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Accelerometer Signal-based Human Activity Recognition Using Augmented Autoregressive Model Coefficients and Artificial Neural Nets

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Abstract— **Automatic recognition of human activities is one of the important and challenging research areas in proactive and ubiquitous computing. In this work, we present some preliminary results of recognizing human activities using augmented features extracted from the activity signals measured using a single triaxial accelerometer sensor and artificial neural nets. The features include autoregressive (AR) modeling coefficients of activity signals, signal magnitude areas (SMA), and title angles (TA). We have recognized four human activities using AR coefficients (ARC) only, ARC with SMA, and ARC with SMA and TA. With the last augmented features, we have achieved the recognition rate above 99% for all four activities including lying, standing, walking, and running. With our proposed technique, real time recognition of some human activities is possible.**

I. INTRODUCTION

QUANTIFICATION of daily physical activity plays a vital role in the evaluation of the quality of life for most humans. It becomes more critical for people with limited mobility, such as elderly persons [1]. By analyzing, monitoring, and recognizing human activity, much useful information about human's health condition can be extracted.

The quantitative assessment of daily activity in humans requires an objective and reliable technique that can be used under conditions of daily living. Complex sensors such as cameras in computer vision have been extensively used for recognizing activities. Computer vision sensing for tracking and recognizing activity often works in the laboratory but becomes difficult in real home settings due to clutter, variable lighting, and highly varied activities that take place in natural environments. Complexity of dealing with changes in the scene, such as lighting, multiple people and clutter offers additional challenges. Finally, because sensors such as microphones and cameras record biometric information, they can also be perceived as invasive (i.e., violating privacy) by some people.

Thus, interest in the use of direct and indirect measures of energy expenditure, using measurement techniques such as observations, questionnaires, heart rate recordings, or motion capture is increasing. Motion capture with body-fixed sensors offers an appropriate alternative for assessment of daily physical activity. In the past, ambulatory measurement of physical activity was based on various motion sensors such as pedometers, actometers [3], or accelerometers strapped onto the waist, wrists, or ankles [4], [5].

Accelerometry has proved itself as a practical, inexpensive, and reliable choice for monitoring motions and postures under free-living [6], [7]. Some previous studies, incorporating the use of accelerometers, have been reported to identify the type of activity [8]-[11], but their methods are cumbersome because they use two or more different sites of attachments to the body and cable connections, reducing their applicability for long-term monitoring of physical activity: in fact they interfere with normal activities. Comparatively, a very small number of studies have investigated the use of a single accelerometer mounted at waist, sternum or back [6], [7], [12]-[16].

In their works, a large number of recognition methods have been investigated. Many studies incorporated the idea of simple heuristic classifiers for the classification of possible motions and postures [6]-[8], [12], [17]. While other employed more generic and automatic methods from machine learning including decision trees, nearest neighbor and Bayes [10], [14], support vector machines [14], neural networks [16], [18], Gaussian mixture models and Markov chains [13], [15].

Thus, existing literature on activity classification by means of accelerometers varies in approach, intention, and outcome. A wide variety of recognition techniques and algorithms had been investigated by individual researchers for classifying their own set of movements using their own devices and data collection methods. Consequently, it is difficult to make significant comparisons or draw meaningful conclusions from the existing literature beyond noting that accelerometer shows promise in human activity monitoring and recognition [15].

In this paper, we propose a general, but new framework of human activity recognition (HAR) system using a novel set of features derived from a single triaxial accelerometer and artificial neural nets (ANNs). We use the autoregressive (AR) modeling coefficients of activity signals as key features, but augment them with Signal Magnitude Area (SMA) [6], [7], [15] and Tilt Angle (TA) [6], [7] to distinguish dynamic activity from static, and a general ANNs for recognition.

To test our HAR system, we have tested four activities including lying, standing, walking, and running with different combinations of our proposed features.

Our preliminary results show using our augmented features a recognition rate of above 99% for all four activities, thus indicating the feasibility of recognizing human activities in real time with a single or multiple accelerometer(s).

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II. METHODS

A. The Sensor Device

We make use of an accelerometer sensor called Witilt v2.5 which is a 2.4GHz Wireless triaxis Tilt sensor from Sparkfun Electronics [19]. It consists of a MMA7260Q (triple-axis accelerometer) along with a Bluetooth module mounted at the subject's chest. This module communicates with a USB dongle, attached to a computer, working as a transceiver to receive and store the sensor data where further processing is carried out as shown in Fig 1.

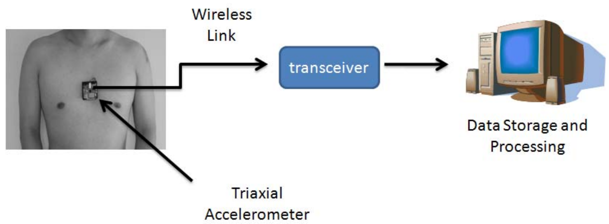

Fig. 1. The device being worn by a subject and the schematic diagram of data acquisition.

B. Data Acquisition

The data for our experiment was gathered in an experimental setting in which a sensor, with a sampling frequency of 10 Hz, was mounted at the chest of 7 healthy subjects of different age, weight, and height to collect four types of activity patterns. These four activities were specifically lying, standing, walking, and running. The data was collected in the form of following directed routine.

1. Lying (10 sec)
2. Stand-up
3. Standing (10 sec)
4. Walking (10 sec)
5. Running (10 sec)
6. Standing (10 sec)

Separate instances of each movement type were segmented out into separate files so that each file would contain the complete duration of one particular movement or posture occurrence only. We have collected over 50 instances of each activity and each having a length of 10 sec. A representative set of activity signal is shown in Fig. 2.

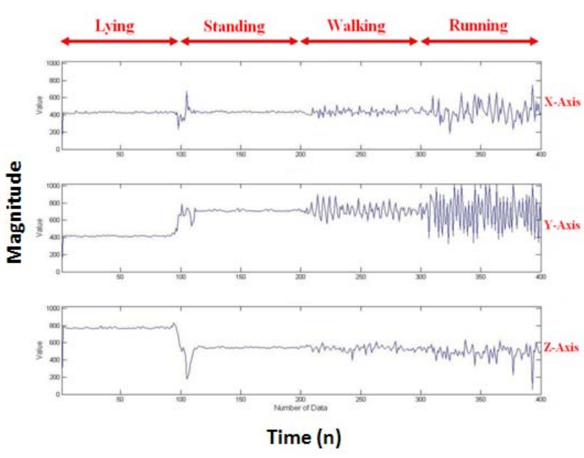

Fig. 2. Sample signals of human activities for each axis of a triaxial accelerometer

C. AR Modeling

The AR model is used to model the time series signals of the four different activities. The AR-model of a random process $y(t)$ in discrete time t is defined by (1).

$$y(t) = \sum_{i=1}^{p} a(i)\, y(t-i) + \varepsilon(t), \qquad (1)$$

where a_1, a_2, ... , a_p are the coefficients of the model, p the order of the model and $\varepsilon(t)$ the output uncorrelated error.

The order of an AR model refers to the number of past values of $y(t)$ used to estimate the current value of $y(t)$. The order of an AR model can be decided by performing a careful analysis of the extent to which the current value of a signal $y(t)$ is dependent on its past values.

To analyze this, we performed autocorrelation and partial autocorrelation on the accelerometer signal. These techniques are a measure of how well a signal matches a time-shifted version of itself, as a function of the amount of time shift. This analysis led us to fix the order of our model to 3. The AR coefficients were then estimated for each axis using the Burg method [20]. Finally, we end up with the following coefficient sets:

i) *{a(1),…, a(3)}*: Coefficients for x-axis acceleration signals

ii) *{a(4),…, a(6)}*: Coefficients for y-axis acceleration signals

iii) *{a(7), …, a(9)}*: Coefficients for z-axis acceleration signals

Some exemplary fitting results for our model for a single instance of walking are shown in Fig. 3.

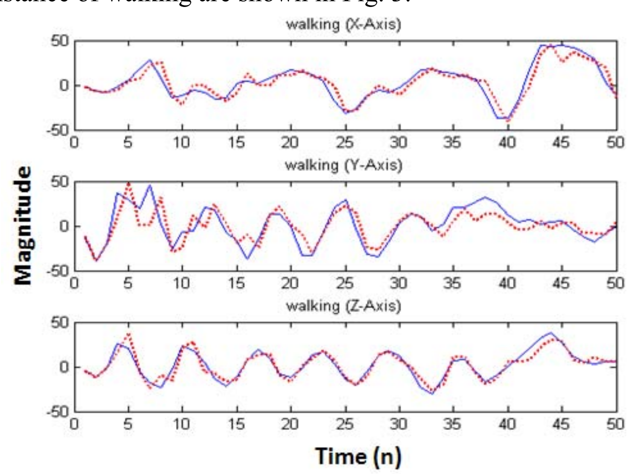

Fig. 3. Fitting results for acceleration signals of walking for three axes respectively: dotted-line (model fit) and solid-line (activity signal).

D. Augmented Feature Vector

In our study, we first tested the AR coefficients for activity recognition. However, we noticed that activities such as walking and running generated very similar coefficients, requiring some other features for better representation of activities. Especially a feature is needed to separate between the static and dynamic activities. In this study, we augmented the AR features with two other features (e.g., SMA and TA).

1) SMA: The SMA has been found to be a suitable measure for distinguishing between static vs. dynamic activities using triaxial accelerometer signals [6], [7], [14]. It is calculated according to

$$SMA = \sum_{i=1}^{n} (|x(i)|) + (|y(i)|) + (|z(i)|), \quad (2)$$

where $x(i)$, $y(i)$, and $z(i)$ indicate an acceleration signal of each axis. In our study, SMA for an activity such as walking or running was higher than 50 and it ranged from 3 to 10 for an activity such as lying and standing.

2) TA: It refers to the relative tilt of the body in space and helps in distinguishing postures different in angle such as standing and lying [6], [7]. It can be defined as the angle between the positive z-axis and the gravitational vector *g* and can be calculated according to

$$\theta = ar\cos(z). \quad (3)$$

In our study, tilt angle (TA or θ) for standing and lying was lower than 20^0 and higher than 50^0 respectively. The final feature vector is shown in Fig. 4.

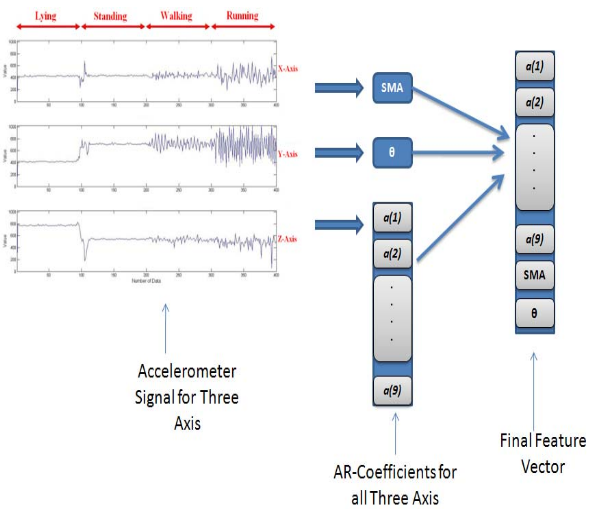

Fig. 4. Block diagram, showing components of the feature vector

E. Classifier

It is the fundamental element of the system which should be adaptive and capable to provide correct answers in real time. In other words, it must correctly understand the features even if those features are considerably different from the ones it has seen before. For this reason, we had decided to use ANNs based on the feed-forward backpropagation algorithm.

The back-end classification was performed using a multilayer perceptron (MLP) neural network trained using Levenberg-Marquardt back propagation which is often termed as the fastest backpropagation algorithm. We used one hidden layer assigned with eleven neurons and one output layer with four neurons corresponding to the four classification outputs. The training and testing sequences of data were randomly selected. For an unknown sequence of data, the correct movement was then classified according to the output of MLP NNs that gave the highest likelihood score. The subject-independent classifier performance was estimated using cross-fold validation.

III. Experiments and Results

The overall system was evaluated in three different trials, each involving different combination of features for training the neural network and classifying the test activities.

A. First Trial

This trial was designed to evaluate the usefulness of AR coefficients only for classifying the test activities into four classes. Thus our feature vector was 9-dimensional for this particular trial. That is our feature vector was expressed as $f = \{a(1),...,a(9)\}$. A total of 15 instances of each activity signals were modeled and the resulting coefficients were used to train the neural network. During testing, each test activity was modeled in a similar fashion and the resulting coefficients were used by the neural network to classify the test activity as lying, standing, walking, or running. The recognition results are summarized in Table I.

TABLE I
Recognition results only with AR-Coefficients

Activity	Number of Training datasets	Number of Test datasets	Accuracy
Lying	15	35	59%
Standing	15	35	61%
Walking	15	35	63%
Running	15	35	64%

B. Second Trial

As shown in Table I, AR coefficients only were unable to provide promising recognition results for test activities. This trial was designed to evaluate the usefulness of SMA as an augmented feature along with the previous coefficients to classify the test activities into four classes. Thus our feature vector was 10-dimensional for this particular trial. That is $f = \{a(1),...,a(9), SMA\}$.

Feature vectors for 15 instances of each activity were used to train the neural network. During testing, each test activity was modeled and its magnitude area was calculated. The resulting 10-dimensional feature vector was used by the neural network to classify the test activity. Results for this trial are summarized in Table II, showing some improvements in recognition.

TABLE II
Recognition results only with Ar-Coefficients and SMA

Activity	Number of Training datasets	Number of Test datasets	Accuracy
Lying	15	35	71%
Standing	15	35	72%
Walking	15	35	90%
Running	15	35	92%

C. Third Trial

The use of SMA as an added feature along with the AR coefficients improved the recognition rates for running and walking: reason being a significant difference between the magnitude areas of these two activities. The magnitude area for lying and standing is almost the same since the subject is at rest in both cases. Hence, the use of SMA could not improve the recognition rates for lying and standing as shown in Table II. This trial was designed to evaluate the use of tilt angle as an added feature to our feature vector to classify the test activity into four classes. Thus our feature vector was 11-dimensional for this particular trial. That is $f = \{a(1),...,a(9), SMA, TA\}$.

Feature vectors for 15 instances of each activity in the first case, and 12 instances of each activity in the second case were used to train the neural network. During testing, each test activity was modeled and its magnitude area and tilt angle were calculated. The resulting 11-dimensional feature vector was used by the neural network to classify the test activity. Results for this trial are summarized in Table III, showing 99% of recognition rate for all activities.

TABLE III
RECOGNITION RESULTS ONLY WITH AR-COEFFICIENTS, SMA, AND TILT ANGLE

Activity	Number of Training datasets	Number of Test datasets	Accuracy
Lying	15	35	99%
	12	37	99%
Standing	15	35	99%
	12	37	99%
Walking	15	35	99%
	12	37	99%
Running	15	35	99%
	12	37	99%

IV. CONCLUSION

We have proposed a new human activity recognition technique using only one triaxial accelerometer and augmented features for categorizing human body postures such as sitting and standing and locomotion such as walking and running. Our proposed framework is general such that it could be extended into the use of several accelerometers. Also we have combined features such as SMA and TA, which have been used separately to distinguish dynamic and static activities, into one system such that dynamic and static activities could be recognized via the same system.

In future, we plan to investigate other modeling techniques including autoregressive and moving average models (ARMA), kalman filters, particle filters, etc. We also intend to test more complicated activities in automatic recognition.

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