment.

TABLE 1
CLASSIFICATION ACCURACIES OF 10-NN

Subject	Floor sensor only	Wearable sensor only	Both sensors	Proposed method
All Features	77.87	74.74	88.94	90.19
Beast set of features SFFS	77.66	81.63	94.36	88.10
Union of the most consistent features (3/class)	77.87	72.44	82.25	79.96
Union of the most discrimi-native features (3/class)	77.87	79.54	88.94	86.22

IX. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a hierarchical classification technique for physical movement monitoring application that utilizes both environmental and on-body sensors. Our scheme simplifies the signal processing on on-body sensors by extracting conditional and pre-classification information from environmental sensors. We illustrate the effectiveness of our method by implementing signal processing in MATLAB using data collected from our platform. We intend to implement the feature extraction and classification modules on sensor nodes, and assess the real-time performance of the system.

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TABLE 2
COMPUTATIONAL AND COMMUNICATION COMPLEXITIES

	Wearable sensor only		Both sensors		Proposed method	
	Computational complexity	Communication complexity	Computational complexity	Communication complexity	Computational complexity	Communication complexity
All Features	40 * 8 =320	0	47 * 8 =376	7	40 * 2.38 =95.2	2.38
Beast set of features SFFS	13 * 8 =104	0	14 * 8 =112	6	13 * 2.38 =30.9	2.38
Union of the most consistent features	16 * 8 =128	0	14 * 8 =112	6	5.09 * 2.38 =12.1	2.38
Union of the most discriminative features	16 * 8 =128	0	18 * 8 =144	5	4.65 * 2.38 =11.1	2.38

Our relative computational complexity of classification is a product of the amount of features and the amount of classes used in classification. It does not consider the computation of feature values or the computation of which features are used in each case in our proposed method.
Communication complexity is the number of features transmitted from the environment sensor to the on body sensor in the case of normal classification and the average number of the indexes of classes transmitted in our proposed method.