A Triaxial Accelerometer-Based Physical-Activity Recognition via Augmented-Signal Features and a Hierarchical Recognizer

Adil Mehmood Khan, Young-Koo Lee, Sungyoung Y. Lee, and Tae-Seong Kim, *Member, IEEE*

***Abstract*—Physical-activity recognition via wearable sensors can provide valuable information regarding an individual's degree of functional ability and lifestyle. In this paper, we present an accelerometer sensor-based approach for human-activity recognition. Our proposed recognition method uses a hierarchical scheme. At the lower level, the state to which an activity belongs, i.e., static, transition, or dynamic, is recognized by means of statistical signal features and artificial-neural nets (ANNs). The upper level recognition uses the autoregressive (AR) modeling of the acceleration signals, thus, incorporating the derived AR-coefficients along with the signal-magnitude area and tilt angle to form an augmented-feature vector. The resulting feature vector is further processed by the linear-discriminant analysis and ANNs to recognize a particular human activity. Our proposed activity-recognition method recognizes three states and 15 activities with an average accuracy of 97.9% using only a single triaxial accelerometer attached to the subject's chest.**

***Index Terms*—Accelerometer, artificial-neural nets (ANNs), autoregressive (AR) modeling, human-activity recognition.**

I. Introduction

AUTOMATIC recognition of human activities is one of the important and challenging research areas in proactive and ubiquitous computing: first, due to its potential in providing personalized support for many different applications such as smart environments and surveillance and second, due to its connection to many different fields of studies such as lifecare and healthcare.

Human-activity recognition requires an objective and reliable technique that can be used under the conditions of daily living. Complex sensors such as cameras in computer vision have been used to recognize activities. In general, the computer vision-based techniques for tracking and activity recognition often work well in a laboratory or well-controlled environment. However, they fail in achieving the same level of accuracy under a real-home setting due to the clutter, variable lighting, and highly varied activities that take place in the natural environments [1]. Motion capture with the body-fixed accelerometers offers an appropriate alternative for the assessment of daily physical activities [2].

Many human-activity recognition systems have been developed in the past which incorporate the use of accelerometers. Some of these investigated the use of acceleration signals to analyze and classify different types of the same physical activity, e.g., walking along the corridor, upstairs, and downstairs [3], [4]. Others employed them for recognizing a wide set of daily physical activities such as lying, sitting, standing, walking, and running [2], [5]–[19]. Minnen *et al.* [20] have explored the discovery of recurring activities such as hammering, sawing, filling, drilling, sanding, and grinding from the accelerometer data, while [21]–[23] focused on the elderly persons' fall detection and prevention.

Most of these systems investigated the use of multiple accelerometers attached to different sites on a subject's body [2], [3], [5], [8], [10], [11], [15], [17]–[21]. However, this approach is not feasible for the long-term activity monitoring because of two or more sensor-attachment sites and cable connections. Comparatively, a small number of studies have investigated the use of a single accelerometer mounted at waist or sternum [4], [6], [7], [9], [12]–[14], [16], [22], [23]. Such systems achieved good recognition results for some basic activities including lying, walking, and running. However, they could not achieve the same level of accuracy for some static activities such as standing and sitting, transitions such as lie-stand, sit-stand, and stand-sit, and dynamic activities such as walking downstairs and walking upstairs.

As for the features, most studies have used the frequency-derived features employing fast Fourier transform [17], [20] and wavelet transform [2]–[4]. Others used the signal-magnitude area (SMA) [6], [7], [16], [24], tilt angle (TA) [6]–[8], [16] or parameters such as averages, energy, entropy, standard deviation, or correlations [10], [13], [18]. However, these features are calculated over long time-windows which reduce their ability to detect the short-duration movements, e.g., the transitions between sitting and standing or taking a couple of steps.

As for the recognition techniques, a large number of classification methods have been investigated. Some studies incorporated the idea of simple heuristic classifiers [2], [5]–[9], [11], [16], whereas others employed more generic and automatic methods from the machine learning literature including the

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A. M. Khan, Y.-K. Lee, and S. Y. Lee are with the Department of Computer Engineering, Kyung Hee University, Yongin-si 446-701, Korea (e-mail: kadil@oslab.khu.ac.kr; yklee@khu.ac.kr; sylee@oslab.khu.ac.kr).

T.-S. Kim is with the Department of Biomedical Engineering, Kyung Hee University, Yongin-si 446-701, Korea (e-mail: tskim@khu.ac.kr).

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decision trees, nearest neighbor and Bayesian networks [10], [13], [17], [18], support vector machines [13], neural networks [3], [15], [17], [21], Gaussian mixture models (GMM) [14], and Markov chains [12], [19], [20].

Thus, the existing literature on physical-activity recognition using accelerometers varies in approach, intention, and outcome. Individual researchers have employed their own device(s) to collect the data for a particular set of movement(s) and have investigated a wide variety of algorithms and methods. The most significant breakthrough is presented in [24], where a single triaxial accelerometer is developed and evaluated for accessing daily physical activities. It was later used in [6], [7], and [16] with varying success rates. However, the primary drawback of these systems is their rule-based heuristic nature as finding such a set of rules is a time-consuming process. Allen *et al.* [14] proposed an improvement by employing a GMM-based approach as a more general and sophisticated approach to physical-activity recognition using a single triaxial accelerometer. However, this scheme introduces more complexity because it requires training a separate GMM for each physical activity. It also requires an adaptation method to adapt the system to a particular subject when faced with the limited training data. Moreover, all previous studies presented some difficulty in distinguishing between the sitting and standing postures. Accuracy of 78% has been achieved so far by relying on the improved knowledge of the transitional movements between sitting and standing to distinguish these postures.

In our previous study on human-activity recognition using a triaxial accelerometer [25], we proposed the autoregressive (AR) modeling [26] of the triaxial acceleration signals and used the AR-coefficients augmented with the SMA and TA to form an augmented-feature vector. The proposed feature vector was then used to recognize lying, standing, walking, and running. It outperformed the features used in the previous studies by achieving a recognition rate of 99%. However, the accuracy decreased significantly with the addition of the new activities.

In this paper, we aim to overcome the limitations of our previous physical-activity recognition system and intend to develop a system that is capable of recognizing a broad set of daily physical activities using only a single triaxial accelerometer. Our proposed system uses a hierarchical-recognition scheme, i.e., the state recognition at the lower level using statistical features and the activity recognition at the upper level using the augmented-feature vector [25] followed by the linear-discriminant analysis (LDA) to extract only the meaningful features. Our proposed system is capable of recognizing 15 physical activities of daily living with a much improved recognition rate compared to the previous studies.

II. Method

A. Sensor Device and Data Collection

We used an accelerometer sensor called Witilt v2.5, a 2.4-GHz wireless triaxial tilt sensor from Sparkfun. It employs a FreeScale MMA7260Q triple-axis accelerometer and a Class 1 Bluetooth link from BlueRadios. The sampling frequency was 20 Hz and the range of the sensor output was $\pm 6g$. The bluetooth module communicated with a universal serial bus dongle attached to a computer working as a transceiver to receive and store the sensor data. In general, the output of any body-worn accelerometer depends on the position at which it is placed [27]. Accelerometers are normally attached to the part of the body whose movement is being analyzed such as arm, wrist, thigh, etc. However, since we wished to study the whole body movements, we decided to place the sensor at a position closer to the center of mass, i.e., the subject's chest as shown in Fig. 1.

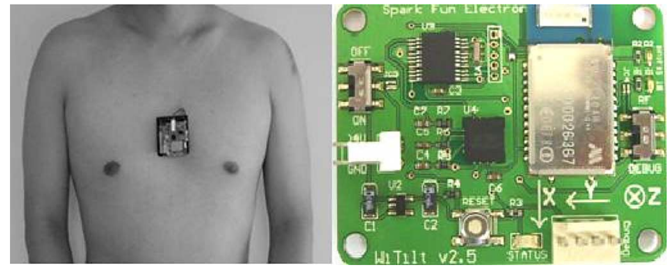

Fig. 1. Sensor device being worn by a subject.

TABLE I
CLASSIFIED STATES AND ACTIVITIES RECOGNIZED IN THIS STUDY

State	Activity
Static	Lying
	Sitting
	Standing
Transitions	Lie-Stand
	Stand-Lie
	Lie-Sit
	Sit-Lie
	Sit-Stand
	Stand-Sit
	Walk-Stand
	Stand-Stand
Dynamic	Walking
	Walking-upstairs
	Walking-downstairs
	Running

The dataset for our experiment was collected in an unsupervised study. Six healthy subjects, i.e., three females and three males with the mean age of 27, wore the device each day for a period of one month to collect the 15 activities which are listed in Table I. Annotations were performed using a bluetooth headset combined with a speech-recognition software [28]. A sample sequence of the activities performed at home is: sitting (2 min) → sit-stand → standing (2 min) → stand-lie → lying (2 min) → lie-stand → standing (40 s) → walking (2 min) → standing (40 s) → walking-upstairs → standing (40 s) → walking-downstairs → standing (40 s) → stand-sit → sitting (40 s) → sit-lie → lying (40 s) → lie-sit.

The subjects were provided with approximate time duration for each activity, as shown in the activity sequence, except for the walking upstairs and downstairs. The time duration of these activities depended on the length of stairs at each subject's home and, thus, varied among the subjects. Although the dataset collected under this protocol was structured, it was still acquired

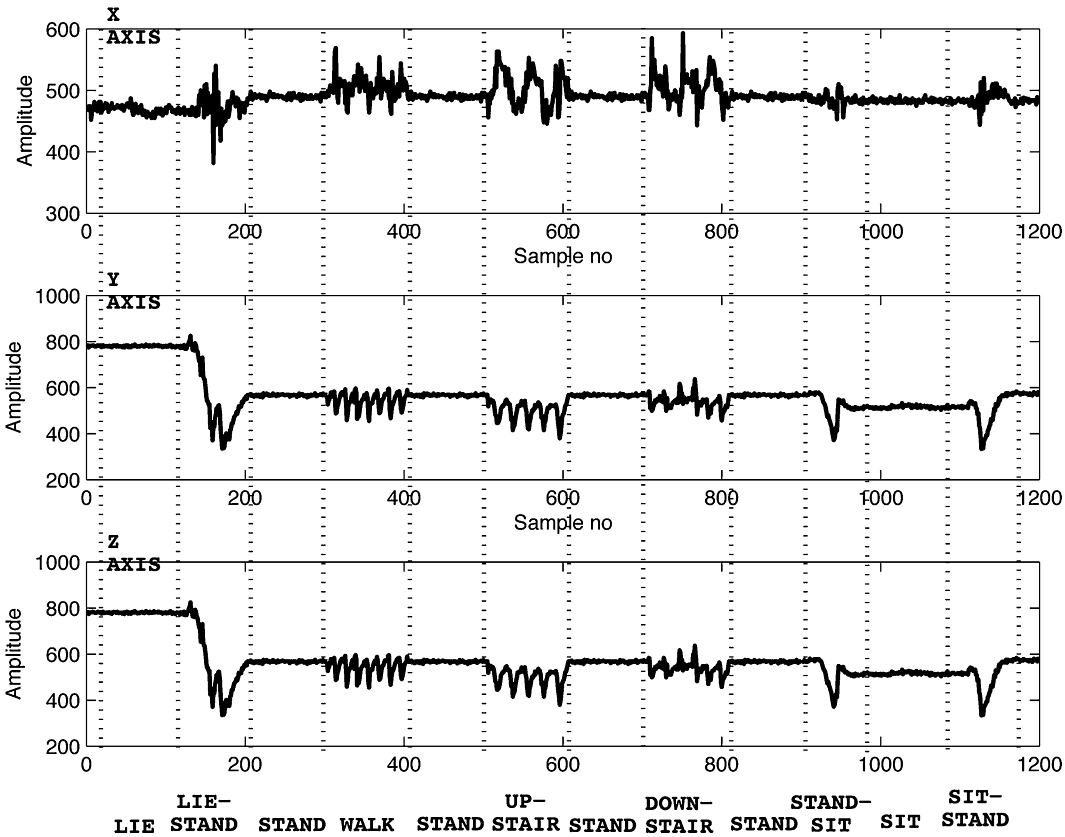

Fig. 2. Set of the sample acceleration signals of the human activities for each axis of the triaxial accelerometer.

under the less controlled conditions than in the most prior studies.

The subjects were trained on the use of data collection and annotation applications. Each subject then collected the activity data at home without the researchers' supervision. They made the annotations themselves throughout the data collection. We collected approximately 21 h of the activity data, i.e., 3.5 h per subject. The activity dataset for each subject was then divided randomly into the training and test sets in a roughly 40%–60% split. A representative set of the activity signals is shown in Fig. 2.

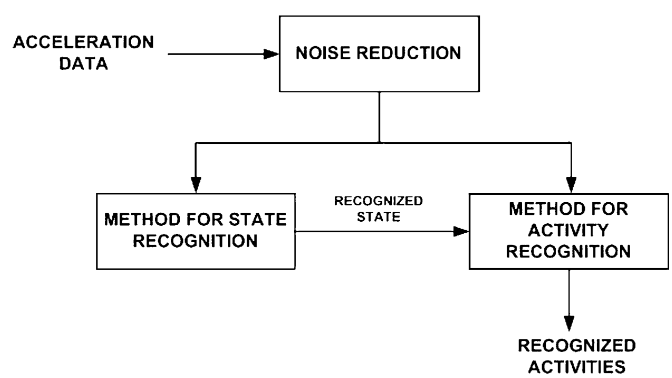

Fig. 3. Block diagram for our proposed recognition technique.

B. Proposed System Architecture

The architecture of our proposed activity-recognition system is illustrated in Fig. 3. A component-based description of the system is given in the following.

1) Noise Reduction: The real-time output of an accelerometer contains some noise that needs to be filtered out before using it for the activity recognition. The noise reduction unit, shown in Fig. 3, incorporates a three-point moving average filter to filter out the signal outliers.

2) State Recognition: The purpose of the state recognition is to determine the state to which an activity belongs. Features, including the mean, standard deviation, spectral entropy, and correlation, as the state features, are extracted from the noise-reduced acceleration signal and processed by a classifier. These parameters have been used for physical-activity recognition in several existing studies with varying success rates [10], [13], [18]. However, we proposed their usage for the state recognition only. The mean, range of the possible acceleration values, and periodicity in the acceleration data differ slightly between the physical activities but greatly between the states. Hence, they are more suitable for the state recognition.

3) Activity Recognition: Once the state of a given activity is recognized, the noise-reduced acceleration signal is fed to the activity-recognition module which uses our proposed augmented-feature vector [25], i.e., the AR-coefficients, SMA, and TA. Though the TA has been used previously to differentiate certain postures [6]–[8], [16], the decisions made on its values were purely heuristic and rule based. We proposed using the TA

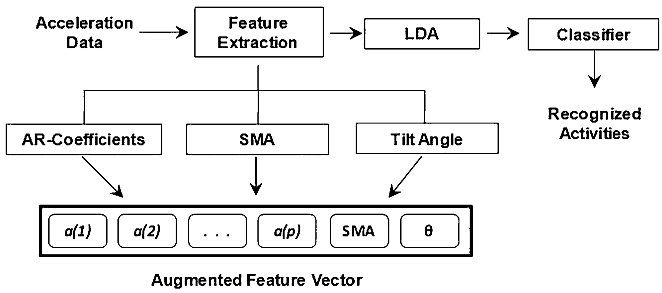

Fig. 4. Block diagram for our activity-recognition method, showing the components of the augmented-feature vector.

as a part of an augmented-feature vector. The block diagram of this module is shown in Fig. 4. A brief description of each feature is given as follows.

1) *Autoregressive coefficients*: An AR model can be represented as

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

where $\alpha(i)$ is the AR-coefficients, $y(t)$ the time series under investigation which in our case is the acceleration signal, p the order of the filter, and $\varepsilon(t)$ the noise term.

2) *Signal-magnitude area (SMA)*: It is calculated according to

$$\text{SMA} = \sum_{i=1}^{N} (|x(i)|) + (|y(i)|) + (|z(i)|) \tag{2}$$

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

3) *Tilt angle (TA)*: It refers to the relative tilt of the body in space. It is defined as the angle between the positive *z*-axis and the gravitational vector *g* and is calculated according to

$$\vartheta = \arccos(z). \tag{3}$$

C. Linear-Discriminant Analysis (LDA)

The LDA module takes the augmented-feature vector as input and utilizes the class specific information to maximize the ratio of the between and within-class scatter information. It seeks the vectors in the underlying space to create the best discrimination among different classes. It is well known for the feature extraction and dimension reduction. The optimal discrimination projection matrix D_{opt} is chosen from the maximization of the ratio of the determinant of the between and within-class scatter matrices as

$$D_{\text{opt}} = \arg\max_{D} \frac{|D^T S_B D|}{|D^T S_W D|} = [d_1, d_2, \ldots, d_t]^T \tag{4}$$

where S_B and S_W are the between and within-class scatter matrices, respectively. Further details on the LDA are available in [29]. The 3-D feature plots for the four transitions before and after applying the LDA are shown in Figs. 5 and 6, respectively.

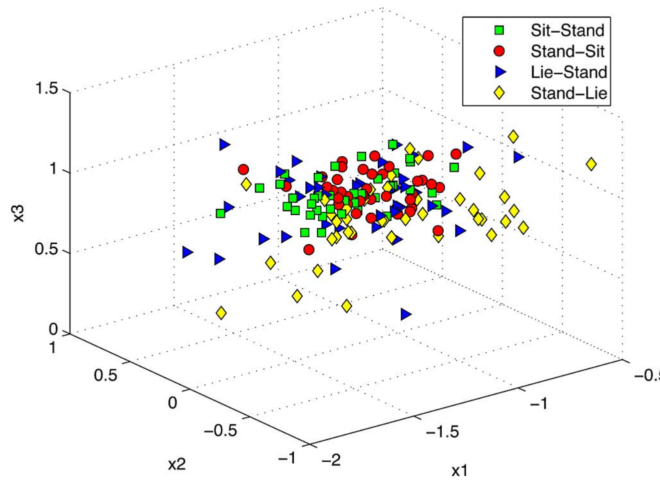

Fig. 5. 3-D feature plot for the four transitions before the LDA.

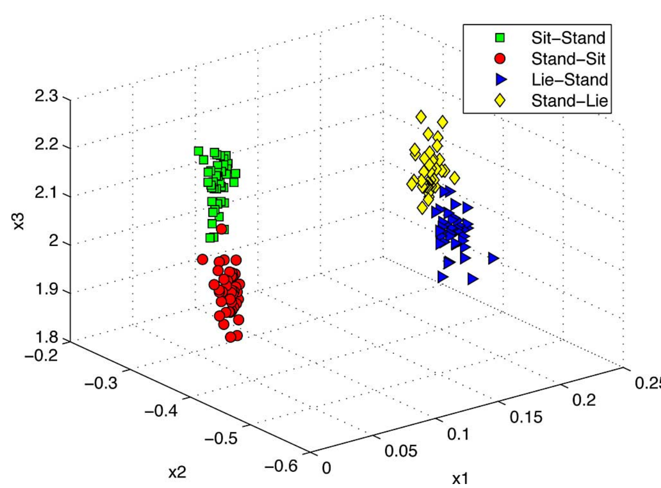

Fig. 6. 3-D feature plot for the four transitions after the LDA.

D. Classifier

It is the fundamental element of the system which should be adaptive and capable of providing the correct classification. In other words, it must correctly understand the features even if those features are considerably different from the ones it was fed before. For this reason, we decided to use artificial-neural nets (ANNs) based on the feed-forward backpropagation algorithm. Perceptron neural nets with different number of layers and neurons were tested in order to optimize the performance. The maximal value of the weights in the neuron connections was normalized to the modulus of 1. Different steps of the increment for the weights were also investigated. The training of ANNs was also repeated several times by changing the input order in a random fashion.

For the state recognition, only one network (SNN) was trained. The inputs to SNN were the state features. For the activity recognition, three networks were trained for three states, i.e., an ANN to recognize the static activities, an ANN to recognize the transitions, and an ANN to recognize the dynamic activities.

The inputs to each of these ANNs were the output of the LDA module as shown in Fig. 4.

III. Experimental Results

A. Determination of the AR-Model Order

In order to determine the optimal AR-model order, root mean square error (rmse) values were calculated for each activity and the behavior of the rmse curve against different model orders was analyzed. We observed a decreasing trend against the AR-model order. The curve tended to even out near the model order of 10 which suggested that the optimum model order lied in the neighboring values of 10.

B. Classification Results

In order to get the meaningful coefficients, the AR-modeling of any time series generally requires the length of the series to be significantly larger than the model order. We used a sampling frequency of 20 Hz. It resulted in the failure of seizing the meaningful AR-coefficients on the second-by-second basis, i.e., a window size of 20 samples. After several trials, we concluded that the window size of 64, i.e., 3.2 s, with no overlapping between consecutive windows, is the most appropriate in our case. First, this time interval was not too long to result in a delayed response. Second, it provided enough raw data for extracting the meaningful AR-coefficients. Thus, for the classification, acceleration data was fed every 3.2 s to the recognition system and the output was compared to the true activity. The performance of the proposed-recognition system was then validated in the following four studies.

1) Test on State Recognition: The state features were extracted and the SNN was trained to recognize the three states. The average-recognition accuracy was almost 99% which indicates the feasibility of employing the proposed features for the state recognition.

2) Test on Feature Augmentation: This study was performed in order to try a number of configurations of the front-end features for the activity recognition before landing on the augmented-feature vector which is shown in Fig. 4. We performed three different trials. Each trial involved a different combination of the features for classifying the test activities, i.e., {AR-coefficients}, {AR-coefficients, SMA}, and {AR-coefficients, SMA, and TA}. The recognition system used in this study was single-level (SL-HAR), i.e., the features were calculated and fed directly to the activity-recognition module without the state recognition and a single ANN was trained to recognize only the four basic activities, including lying, standing, walking, and running. The recognition results are summarized in Table II.

3) Single-Level (SL) Versus Hierarchical (H)-HAR System: The purpose of this study was to evaluate the performance of the SL-HAR versus H-HAR system to recognize the 15 activities which are listed in Table I. This study was performed in two steps. First, the state features and augmented-feature set were calculated and fed to the SL-HAR system to recognize the test activities. Second, the proposed H-HAR system was used to recognize the test activities. The recognition results are summarized in Table III. They clearly indicate that the H-HAR system outperformed the SL-HAR system by achieving an average recognition accuracy of 97.9%. The choice of 15 physical activities, belonging to three states, generated complex decision boundaries in the feature space. The two-level recognition broke down the overall recognition problem into two subproblems and, thus, enabled the H-HAR to incorporate a set of two ANNs to solve these complex decision boundaries.

4) Performance Evaluation With Limited Training Data: Accelerometer-based human-activity recognition systems usually suffer a loss in accuracy during the practical deployment, which is caused by either training the system with the data from other people or with the limited training data from the person for whom it is intended. To address this problem, we estimated the subject independent classifier performance of the H-HAR system using the sixfold cross validation, where six represents the number of subjects participated in our study. Of these six subjects, the activity dataset from a single subject was retained as the validation dataset for testing the model and the activity datasets from the remaining five subjects were used as the training datasets. This process was repeated six times, i.e., the number of folds. The results from these folds are summarized in Table IV. The average recognition accuracy of 97.65% indicates that our proposed human-activity recognition scheme can achieve high recognition rates for a specific subject even if an adequate amount of training data from the intended subject is unavailable.

TABLE II
Average-Recognition Results(in percent) for the Four Activities for the Feature-Augmentation Tests

Activity	[AR]	[AR, SMA]	[AR, SMA, TA]
Lying	59	70	99
Standing	61	71	99
Walking	83	90	99
Running	85	95	99
TOTAL	72	81.5	99

TABLE III
Average Recognition Results(in percent) for all Activities for the SL-HAR versus H-HAR Test

State	Activity	SL-HAR	H-HAR
Static	Lying	95	99
	Sitting	74	95
	Standing	63	99
Transition	Lie-Stand	64	94
	Stand-Lie	90	96
	Lie-Sit	61	92
	Sit-Lie	54	94
	Sit-Stand	68	99
	Stand-Sit	50	99
	Walk-Stand	81	99
	Stand-Walk	74	99
Dynamic	Walking	74	99
	Walking-upstairs	72	99
	Walking-downstairs	70	99
	Running	85	99
	TOTAL	71.6	97.9

TABLE IV
AVERAGE RECOGNITION RESULTS FOR ALL ACTIVITIES WHEN THE TRAINING DATA FROM THE INTENDED SUBJECT IS NOT AVAILABLE

State	Activity	Accuracy(%) Subject 1	2	3	4	5	6	Mean
Static	Lying	100	95	98	100	100	100	98.6
	Sitting	90	91	92	90	92	90	90.83
	Standing	93	95	96	97	96	95	95.3
Transitions	Lie-Stand	100	100	99	100	100	99	99
	Stand-Lie	100	100	98	100	100	99	99
	Lie-Sit	100	99	100	99	100	100	99
	Sit-Lie	100	100	99	100	99	99	99
	Sit-Stand	100	95	97	100	100	99	98.5
	Stand-Sit	100	100	100	95	100	96	98.5
	Walk-Stand	97	99	95	94	95	96	96
	Stand-Walk	95	98	94	94	95	94	95
Dynamic	Walking	100	96	99	100	100	100	99
	Walking-upstairs	100	95	100	100	100	100	99
	Walking-downstairs	100	100	96	100	100	99	99
	Running	100	100	98	100	100	99	99
	Total accuracy				97.65%			

IV. DISCUSSION AND CONCLUSION

The aim of this paper is to provide an accurate and robust human-activity recognition system for the u-lifecare environments. The proposed system incorporates the use of a single triaxial accelerometer. It is feasible to be used by the free-living subjects as it relies only on a single point of sensor's attachment to their bodies. It is effective in a sense that it is capable of recognizing a broad set of daily physical activities with an average accuracy of 97.9%. It is able to distinguish between the sitting and standing postures, sit-stand and stand-sit transitions, and walking-upstairs and walking-downstairs movements using only a single triaxial accelerometer.

Although several systems have been proposed in the past to monitor daily physical activities using accelerometers, this system appears promising in several regards. First, its performance compares favorably with the previously proposed systems. Mathie *et al.* proposed a rule-based heuristic system for the classification of daily physical activities. However, the primary drawback of this system is its rule-based heuristic nature as finding such a set of rules is a time-consuming process. It also showed difficulty in distinguishing between the sit-stand and stand-sit transitions and between the sitting and standing postures [6], [16]. Allen *et al.* proposed an improvement by employing a GMM-based approach but it also exhibited difficulty in distinguishing between sitting and standing postures [14]. Bao *et al.* used an ambulatory system based on the decision trees to classify 20 activities using a seminaturalistic dataset collected outside the laboratory [10]. However, the recognition accuracy was only 84.26%. It also required subjects to wear five biaxial accelerometers simultaneously on different parts of their bodies and, thus, may not be feasible for the long-term activity recognition in the free-living subjects. Ermes *et al.* proposed a system based on a hybrid model classifier to assess the feasibility of the activity recognition in out-of-lab settings using both the supervised and unsupervised activity data [17]. However, the overall accuracy was 89% and the system showed inability in differentiating between the sitting and standing postures.

Second, the dataset used in this study was collected by the subjects at home without the researchers' supervision and the annotations were made on the spot. The use of a bluetooth headset together with a speech-recognition software for the annotations resulted in very little interference while performing the activities. Third, our proposed system is based on a novel hierarchical recognition scheme. Our results show that it is superior to a single-level recognition system as a large number of activities result in complex decision boundaries in the feature space which are difficult for a single classifier to solve.

Fourth, a novel augmented-feature vector was employed to achieve the activity recognition within each state. It was composed of the AR-coefficients, SMA, and TA. The AR-coefficients were obtained by modeling the triaxial acceleration signals using the AR-models. The recognition accuracy of 97.9% illustrates the success of employing the proposed augmented-feature vector for the activity recognition which indirectly signifies the feasibility of using the AR-analysis. Fifth, our results illustrate the success of our proposed recognition system in achieving an acceptable recognition rate even in the absence of an adequate amount of the training data from the intended subject.

Thus, the experimental results of our proposed hierarchical recognition scheme have shown significant potential in its ability to accurately and robustly model the ambulatory data using a single triaxial accelerometer. The next stage of evaluation will be the assessment of our classification technique for the elderly in a free-living context.

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Adil Mehmood Khan received the B.S. degree in information technology from the National University of Sciences and Technology (NUST), Rawalpindi, Pakistan, in 2005. He is currently working toward the Ph.D. degree in the Department of Computer Engineering, Kyung Hee University, Yongin-si, Korea.

His current research interests include ubiquitous computing, context-aware computing for handheld devices, wearable sensing, and pattern recognition.

Young-Koo Lee, photograph and biography not available at the time of publication.

Sungyoung Y. Lee, photograph and biography not available at the time of publication.

Tae-Seong Kim, photograph and biography not available at the time of publication.