Accelerometer's Position Free Human Activity Recognition Using A Hierarchical Recognition Model

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***Abstract*—Monitoring of physical activities is a growing field with potential applications such as lifecare and healthcare. Accelerometry shows promise in providing an inexpensive but effective means of long-term activity monitoring of elderly patients. However, even for the same physical activity the output of any body-worn Triaxial Accelerometer (TA) varies at different positions of a subject's body, resulting in a high within-class variance. Thus almost all existing TA-based human activity recognition systems require firm attachment of TA to a specific body part, making them impractical for long-term activity monitoring during unsupervised free living. Therefore, we present a novel hierarchical recognition model that can recognize human activities independent of TA's position along a human body. The proposed model minimizes the high within-class variance significantly and allows subjects to carry TA freely in any pocket without attaching it firmly to a body-part. We validated our model using six daily physical activities: resting (sit/stand), walking, walk-upstairs, walk-downstairs, running, and cycling. Activity data is collected from four most probable body positions of TA: chest pocket, front trousers pocket, rear trousers pocket, and inner jacket pocket. The average accuracy of about 95% illustrates the effectiveness of the proposed method.**

***Index Terms*—Human activity recognition; Autoregressive Models; Linear Discriminant Analysis; Accelerometer**

I. INTRODUCTION

The United Nations predicts that by 2100, 28.1% of the world population will be aged 65 years or older [1]. With this aging population comes an increased demand for ongoing health monitoring and support for the elderly. Quantification of daily physical activities is a key determinant in the evaluation of the quality of life of subjects with limited mobility [2]. By analyzing, monitoring, and recognizing human activities, much useful information about human health condition can be extracted.

Over the past decade, many systems incorporating the use of triaxial accelerometers (TA) have been developed to recognize daily human activities. Some of these investigated the use of accelerometers to analyze and classify different types of the same physical activity, e.g., walking (along corridor, upstairs, downstairs) [3], [4]. Others employed it for recognizing a wide set of daily activities such as lying, sitting, standing, walking and running [2], [5]–[15]. Most studies employed multiple TAs attached at different sites on a subject's body [2], [3], [8], [9], [13]–[17]. While others investigated the use of a single TA mounted at waist or sternum [4]–[7], [10]–[12], [18]–[20].

A large number of features have been explored including wavelets [2]–[4], Signal Magnitude Area (SMA) and tilt angle [5], [6], and Spectral Entropy (SE) [13]. As for the recognition techniques, some studies incorporated the idea of simple heuristic classifiers. Whereas others employed more generic and automatic methods from machine learning literature. Thus, existing literature on physical activity recognition using accelerometers varies in approach, intention, and outcome.

In general, the output of any body-worn TA depends on the position at which it is placed and can vary for the same activity for different positions along the subject's body resulting in high within-class variance. The TA signals for walking, for example, vary at three different positions as shown in Fig. 1. Therefore almost all previous works require accelerometers to be firmly attached to a specific body part such as arm, wrist, chest, thigh etc, making them impractical for long-term activity monitoring during unsupervised free living.

In our previous study on human activity recognition using a TA [21], we proposed Autoregressive (AR) modeling [22] of TA signals and used the AR-coefficients augmented with SMA and tilt angle to form an augmented feature vector. A two-level classification approach was then employed to recognize eleven activities with an average recognition rate of about 98%. However, it also relied on firm attachment of TA to subjects' chests.

In this paper, we present a comprehensive approach to address the TA's position-independent activity recognition problem. We validated our approach using six daily physical activities. Activity data was recorded from four most probable body positions of TA. The average accuracy of about 95% illustrates the effectiveness of the proposed method.

II. METHODS

A. Sensor Device and Data Collection

In this study, we used a 2.4GHz Wireless triaxial Tilt Sensor from Sparkfun called Witilt v2.5, shown in Fig. 2.

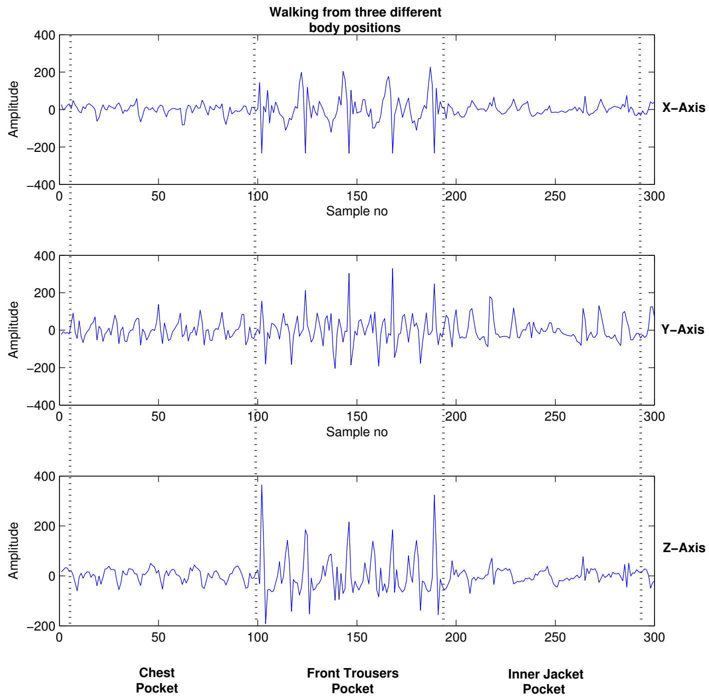

Fig. 1. Sample acceleration signals for walking from three different positions.

It employs a FreeScale MMA7260Q triple-axis accelerometer and a class 1 Bluetooth link from BlueRadios and features a 4-level sensitivity scale (1.5g, 2g, 4g, and 6g). 20 hours of activity data was collected in a home setting, outside the laboratory. The sensor, with a sampling frequency of 90 Hz, was placed on 10 healthy subjects (seven males, three females, age: Mean = 45, SD = 5 years old) on 4 different positions: chest pocket, front trousers pocket, rear trousers pocket, and inner jacket pocket. We collected approximately 34 hours of activity data. The activity dataset for each subject was then divided randomly into the training and test sets in a roughly 40-60% split.

The six activities to be recognized were the resting activity (sit/stand) and five dynamic activities i.e., walking, walk-upstairs, walk-downstairs, running, and cycling. For realistic recognition, brief movements such as stretching or changing posture were allowed during resting. For a natural setting, walking, walk-upstairs, walk-downstairs, and running were performed outdoor at various speeds. The cycling activity was recorded in a gym. Annotations were performed using a bluetooth headset combined with a speech recognition software [23].

B. Signal Processing

The real time data from an accelerometer contains some noise that needs to be filtered out before using it for activity recognition. A moving average filter of order 3 was incorporated to filter out random noise. Signal features were then calculated for each second of the data collection i.e., a window size of 90, with no overlapping between consecutive windows. A brief description of these features is given below:

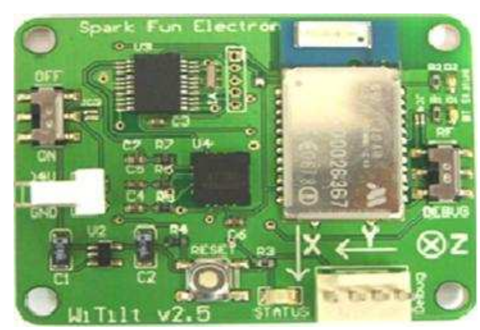

Fig. 2. Witilt triaxial tilt sensor from Sparkfun.

1) Spectral Entropy (SE): SE of the acceleration signal for the frequency band $f_1 - f_2$ was calculated as

$$S_N(f_1, f_2) = \frac{-\sum_{f_i=f_1}^{f_2} P(f_i)\log(P(f_i))}{\log(N\,[f_1, f_2])} \tag{1}$$

where $P(f_i)$ represents the power spectral density (PSD) value of the frequency f_i. The PSD values are normalized so that their sum in the band $[f_1 - f_2]$ is one. $N[f_1 - f_2]$ is the number of frequency components in the corresponding band in PSD.

2) Autoregressive Coefficients: An AR model can be represented as

$$y(t) = \sum_{i=1}^{p} \alpha(i) y(t-i) + \varepsilon(t) \quad (2)$$

where $\alpha(i)$ are the AR-coefficients, $y(t)$ the time series under investigation which in our case is the acceleration signal from the sensor unit and p the order of the filter which is generally very much less than the length of the series. The noise term or the residue $\epsilon(t)$ is assumed to be the Gaussian white noise. In other words, the order of an AR model refers to the number of past values of $y(t)$ used to estimate the current value of $y(t)$.

3) Signal Magnitude Area: SMA has been found to be a suitable measure for distinguishing between static vs. dynamic activities using TA signals. It was calculated according to

$$SMA = \sum_{i=1}^{N} (|x(i)|) + (|y(i)|) + (|z(i)|) \quad (3)$$

where $x(i)$, $y(i)$, and $z(i)$ indicate the acceleration signal along x-axis , y-axis, and z-axis respectively.

The feature extraction proceeded by analyzing the behavior of these features for different body positions for the same activity. The performance of these features in discriminating the corresponding activity from other activities for the same position was also analyzed. This analysis lead to the following findings:

1) SE differed slightly among different activity classes for the same position except the resting activity. However, the acceleration data for all dynamic activities registered higher frequency components for lower-body positions of TA i.e., front and rear trousers pocket. Whereas, lower frequency components were registered for upper-body positions of TA i.e., chest and inner jacket pocket.
2) AR-coefficients and SMA proved to be good discriminating features for all activity classes. However, they registered high within-class variance for each activity class for different body positions of TA.

C. Classification Scheme

Based on the above findings, we devised a two-level recognition approach. Its architecture is illustrated in Fig. 3. At the lower level, SE along with an Artificial Neural Net (ANN) is employed to recognize three classes i.e., the resting activity, dynamic activity (upper-body), and dynamic activity (lower-body). Such a devision helped reducing the within-class variance for a particular dynamic activity resulting from the upper and lower-body positions of TA. Separate ANNs are then trained to recognize dynamic activities from these positions.

If the resting activity is not recognized at the lower level, then the AR-coefficients and SMA are calculated from the noise reduced acceleration signal to form an augmented feature vector. A high within-class variance and low between-class variance due to different positions: front and rear trousers

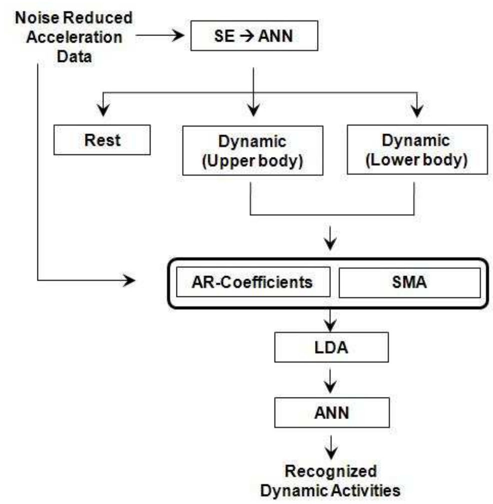

Fig. 3. Block diagram of the proposed two-level recognition scheme.

pockets in the case of lower-body; chest and inner jacket pockets in the case of upper-body, could still exist in this new augmented feature space. Therefore, Linear Discriminant Analysis (LDA) [24] is employed to minimize and maximize these variances respectively. LDA patterns are then used by the corresponding ANN to recognize the true activity. A brief description on LDA is given below.

1) Linear Discriminant Analysis: LDA, a second order statistical approach, is a supervised classification approach that utilizes the class specific information maximizing the ratio of the within and between class scatter information. In order to obtain the maximum discrimination, it projects data onto the lower dimensional space so that the ratio of the between and within class distance can be maximized. The within S_w and between S_b class comparison is done by following equations:

$$S_b = \sum_{i=1}^{c} J_i (\overline{m}_i - \overline{\overline{m}})(\overline{m}_i - \overline{\overline{m}})^T \quad (4)$$

$$S_w = \sum_{i=1}^{c} \sum_{m_k \in C_i} (m_k - \overline{m}_i)(m_k - \overline{m}_i)^T \quad (5)$$

where J_i is the number of vectors in $i-th$ class C_i. c is the number of classes and in our case it represents the number of activities. $\overline{\overline{m}}$ represents the mean of all vectors, $\overline{m}$ the mean of the class C_i and m_k the vector of a specific class. The optimal discrimination projection matrix D_{opt} is chosen from the maximization of ratio of the determinant of the between and within class scatter matrix as

$$D_{opt} = \arg\max_{D} \frac{|D^T S_b D|}{|D^T S_w D|} = [d_1, d_2, ..., d_t]^T \quad (6)$$

where D_{opt} is the set of discriminant vectors of S_w and S_b corresponding to the $c-1$ largest generalized eigenvalues λ

and can be obtained via solving (7). The size of D_{opt} is $t \times r$ where $t \leq r$ and r is the number of elements in a vector.

$$S_b d_i = \lambda_i S_w d_i \quad i = 1, 2, ..., c-1 \tag{7}$$

where the rank of S_b is $c-1$ or less and hence the upper bound value of t is $c-1$.

2) Classifier: As validated by us in [21], we used ANNs based on the feed-forward backpropagation algorithm. Different number of layers and neurons were tested in order to optimize the performance. The training of ANN was also repeated several times by changing the input order in a random fashion. The training and the testing datasets were composed of mixture of activity data collected from four body positions.

III. Results

Performance of the proposed recognition system is then validated in the following three studies:

A. Single-Level Recognition Without LDA

In this study, features including the AR-coefficients, SMA, and SE were calculated to form a single feature vector. A 3D-representation of the feature space is shown in Fig. 4, only four classes are shown for the sake of visualization. Severe non-linearity and a high within-class variance could be observed. These features were used to train an ANN without employing the proposed two-level recognition scheme and LDA. During testing, each test activity was modeled in a similar fashion and the corresponding ANN was used for recognition. Results are summarized in Table I, showing an average recognition of only 47.3%.

B. Single-Level Recognition With LDA

In this study, features including the AR-coefficients, SMA, and SE were calculated. LDA was applied directly on the feature space without employing the proposed two-level recognition scheme. LDA patterns for four dynamic activities are shown in Fig. 5. They show improved class separability but a high within-class variance could still be observed. Results for this study are also summarized in Table I, showing an average recognition of only 57.3%.

C. Proposed Two-Level Recognition

In this study, the proposed two-level recognition scheme was employed to achieve TA's position independent activity recognition. LDA patterns for four dynamic activities for lower-body positions i.e., front and rear trousers pockets, are shown in Fig. 6. A significant improvement on class separability and low within-class variance could be observed. Results for this study are also summarized in Table I with an average recognition rate of about 95%.

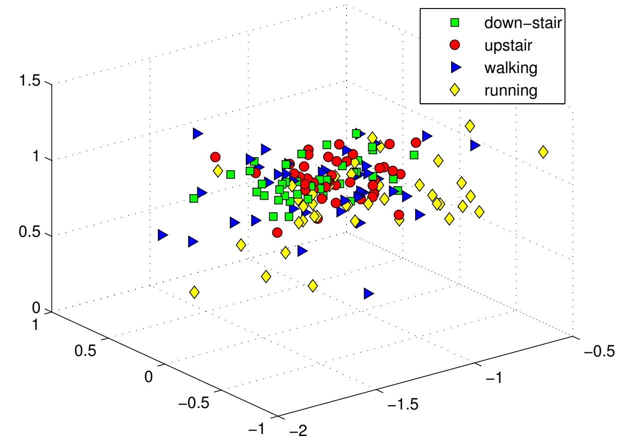

Fig. 4. 3D-feature plot for four dynamic activities recorded from four different body positions, showing a high within-class variance.

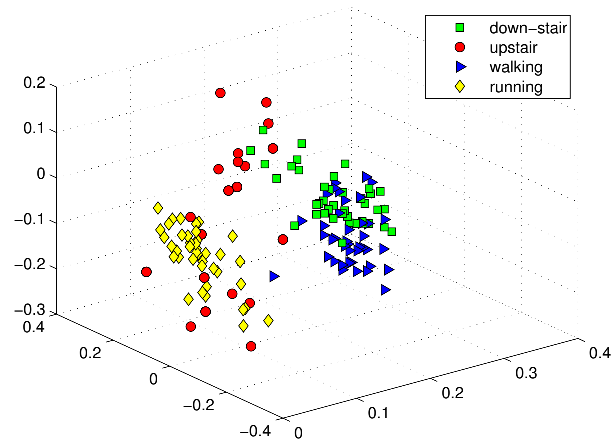

Fig. 5. LDA feature space for four dynamic activities, recorded from four different body positions, after applying the single-level recognition system.

IV. Conclusion

Recognizing physical activities without firm attachment of an accelerometer to a specific body part results in high within-class variance and low between-class variance in activity data. In this work, a novel recognition scheme is developed and evaluated to recognize physical activities independent of accelerometer's position along a subject's body. The proposed technique is validated using six physical activities recorded via a triaxial accelerometer from four different body positions. With our proposed technique, activities could be monitored throughout a longer period of time during unsupervised free living as subjects could carry the accelerometer in their pockets without attaching it firmly to a specific body part.

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TABLE I
AVERAGE RECOGNITION RESULTS(%) FOR THREE STUDIES

Activity	Single-Level Recognition	Single-Level Recognition with LDA	Proposed Two-Level Recognition
Resting (Sit/Stand)	61	69	95
Walk down-stairs	40	51	96
Walk upstairs	44	51	95
Walking	44	52	96
Running	52	71	99
Cycling	43	50	89
Total	47.3	57.3	95

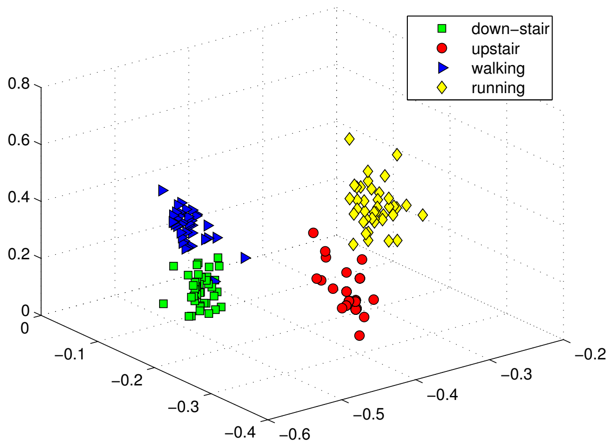

Fig. 6. LDA feature space for four dynamic activities, from lower-body i.e., front and rear trousers pockets, after applying the proposed hierarchical recognition system.

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