A Comparative Study of User Dependent and Independent Accelerometer-Based Gesture Recognition Algorithms

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Abstract. In this paper, we introduce an evaluation of accelerometer-based gesture recognition algorithms in user dependent and independent cases. Gesture recognition has many algorithms and this evaluation includes Hidden Markov Models, Support Vector Machine, K-nearest neighbor, Artificial Neural Network and Dynamic Time Warping. Recognition results are based on acceleration data collected from 12 users. We evaluated the algorithms based on the recognition accuracy related to different number of gestures from two datasets. Evaluation results show that the best accuracy for 8 and 18 gestures is achieved with dynamic time warping and K-nearest neighbor algorithms.

Keywords: Gesture recognition, Accelerometers, Human Computer Interaction.

1 Introduction

Hand gesture is a form of non-verbal communication for human, people use gestures to express their intentions and deliver particular message [1]. Hand gesture interaction considered a natural way of interaction between humans and computers. It was a motivation to build gesture recognition systems to interpret and explain hand gestures as meaningful command for more natural communication between humans and computers. Hand gesture recognition has great impact on designing an efficient natural interface. Hand gesture based interface used in controlling TV like Samsung SMART TV or play console games like Nintendo Wii and Microsoft Xbox Kinect.

Hand Gesture recognition has many techniques, there are two main techniques for hand gesture recognition: vision based and sensor based [2] [3]. Vision-based technique based on camera as input device, this technique extract information about the user's hand gestures from a visually captured stream (camera) [4]. In a second step, the position of the hand and its fingers are calculated and used for recognizing predefined gestures by use of statistical methods. Vision-based technique has some limitations such as the quality of the captured images, which is sensitive to lighting conditions, cluttered backgrounds and camera facing angles. Thus it is usually not able to detect and track the hands robustly which highly affects the system performance.

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In addition, it is also inconvenient if users are always required facing the camera directly to complete a gesture. On the contrary, Sensor based technique required only a wearable or portable accelerometer equipped device. The majority of personal electronic devices like the Apple iphone and Wiimote's are embedded with accelerometer. Sensor based gesture recognition system tracking the hand by gathering information about the hand position and orientation from the accelerometer for gesture recognition. Sensor based technique is resistant for changing environment, as it's not affected by lighting conditions or cluttered backgrounds. Accelerometer-based gesture recognition system can be used in control home appliances [5], computer applications such as media player and play games.

Gesture recognition systems can be implemented and evaluated for user-dependent and user-independent or both of them. In user dependent case, each user is required to train system before using it by performing number of training samples. In user independent user do not perform any gesture training samples for the system before using it. The user-independent gesture recognition is more difficult than the user-dependent since there is variation for the same gesture from user to another user.

Hand gesture recognition recently became a highly active research area with motivating applications such as sign language recognition [6], interact with medical instrumentation in operation room [7] and control through facial gestures [8]. Another application for accelerometer-based human motion capture and classification is in the monitoring of elderly at home for detection of falls or other abnormal ambulation patterns [9]. Moreover, this approach applied for driving awareness system [10].

Hand gestures are powerful human interactive tool. However, their fluency and intuitiveness have not been utilized as computer interface. Recently, hand gesture applications have begun to emerge, but they are still not robust and are unable to recognize the gestures in a convenient and easily accessible manner by the human. Thus, the main challenge of the gesture recognition systems is to recognize hand gestures in a fast, accurate, robust and easily accessible manner. To achieve this goal, there's many requirements need to be met by the gesture recognition system such as: accuracy, scalability and user-independence. First, accuracy means a hand gesture recognition system should be able to recognize different hand gestures without confusion among them. Second, scalability means a large gesture vocabulary can be included into system and recognized with high accuracy. Third, user-independence means the system should be able to work for different users rather than a specific user. Several gesture recognition systems based on accelerometer have been developed using a well known algorithms such as Hidden Markov Models [11] [12] and Dynamic Time Warping [13] [14]. However, most of the systems in the literature being target user-dependent or user-independent using single algorithm, or have a small dictionary size.

In this work, we evaluated the accuracy of these gesture recognition algorithms: Hidden Markov Models (HMMs), Artificial Neural Networks (ANNs), Dynamic Time Warping (DTW), Support Vector Machine (SVM) and K-nearest neighbor (k-NN) for 18 gestures dataset shown in figure 1(a) obtained from [15] and 8 gestures dataset shown in figure 1(b) obtained from [13]. We conducted two experiments to measure the accuracy of each algorithm in the case of user-dependent and user-independent recognition with 18 and 8 gestures datasets.

This paper is organized as follows. Related work is discussed in section 2, Section 3 describes datasets and the studied algorithms, the evaluation of experiments and its results has been determined in section 4, discussion about the experiments is given in section 5, and finally, section 6 summarizes our conclusion and future work.

2 Related Work

Accelerometer-based gesture recognition systems design can follow a user-independent or a user-dependent approach. The difference lies in whether the user has to train the system before utilize it. User-independent systems are oriented to general users and do not needs a training phase before being usable; conversely, user-dependent systems require the user to repeat the gesture movements several times to train the system.

User-dependent gesture recognition was stated in several literature papers. Liu et al. [13] presented personalize gesture recognition algorithm based on 3D-Accelerometer data. uWave recognized user-defined gestures with 98.6% accuracy for a gesture vocabulary with eight gesture patterns. uWave required a single training sample for each pattern. Its results show that DTW and template adaptation is effective with limited training data and a small vocabulary. Niezen presented in [14] implementation of gesture recognition system using dynamic time warping on mobile phone. They use 8 gestures with 10 samples per gesture were collected using mobile accelerometer. Results show that dynamic time warping algorithm recognizes 77 out of the 80 samples with accuracy of 96.25%. Joselli et.al presented in [12] a framework for touch and accelerometer gesture recognition for mobile games. They used HMMM algorithm for user-dependent recognition. Recognition accuracy was 89% for ten different gesture patterns. Schlömer et al. presented in [11] gesture recognition with a Wii controller for 3D hand gesture recognition using K-mean algorithm, classic Bayes-classifier and HMM for small vocabulary of five gesture patterns. The recognition results were between 85 to 95%.

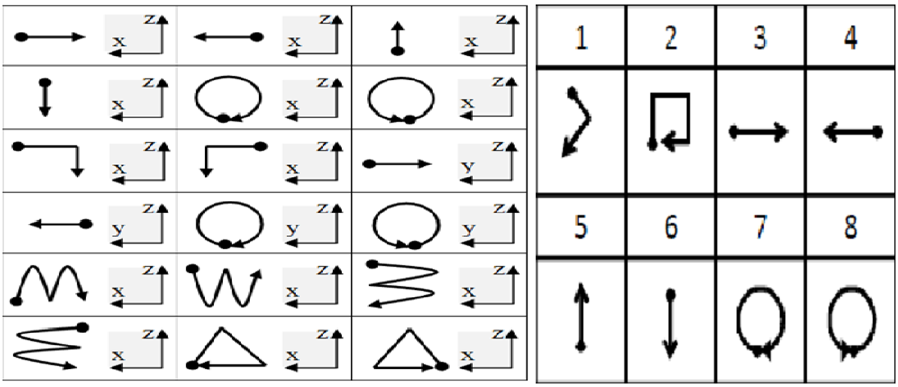
Some literature work target user-dependent and user-independent or user-independent only. Arce et al presented in [16] accelerometer-bases gesture recognition system using Artificial Neural Networks. They evaluated ANN algorithm for user-independent. ANN achieved 83.33% accuracy for five gesture patterns. Zhenyu et al. [17] developed gesture recognition system based on single 3-axis accelerometer mounted on mobile phone. It use three feature extraction methods discrete cosine transform (DCT), fast Fourier transform (FFT) and a hybrid approach which combine wavelet packet decomposition (WPD). Recognition of gestures performed using Support Vector Machine for 17 gestures from 67 users. Results showed that the best recognition accuracy is achieved with wavelet-based method by 87.36% and DCT and FFT are achieved 85.16% and 86.92%. Pylvänäinen presented in [18] accelerometer-based gesture recognition recognizer using continuous HMMs algorithm. Data was collected using an accelerometer embedded in a mobile phone and gesture recognition performed on desktop PC. Recognizer tested on 10 gestures and 20 samples per gesture from 7 users with 8 states model. Results show that recognizer accuracy 99.76%

with user independent and mixed user recognition. Most of previous work described so far, depended on user-dependent recognition or small gesture vocabulary. In this paper, we aim to evaluate the accuracy of different algorithms with different datasets for user-dependent and user-independent gesture recognitions.

3 Experiments Setup

3.1 Dataset

Sensor data were collected using Wiimote's embedded 3-axiz accelerometer. We used two predefined datasets [13] and [14] gestures libraries. First dataset shown in figure 1 (a) consists of 1,800 gestures for 4 users. Each user repeated each gesture 25 times with total 450 for 18 gestures per user. Second dataset shown in Figure 1(b) consists of 4,480 gestures for 8 participants collected over days per multiple weeks. Each user repeated each gesture 10 times with total 80 for 8 gestures per day for 7 days. Data features are represented by feature vector consists of X, Y, Z readings.



(a) (b)

Fig. 1. Datasets vocabulary

3.2 Gesture Recognition Algorithms

Hidden Markov Model. Hidden Markov Models algorithm is a probabilistic model representing a process with states and only the output of the model is visible and states are hidden. Hidden Markov Models used in many applications such as speech recognition, sign language recognition [19] and biometric gait recognition [20]. For building and training Hidden Markov Models, we used Hidden Markov Model Tool-kit [21]. It has helped in the training and testing of Hidden Markov Models. Data represented by matrix of 3 columns x, y and z acceleration values. A 4-state HMM was used for user-dependent recognition and 8-state HMM was used for user-independent recognition.

Support Vector Machine. Support vector machine is a supervised machine learning method that is widely used for data analyzing and pattern recognizing. The algorithm was invented by Vladimir Vapnik and the current standard incarnation was proposed by Corinna Cortes and Vladimir Vapnik [22]. SVM has been widely used in various applications, such as face detection [23] and activity recognition [24].Support Vector Machines (SVM) is originally designed for solving binary classification problems [25]. A gesture recognition system is supposed to recognize more than two types of gestures. For this reason, a multi-class SVM is required. The conventional way to extend binary-class SVM to multi-class scenario is to decompose an M-class problem into a series of two-class problems, for which one-against-all is the earliest and one of the most widely used implementations [26]. We extended the Matlab SVM binary classifier to implement the multi-class SVM.

K-nearest Neighbor. K-nearest neighbor (k-NN) is one of the oldest and simplest machine learning algorithms for pattern classification [27]. K-Nearest Neighbor is a supervised learning algorithm where the result of new instance query is classified based on majority of K-Nearest Neighbor category. k-NN used in many applications such as Handwritten Digit Recognition [28] and breast cancer diagnosis[29]. An object is classified by the distance from its neighbors, with the object being assigned to the class most common among its k distance nearest neighbors in the training set. We used Matlab k-NN classifier; K was empirically fixed to 5 a value that turned out to be optimal. Euclidean distance used to compute the distance between pairs of data points.

Dynamic Time Warping. Dynamic time warping [30] is an algorithm used to measure similarity between two different two sequences in time or speed. Dynamic Time Warping (DTW) is based on the Levenshtein distance algorithm. It has been used in video, audio and graphics or any data which can be turned into a linear representation such speech recognition [31]. Dynamic time warping matches gesture sample against the template gestures. Every gesture represented by sequence of feature vectors. Assume that S is sample and T is template, where $S=\{s_1,\ldots,s_i\}$ and $T=\{t_1,\ldots,t_i\}$ and each feature vector consists of the x, y, z-axis acceleration values. The matching cost by DTW(S, T) must be calculated. The first step is construct distance matrix D by compute the distance between each vector in S and T using formulation 1 foreach S(x, y, z) and T(x, y, z).

$$d(s_i, t_j)=(s_i - t_j)^2 \tag{1}$$

After that we compute the matching cost: DTW(S, T) using this formulation 2, Sample is then recognized as the gesture corresponding to the template with the lowest matching cost.

$$D(i, j) = d(s_i,t_j) + \min\{D(i-1, j), D(i-1, j-1), D(i, j-1)\} \tag{2}$$

Artificial Neural Networks. An artificial neural network is an algorithm based on simulation of the brain. Artificial neural networks have been applied to problems ranging such as speech recognition, predictions of time series, classification of cancers and gene prediction. We have used ANN Encog2.5 for C# [32] during our experiments. Neural network required a fixed length feature vector; the data need to re-sampled and normalized between 0 and 1 for Sigmoid activation function. Data normalized using Encog's normalization class. Data re-sampled using an algorithm described in [33] to 100 points. With 100 points each for the three x, y and z. Feature vector of size 300 points was used as input to neural network. We used backpropagation neural network and desired error 0.001. Neural network architecture depends on the number of gestures. The configuration parameters of the neural network can be seen in Table 1 used for user-dependent and independent recognitions.

4 Experiments

This section presents the implementation and evaluation of HMM, ANN, k-NN, SVM and DTW algorithms for user-dependent and user-independent recognitions with 18 and 8 gestures datasets shown in Figure 1.

4.1 User-dependent Recognition

Hidden Markov Model: In this experiment, we evaluated HMM for user-dependent recognition with 18 gestures dataset and 8 gestures dataset. In case of 18 gestures dataset, we used 20 samples for training and 5 samples for testing per gesture. For 18 gestures samples were correctly classified with accuracy 99%. In case of 8 gestures dataset, Data selected from different 7 days over multiple weeks. We used 50 samples for training and 20 samples for testing. For 8 gestures and 4 users, testing samples were correctly classified with accuracy 96.01%. HMM user-dependent results are shown in Figure 2.

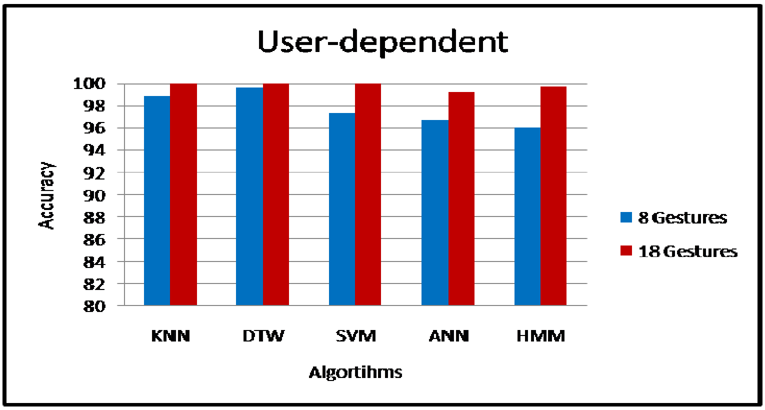


Fig. 2. Algorithms results for User-dependent Recognition

Support Vector Machine: We evaluated SVM with 18 gestures dataset and 8 gestures dataset for user-dependent recognition. In case of 18 gestures dataset, we used 20 sample for training and 5 for testing per gesture. For 18 gestures, testing samples were correctly classified with accuracy 100%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks. We used 50 samples for training and 20 samples for testing per gesture for every user. For 8 gestures, testing samples were correctly classified with accuracy 97.3%. SVM user-dependent results are shown in Figure 2.

k-nearest Neighbor. We evaluated k-NN with 18 gestures dataset and 8 gestures dataset for user-dependent recognition. As k-NN builds its classification decision based on the distances between the training dataset samples and the test sample(s) there's no actual training is performed. A certain number (k) of nearest neighbors is selected based on the smallest distances and the labels of these neighbors samples are fed into a voting function to determine the labels of the test sample. In case of 18 gestures dataset, we used one sample for training and 5 gestures for testing per gesture for every user. For 18 gestures, testing samples were correctly classified with accuracy 100%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks. We used 7 samples for every gesture, every template represent day and 20 samples for testing per gesture. For 8 gestures, testing samples were correctly classified with accuracy 98.9%. k-NN user-dependent results are shown in Figure 2.

Artificial Neural Networks. We evaluated ANNs with 18 gestures dataset and 8 gestures dataset, ANNs used backpropagation neural network. The ANNs architecture has 300 input layers, 1 hidden layer, number of hidden neurons and output layers depend on the number of gestures as shown in table 1.In case of 18 gestures dataset, we used 20 sample for training and 5 for testing per gesture. For 18 gestures, testing samples were correctly classified with accuracy 99.2%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks. We used 50 samples for training and 20 samples for testing per gesture for every user. For 8 gestures, testing samples were correctly classified with accuracy 96.7%. ANN user-dependent results are shown in Figure 2.

Table 1. Conguration parameters of the neural network

	8 gestures	18 gesture
Number of input layers	300	300
Number of output layers	8	18
Number of hidden layers	1	1
Number of hidden neurons	80	180

4.2 User-independent Recognition

Hidden Markov Model. In this experiment, we evaluate HMM with 18 gestures dataset 8 gestures dataset. In case of 8 gestures dataset, Data selected from different 7 days over multiple weeks for all the users. We used 400 samples for training and 160 samples for testing. For 8 gestures, testing samples were correctly classified with accuracy 95%.In case of 18 gestures dataset for user-independent recognition; we used 80 samples for training and 20 samples for testing per gesture selected from all the users. For 18 gestures samples were correctly classified with accuracy 90%. HMM user-independent experiment results are shown in Figure 3.

Support Vector Machine. We evaluated SVM with 18 gestures dataset and 8 gestures dataset. In case of 18 gestures dataset, we used 80 sample for training and 20 for testing per gesture selected from all the users. For 18 gestures, testing samples were correctly classified with accuracy 96%. In case of 8 gestures dataset for user-independent recognition, data selected from different 7 days over multiple weeks. We used 400 samples for training and 160 samples for testing per gesture for all the users. For 8 gestures, testing samples were correctly classified with accuracy 96.9%. SVM user-independent results are shown in Figure 3.

k-nearest Neighbor. We evaluated k-NN with 18 gestures dataset and 8 gestures dataset. In case of 18 gestures dataset, we used one sample for training and 20 samples for testing per gesture for all the users. For 18 gestures, testing samples were correctly classified with accuracy 99.8%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks. k-NN used 8 samples for every gesture from different days and users, for testing we used 160 samples per gesture for all the users. For 8 gestures, testing samples were correctly classified with accuracy 99%. k-NN user-independent results are shown in Figure 3.

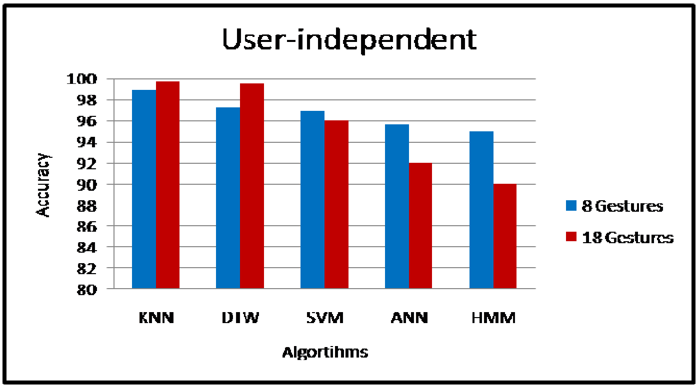


Fig. 3. Algorithms results for User-dependent Recognition

Dynamic Time Warping. In case of 18 gestures dataset, Dynamic time warping algorithm used one template matching for training per gesture for every user and 20 samples for testing. For 18 gestures, testing samples were correctly classified with accuracy 99.7%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks. DTW used 8 templates for every gesture selected from different days and users, for testing we used 160 samples for testing per gesture for all the users. For 8 gestures, testing samples were correctly classified with accuracy 97.3%. DTW user-independent results are shown in Figure 3.

Artificial Neural Networks. We evaluate ANNs with 18 gestures dataset and 8 gestures dataset. The ANNs architecture is the same as the user-dependent architecture. In case of 18 gestures dataset for user-independent recognition, we used 80 sample for training and 20 for testing per gesture selected from all the users. For 18 gestures, testing samples were correctly classified with accuracy 92%. In case of 8 gestures dataset, data selected from different 7 days over multiple weeks for all the users. We used 400 samples for training and 160 samples for testing per gesture for all the users. For 8 gestures, testing samples were correctly classified with accuracy 95.6%. ANN user-independent results are shown in Figure 3.

5 Discussion

According to [14] 8 gestures dataset show that there are variations between gestures samples by the same user collected over different days. However, according to [16] 18 gestures collected with some restrictions in order to avoid variation in gestures for the same user. Therefore, all participants are asked to perform the gestures without any, or with minimal, tilting of the remote. We conducted ANOVA test for sample from algorithms (DTW and HMM) results per users with 8 gestures in case of user-dependent recognition. P-value was 0.000305 which mean there is a difference in the algorithm accuracy, depending on user. Despite of these limitations, k-NN and DTW achieved the best recognition accuracy for user-dependent and user-independent datasets with 18 and 8 gestures. However, In case of user independent HMM, SVM and ANNs achieved the best accuracy with 8 gestures and in case of user independent they achieved best accuracy with 18 gestures.

6 Conclusions and Future Work

We have evaluated accelerometer-based gesture recognition algorithms: Hidden Markov Models (HMMs), Artificial Neural Network (ANNs), Support Vector Machine (SVM), K-nearest neighbor (k-NN) and Dynamic time warping (DTW) based on accuracy. Our evaluation based on two predefined datasets [16] and [14] gestures libraries. First dataset consists of 1,800 gestures for 4 users. Second dataset consists of 4,480 gestures for 8 participants. User-dependent gesture recognition experiment's results and User-dependent gesture recognition experiment's results showed that Dynamic time warping and K-nearest neighbor algorithms achieved the best accuracy for user-dependent and user-dependent gesture recognitions. In future work, we look forward evaluate the best accuracy algorithms on Smartphone in order to use them in developing abnormal driving behavior detection system using accelerometer.

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