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Telemedicine Based on Human Activity Recognition in Elderly Healthcare

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Abstract. Nowadays, telemedicine can provide remote clinical services for the elderly, using smart devices like embedded sensors, via real-time communication with the healthcare provider. In particular, inertial measurement sensors such as accelerometers embedded in smartphones can provide sensory data fusion for human activities. Thus, the technology of Human Activity Recognition can be applied to handle such data. In recent studies, the three-dimensional axis has been used to detect human activities. Since most changes in individual activities occur in the x- and y-axis, the label of each activity is determined using a new two-dimensional Hidden Markov Mode based on these two axes. To evaluate the proposed method, we use the WISDM dataset which is based on an accelerometer. The proposed strategy is compared to General Model and User-Adaptive Model. The results indicate that the proposed model is more accurate than the others.

Keywords. Human Activity, Healthcare, Bayesian Networks, Markov Model, Recognition

1. Introduction

Medical and assistive systems utilizing wearable sensors are being employed to provide long-term care and enhance the quality of life for the elderly [1]. Human Activity Recognition (HAR) based on wearable sensors, such as those found in smartphones, is being used to monitor patients in hospitals and at home. However, the most significant challenges faced by HAR are scalability, complex actions, and human behaviors in a complex environment [2]. Researchers have proposed several approaches for activity recognition, including Ameva, which uses selection, discretization, and classification techniques [3]. User-adaptive models (UAM) utilize deep transfer learning and data augmentation to improve prediction performance with limited training data [4]. Furthermore, a new method has been presented that integrates personal experience into the HMM for activity recognition using a personal wearable computer eButton, which includes multiple sensors [5]. Additionally, some approaches for HAR using deep

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learning techniques have been introduced. In [6], a model is presented that combines residual block and bi-directional LSTM to extract features from multidimensional signals of microelectromechanical system inertial sensors, and the features are classified using a Softmax layer. In [7], a method based on Encoder-Decoder Convolutional Neural Networks is introduced, which uses both publicly labeled and private unlabeled raw sensor data to extract relevant features and enhance knowledge in the innermost layers. In [8] an ensemble approach called EnsemConvNet is presented, which combines three classification models to predict human activity based on time series data. Finally, in [9], a new approach is introduced that uses inertial wearable sensors to detect and classify human activities by jointly segmenting multidimensional time series using an HMM in a multiple regression context. The proposed method in this study aims to use smartphone-based accelerometers to detect physical human activities and categorize similar activities using Bayesian Networks (BNs). Additionally, a two-dimensional HMM is used to determine the label of each activity based on the x- and y-axis. The rest of this study is organized as follows. The proposed approach is explained in Section 2. The experimental results present in Section 3. Section 4 concludes and describes the ongoing work to improve the proposed approach.

2. Proposed Method

In this study, a set of motion data received from phone-based accelerometers is used to identify the user's physical activity. People were asked to walk, run, climb stairs, descend stairs, sit, and stand while holding their cell phone. It is clear that sitting and standing do not exhibit distinct behavior pattern while the other four activities include repetitive movements and show periodic behavior [9]. In this study, detecting different physical activities by analyzing the patterns in the accelerometer data of participants performing six activities for four activities but not for sitting and standing is analyzed.

The proposed strategy has two phases, in the first phase, we use BNs to classify time series data into three groups based on some features [10]. A BN is formally shown by a pair $B = \langle G, \Theta \rangle$ for the set U so that G represents a directed acyclic graph whose vertices are the random variables $X_1, \dots, X_n$ and edges in this network represent dependencies between these variables [11]. The second component Θ is related to parameters which quantify the network. For each possible value x_i, this parameter contains $\theta_{x_i|\Pi_{x_i}} = P_B(x_i|\Pi_{x_i})$, and Π_{x_i} of Π_{X_i} , where Π_{X_i} represents the parents of X_i. A unique joint probability distribution over U is given by (11) as follow.

$$P_B(X_1, \dots, X_n) = \prod_{i=1}^{n} P_B\left(X_i \middle| \Pi_{X_i}\right) = \prod_{i=1}^{n} \theta_{X_i|\Pi_{X_i}} \quad (1)$$

In this paper we use BNs to identify possible relationships to evaluate the membership class. In this strategy, the group of “Slow running and walking” belongs to same category, “climbing and descending stair” is classified in another class, and “sitting and standing” is located in the last group. In the second phase, the HMM is designed and trained for each data class. The formal definition of an HMM is as follows [12]:

$$\lambda = (A, B, \pi) \quad (2)$$

A is a transition array, storing the probability of state j following state i . Note the state transition probabilities are independent of time (12):

$$A = [a_{ij}], a_{ij} = P(q_t = s_j | q_{t-1} = s_i) \quad (3)$$

B is the observation array, storing the probability of observation k being produced from the state j, independent of t (12):

$$B = [b_i(k)], b_i(k) = P(x_t = v_k | q_t = s_i) \quad (4)$$

π is the initial probability array (12):

$$\pi = [\pi_i], \pi_i = P(q_1 = s_i) \quad (5)$$

Since a person's movement is mostly observable in the x and y axes, in this paper we use two-dimensional HMM with time series information of these two axes to detect the label of each data. The speed of time series is used as an observation to predict the label. The process of the proposed method is shown in Figure 1.

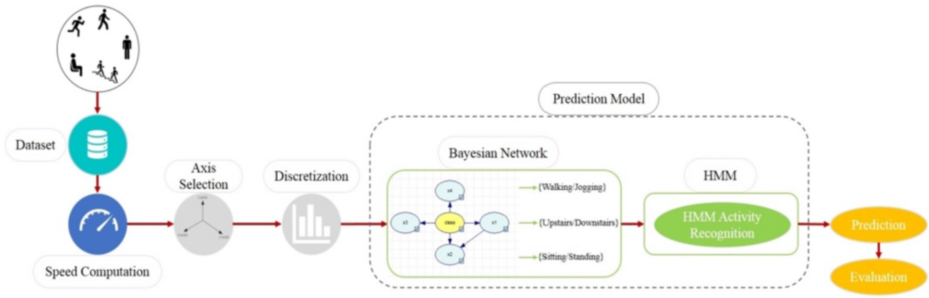

Figure 1. The process of the proposed method

3. Experimental results

To evaluate the performance of the proposed strategy, we use WISDM dataset of 36 users. In this dataset the information about each person and its label recorded [10]. Before collecting dataset, the ethical approval was obtained from the Fordham University IRB (Institutional Review Board) since the study involved “experimenting” on human subjects and there was some risk of harm [10]. The dataset contains six classes of walking, Jogging, Upstairs, Downstairs, Sitting and Standing which are presented by class 1 to 6, respectively. The activity changes of each class in three axes x, y and z are available. In the phase of designing, 70% of the data is considered for training, and the remaining 30% is for testing. The results show that four features XABSOLDEV, YABSOLDEV, XSTANDDEV, and ZSTANDDEV have the most differences for recognizing the labels {1,2}, {3,4} and {5,6}; therefore, there is a good separation between the classes. Changes in XABSOLDEV feature are given in Figure 2, the changes of similar classes such as {1,2}, {3,4}, and {5,6} are in the same range, which indicates that similar activities are in the same category. Similar changes and interpretations are shown for YABSOLDEV, XSTANDDEV and ZSTANDDEV features in Figure 3, 4 and 5, respectively. In Figure 6, six classes for x-axis time series values are given. After detecting the class, the two-dimensional HMM is applied. Since a person’s movement has the most changes in the x and y-axis, the two-dimensional Markov time series model with two features is used to investigate the effect of the two features at the same time. The result of evaluating the proposed method is given in Figure 7. The Area Under the Curve (AUC) is used to assess the performance of the model. The proposed method has been compared with the General Model (GM) [4] and User-Adaptive Model (UAM) [4] that the result of this comparison is shown in Table 1. According to Table 1, the proposed method is more efficient than two other models.

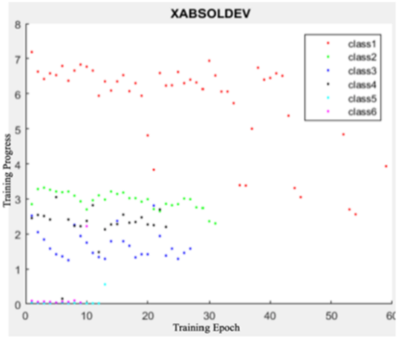

Figure 2. XABSOLDEV feature changes.

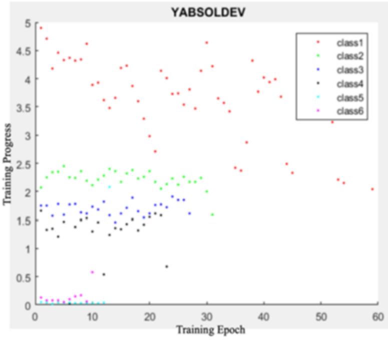

Figure 3. YABSOLDEV feature changes.

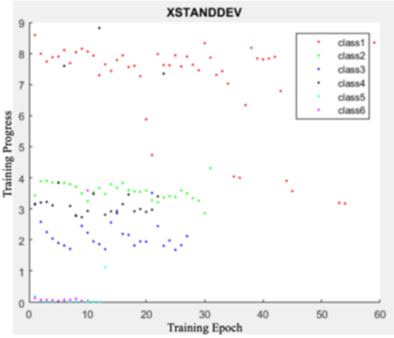

Figure 4. XSTANDDEV feature changes.

Figure 5. ZSTANDDEV feature changes.

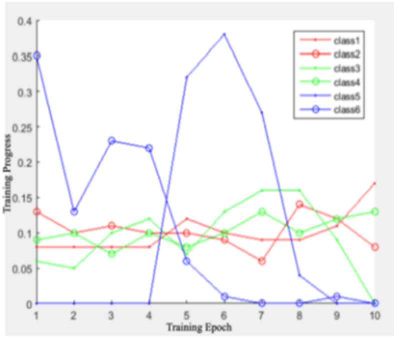

Figure 6. label prediction for each class.

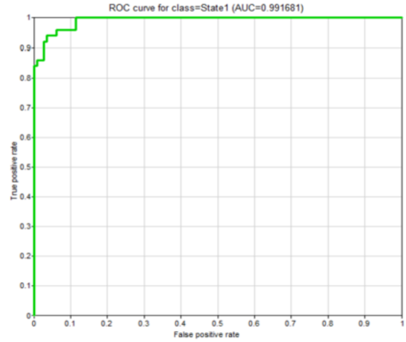

Figure 7. Proposed method evaluation.

Table 1. The accuracy of each class based on each activity for GM, UAM and the proposed method.

Class	**GM** (4)	**UAM** (4)	**Proposed method**
Walking	0.86	1.00	0.98
Jogging	0.75	0.83	0.95
Upstairs	0.28	0.67	0.93
Downstairs	0.29	0.64	0.91
Sitting	0.91	0.96	0.98
Standing	0.91	1.00	0.94
Accuracy	0.80	0.71	**0.94**

4. Conclusion

The aim of this paper is to present a model which be useful in monitoring the daily elderly activities in HAR system. In this study, two-stage classification is used, at first, the model categorizes similar activities by BN into three groups based on the features. In this model, the category of "Slow running and walking" belongs to same category, "climbing and descending stair" is classified in another class, and "sitting and standing" is located in the last group. Then to detect the label of each data, two-dimensional HMM with two features with time series information of the x and y axes are used to investigate the effect of these two features at the same time because a person's movement is mostly observable in these two axes. To evaluate the proposed strategy in this paper, it is compared to GM and UMA methods. The results of the tests indicate that the new model with 94% accuracy is more accurate than other methods.

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