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

Antti Vehkaoja[1], Sameer Iyengar[2], Mari Zakrzewski[1], Roozbeh Jafari[3], Ruzena Bajcsy[2], Steven Glaser[2], Jukka Lekkala[1], Shankar Sastry[2]

antti.vehkaoja@tut.fi, sameer@berkeley.edu, mari.zakrzewski@tut.fi, rjafari@utdallas.edu, bajcsy@eecs.berkeley.edu, glaser@ce.berkeley.edu, jukka.lekkala@tut.fi, sastry@eecs.berkeley.edu

Institute of Measurement and Information Technology
Tampere University of Technology[1]

Center for Information Technology Research in the Interest of Society
University of California, Berkeley[2]

Department of Electrical Engineering
University of Texas at Dallas[3]

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) is 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.

Categories and Subject Descriptors

I.5.2 [**Pattern Recognition**]: Design Methodology – C*lassifier design and evaluation, Feature evaluation and selection*; C.3 [**Special Purpose and Application Based Systems**]: *Real- time and Embedded systems, Signal Processing Systems*

General Terms: Design, Measurement, Performance

Keywords: health-care, wearable computing, sensor networks, physical movement monitoring

1. INTRODUCTION

Continuation of Moore's law along with development of novel sensing devices has 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.

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.

Both of the sensor types we are using for movement classifying are widely studied. Combining these two, on the other hand, has not been so well investigated in the past. Most prior studies have included fairly complex computation in extracting features and/or in running the classification. In this work, we aim at keeping the signal processing simple. Consequently it can be executed in a simple modern microcontroller. We also consider 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. [1-6]

2. SYSTEM ARCHITECTURE

Our system is composed of motion sensors, a pressure measuring floor sensor, tiny processing units, and a gateway station. Currently, we have been sending 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, includes three axis

HealthNet'07, June 11, 2007, San Juan, Puerto Rico, USA.
ACM 978-1-59593-767-4/07/0006.

accelerometer and two axis gyroscope. 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.

3. SIGNAL PROCESSING

We propose the following framework for movement assessment and classification of physical activities.

3.1 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. 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.

3.2 Feature 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 initial set of features that can be calculated for all sensor channels: period of the activity, minimum and maximum of difference signal, RMS power of the difference and the original signal, mean value and standard deviation of the signal, and peak-to-peak amplitude of the signal.

Several other complex features for movement recognition has 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 16-bit microcontrollers with limited memory. All features currently selected can be implemented on our tiny and low-power processors. We normalized all features by linear scaling to unit variance. Currently, we have implemented our feature extractors in MATLAB, and have preformed our analysis off-line.

3.3 Classification

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 implementation, 2) small training set requirement, 3) small memory requirement and 4) its effectiveness.

4. 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.

4.1 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.

4.2 Feature Discriminance

A feature is "discriminative" if its values are consistent across repetitions of each particular movement that is for class and its values in other classes differ from the values in certain class.

Hence, we seek to define the ratio of standard deviation of feature values within a class and the distance from the closest class as the feature discriminance for that particular class. The smaller the value is, the more discriminative the feature is with respect to the particular movement. Therefore, in the case where there exists several features to be communicated with another sensor node, the system may choose the most discriminative features to minimize the communication cost. This may also occur due to bandwidth constraints or 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.

5. PROBLEM FORMULATION

The objective of this study is to utilize environmental and on-body sensors in a manner that environmental sensors simplifies the processing on on-body sensors, and improves 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 suggested by the first phase classifier. In the next level of classification, the on-body sensor node only considers these classes.

6. SETUP OF EXPERIMENT

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

We use eight different movements in the tests. In all movements, the subjects step on the floor sensor with right leg. The movements are repeated for twenty times to create adequate amount of training and testing data. The movements are: normal walking, stepping partly on the sensor (toe only and heel only), changing the walking direction 90 degrees when stepping the sensor (clockwise and counterclockwise), stepping on the sensor and staying standing on it, and stepping off the sensor (backward direction and forward direction).

7. EXPERIMENTAL RESULTS

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

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

Table 1 shows the classification accuracies with different combinations of feature selection methods and sensors used.

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 must be noted at Table 1 that the SFFS feature set optimization algorithm uses 1-NN classification to find the optimal set of features, while we use 10 nearest neighbors in classification. We use 10-NN thus our proposed method can suggest more than one possible class for the next level of hierarchical classification.

When comparing our proposed method to 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 processing units due to the computational complexity of the method. 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.

TABLE 1
CLASSIFICATION ACCURACIES OF 10-NN CLASSIFIER

Subject	Floor sensor only	Wearable sensor only	Both sensors	Proposed method
All Features	77.87	74.74	88.94	90.19
The best set of features by 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 discriminative features (3/class)	77.87	79.54	88.94	86.22

8. CONCLUSION 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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