A Segmentation Technique Based on Standard Deviation in Body Sensor Networks

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***Abstract*— Pervasive health monitoring utilizing wearable wireless sensor nodes can greatly enhance the quality of care individuals receive. Such systems, while in terms of signal processing mostly depend on pattern recognition schemes, must operate independently of human interaction for extended periods. The lack of a general-purpose computationally inexpensive algorithm capable of segmenting sensor readings into discrete actions and non-actions has hindered the development of these systems. We examine a segmentation scheme based on standard deviation metric. We provide experimental verification of the method.**

I. Introduction

The development of small sensor platforms from relatively inexpensive commercially available parts has created interesting new opportunities for data collection. The sensor nodes can communicate wirelessly, feature limited storage capabilities, and are often deployed as networks of sensors. These sensor networks have been used for a wide variety of sensing tasks from individual health monitoring to large scale environmental sensing: employing sensors measuring environmental variables including temperature, humidity, force, acceleration and heartbeat. We are particularly interested in Body Sensor Networks (BSNs) which feature sensor nodes placed on different locations on the human body. These can be used in hospital or clinical settings as a replacement for tethered sensors or for pervasive lifestyle monitoring. For clinical systems, the wireless capabilities offer new freedoms, but are architecturally similar to the systems they replace, allowing workstations to manage most of the heavy computation. However, BSNs offer the unprecedented ability to monitor patients in a naturalistic setting for an extended period. The BSNs in these settings must operate for protracted intervals without communicating with a base-station. Therefore the signal processing and classification must be performed *in situ*. The limited storage and processing capabilities provide many challenges to architects of these systems.

In pattern recognition, segmentation of sensor readings into actions is a key task. In this paper we introduce a segmentation technique based on the notion that regions of interest in a data stream correspond to times when the readings from a sensor change rapidly during a short period of time. A '*rest*' is defined as a time during which the sensor's values remain relatively constant over an interval. Empirically this is true for even seemingly continuous actions, such as walking. We present a method for automatically segmenting actions in a sensor stream. Finally, we experimentally verify the segmentation technique by comparing the results to our manual segmentation.

Manuscript received September 7, 2007.

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II. Related Work

Many researchers have investigated techniques to analyze and record human movement using body sensor networks. Jafari et al. [2] propose a wearable movement monitoring platform. The system consists of lightweight wireless sensor nodes, each equipped with accelerometers and gyroscopes. Sensor readings are separated into primitive actions by manual segmentation in an offline manner. At the next stage, they are classified using a k-NN classifier. In [3], Sherrill et al. introduce a system for activity monitoring according to a clustering approach and hierarchical framework. They utilize unsupervised learning to categorize a dataset and subsequently construct a hierarchy of relationships between clusters. They segment the primary recordings by dividing the signal into fixed time slices with a 66% overlap. Renevey et al. [4] present a technique for activity classification which is used to improve the heart rate estimation in a system composed of optical probes and accelerometers. Feature vectors are extracted from autocorrelation matrices based on data from fixed size segments. In [5] and [6], Chambers et al. present classification results of human gesture for video annotation and retrieval. To perform segmentation, they look into the stationary portions of the signal by employing a sliding window. They assume that the acceleration magnitude is very close to the magnitude of gravity for stationary portions; hence they model gravity plus noise magnitude of stationary signal using a Gaussian distribution. They measure the amount of change in log likelihood of every two subsequent windows. A sharp change in log likelihood corresponds to the commencement of a new action/rest.

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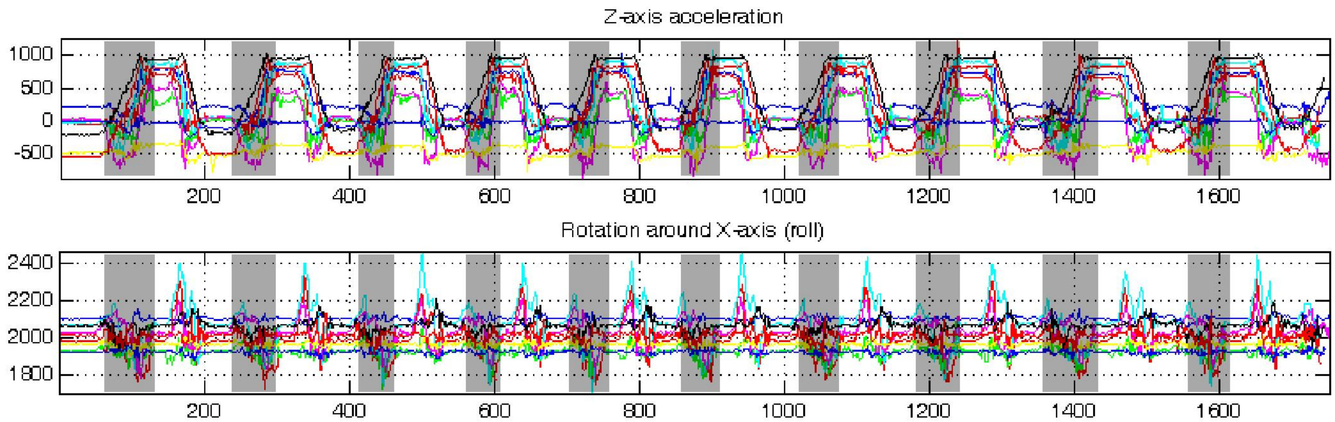

Fig. 2: Manual Segmentation of Sit to Stand

Benbasat et al. [7] propose a gesture recognition platform composed of wireless inertial measurement units. The variance of the data over a fixed window is measured as the potential metric for activity detection. Periods of activity are determined where the variance is greater than a constant threshold value.

Although all aforementioned techniques have been successful in providing a system of physical action classification, they may either use a manual segmentation approach to map original sensor readings to primitive actions (e.g. [2]) or utilize a special purpose auto-segmentation scheme. For instance, the fixed time slice techniques used in [3] and [4] provide excellent results for certain classification schemes; but are not appropriate for others. We are investigating more general segmentation techniques that are capable of becoming integrated within a wide range of classifiers. The technique in [5] and [6] does capture entire movements that occur over differing intervals, but it depends on specific sensor types and a relatively specific posture. The segmentation scheme in [7] uses a hard threshold value and not a moving threshold. Another platform for classification of human movements is introduced by Mathie et al. [8]. Although they can reliably and easily distinguish between periods of activity and rest, the measurement device they use is selected very specifically. In [9], Li et al. propose a similarity measure for segmenting and classifying motion streams. Motion segments are generated by collecting data from primary streams and comparing with predefined reference motions by using some similarity measures.

III. System Architecture

We are using BSNs for physical movement monitoring. Our system includes eight sensor nodes arrayed on the body as shown in Fig. 1. Each sensor node can measure x, y, and z acceleration and angular velocity about the x and y axes. Sampling at 22 Hz, each broadcasts the sensor streams back to a laptop for post-processing.

IV. Manual Segmentation

Manual segmentation can be performed through several approaches. Logging the time of each action is a form of segmentation. Signals can be segmented by synchronizing a video to the signals and dividing based on actions observed on screen. It is also possible to segment into actions by directly examining the signals and utilizing knowledge of the experimental technique.

Fig. 2 shows a portion of the sensor signals from the eight sensor nodes for the movement "Sit to Stand," and highlights the segmentation choices. Each plot in the diagram contains the signals from all the sensor nodes for a given sensor type (such x acceleration). The stand-to-sit motion is implicitly present in the data so the subject returns to the original position. Therefore, *a priori*, we know there will be approximately twenty actions, with every other one being sit-to-stand. Furthermore, all sit-to-stand movements look similar. Using this information, and looking for periods of rapid changes in the sensor data, the segments can be distinguished.

V. Automatic segmentation

For automatic segmentation, the morphology of the desired signals cannot be utilized, as it is not known. Furthermore, since it is important to limit inter-node communication, communicating the complete sensor readings between nodes is inadvisable. Each sensor data stream is filtered to provide a signal representing the level of activity at any given time. We develop a technique based on standard deviation.

The "spread" of changes in a data stream for a short time interval is represented by the standard deviation over this interval. Due to computational limitations, we use standard deviation squared. This is the method proposed by [7]. Formally:

$$\sigma_n^2(x,i) = \frac{\sum_{j=i-(n-1)/2}^{i+(n-1)/2} x_j^2 - \mu_n^2(x,i)}{n} \quad (1)$$

where:

$$\mu_n(x,i) = \frac{\sum_{j=i-(n-1)/2}^{i+(n-1)/2} x_j}{n} \quad (2)$$

The window is of size n and is centered on point x_i. The block diagram for the standard deviation signal activity is shown in Fig. 3.

We observed that during periods of high activity, the threshold that defines a split between actions is higher than the threshold that distinguishes an action from a rest during periods of low activity.

The normalizer takes a moving average of the localized standard deviations over a larger interval. The local standard deviation is divided by this average or by a minimum normalization if the average is too low. This effectively introduces a moving threshold based on whether or not there has been a lot of recent activity.

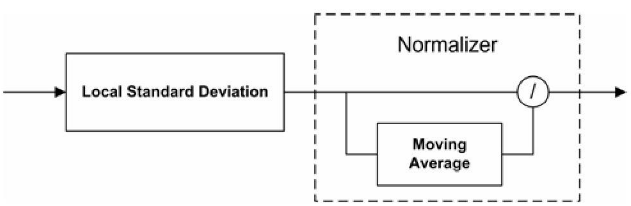

Fig. 3: Standard Deviation Approach

VI. Experiment

For the experiment, three subjects performed twenty-five movements ten times each. Each wore the sensor nodes as illustrated in Fig. 4. We segment the results in two ways: manually and using the localized standard deviation. We consider the manual segmentation results canonical. Errors in the automatic tools are anything that differs from manual segmentation. The exact time value of each segment is not considered important: merely whether or not a given region is marked as containing an action or rest.

A. Results

For individual sensor data streams, the results closely matched manual segmentation, if the manual segmentation only considered that individual stream. For instance, for the movements sit-to-stand and stand-to-sit, the y acceleration from the thigh nodes was only incorrectly segmented twice out of 120 possibilities. However, the wrist and ankle nodes experienced almost 25% segmentation errors when compared to manual segmentation. For sit-to-lie and lie-to-sit the ankle and thigh nodes have the same performance (about 10% errors), but the wrist nodes have about 60% error.

Generally, over 50% of the sensors are correctly segmented for each movement, but not always the same sensors. To achieve high accuracy for global segmentation, we must consider correlations between segmentation of individual streams.

Fig. 4: Sensor Positions

VII. Conclusion And Future Work

In this paper we presented a signal processing model for segmenting data streams from inertial sensors into periods of activity and rest. This segmentation is efficient enough to be deployed on sensor nodes. Our experimental evaluation highlighted both strengths and weaknesses of the technique. The main weakness is a failure to take into account multiple sensor streams for a global segmentation. We have developed a model that combines the results from per-stream segmentation to perform a global segmentation. This collaborative technique exhibits significant improvement over per-node segmentation.

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