A Study on Classifiers in a Gait Classification Method Using Arm Acceleration Data

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Abstract: In previous studies, we proposed a system for classifying gait based on step length and foot-ground clearance using arm acceleration. In the present study, we evaluated the application of machine learning to gait classification. The method was tested empirically on the classification of three gait patterns performed by 10 young and healthy participants. The three gait patterns were normal step, high step, and long step. Using measures of accuracy, precision, recall, and F-measure, we compared the performances of the following six classifiers: naive Bayes, support vector machine, neural network, logistic regression, instance-based classifier, and decision tree. The proposed method was shown to be capable of classifying the three gait patterns of seven participants with an accuracy greater than 0.6. This suggested that the proposed machine learning-based method is appropriate for its application in gait classification systems.

Keywords: Gait classification, Arm, Acceleration, Machine learning, Falling prevention

1. Introduction

Falling accidents involving elderly people are becoming frequent and may result in serious injury [1]. It has been reported that 86.2% of elderly people who experience such accidents later develop a fear of falling, which leads to 44% of them restricting their outdoor activities [2]. Therefore, it is known that falling accidents may severely limit the quality of life. Tripping is the most frequent cause of falling accidents [2,3] and, in the case of elderly people, seems to be related to an inability to accurately detect the position of the feet [4-6]. Therefore, to improve the mobility of elderly people, it is necessary to help them maintain an appropriate stride length and foot-ground clearance.

A number of systems for detecting falls have been proposed, but few of those systems are able to prevent them. In addition, many systems require the use of multiple sensors or cameras, thus limiting the locations in which they can be used or the clothes that the user can wear [7]. We have been developing a fall prevention system using a smart device equipped with acceleration sensors [8]. As the smart device is worn on the arm, it is not limited to particular environments. Previous studies have noted the relationship between the movement of the arm and upper body rotation, energy expenditure, and other dynamic parameters. Therefore, arm movement is influenced by the gait [9-11] and provides a way of tracking it.

A flowchart of our proposed system is given in Figure 1. In an initial procedure, the system learns the arm acceleration associated with different gait patterns. These can then be used for gait classification (Step 1). The gait patterns are identified to estimate the risk of falling (Step 2). When the risk is high, the system prompts the user to modify their gait (Step 3).

In recent studies, we found that the time waveforms of arm acceleration are influenced by the step length and foot-ground clearance [8]. However, it proved difficult to classify the gait pattern solely from the peak values. Therefore, we introduced a method of gait classification in which a decision tree is built using the arm acceleration data as feature quantities [12]. This method was able to classify gait patterns with high accuracy in some test participants. We also found that it was necessary to compare different machine learning...
algorithms (classifiers).

In this study, we investigated the application of a range of classifiers to the proposed method, with the goal of improving the accuracy with which gait patterns could be classified. We also attempted to identify an optimal classifier.

The rest of this paper is organized as follows. Section 2 introduces the proposed gait classification system. Section 3 describes the experiments that were conducted to evaluate the proposed method and compare the classifiers. Section 4 presents and discusses our results. Finally, Section 5 presents the conclusions of the study.

2. Gait Classification Method

The proposed system is shown in Figure 2. In the first step, a machine learning algorithm (classifier) establishes a function that will be used to classify the gait pattern using 3-axis arm acceleration data as the feature quantity (input). A machine learning algorithm (classifier) then builds a classification of gait patterns by applying the function to the acceleration data.

The method by which arm acceleration is measured (Input in Figure 2) is shown in Figure 3. When the gait is unstable, the standard deviation of the arm acceleration data may increase. A set of arm acceleration data is measured for each step by timing the passage of the forearm across the side of the body. This motion is detected by the proximity sensor of a smartphone.

3. Experiments and Evaluation

To investigate the performance of the proposed method, gait experiments were conducted on a treadmill. For safety reasons, 10 male college students were selected as participants. Their mean age was 20.8 ± 0.1 years (mean ± s.d).

The proposed method was tested on the classification of the following three gait patterns: normal step, high step, and long step. We also examined the classifiers by comparing their accuracy, precision, recall, and F-measure.

3.1. Classifiers

We considered the following six machine learning algorithms as classifiers: naive Bayes, support vector machine, neural network, logistic regression, instance-based classifier, and decision tree.
“Weka”, which is developed by the University of Waikato in New Zealand, was used to evaluate classification [13]. This is a collection of machine learning algorithms for data mining tasks. Table 1 shows the manner in which these algorithms were applied in this study.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Algorithm in Weka</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Bayes</td>
<td>Naive Bayes</td>
</tr>
<tr>
<td>Support Vector Machine</td>
<td>SMO (Poly Kernel)</td>
</tr>
<tr>
<td>Neural Network</td>
<td>Multilayer Perceptron (3 layers)</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>Logistic</td>
</tr>
<tr>
<td>Instance Based Classifier</td>
<td>KStar</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>J48</td>
</tr>
</tbody>
</table>

### 3.2. Data collection

The 10 participants were asked to use the three gait patterns while walking on the treadmill (Figure 4). The walking speed was calibrated to each participant and set to be comfortable. A digital camera was used to record the gait.

The step lengths of the long step gait were confirmed to be the largest of the three patterns, which were calculated from the gait speed and the number of steps taken from the recorded gait video.

For the high step gait, foot-ground clearance was measured using infrared sensors (Figure 5). A buzzer was triggered when the foot-ground clearance exceeded 15 cm. This confirmed that the foot-ground clearance was greater than 15 cm in every step of the high step gait.

The 3-axis arm acceleration data were recorded for 60 steps of each gait pattern. The measurement procedure is shown in Figure 3. Previous studies had demonstrated that the acceleration sensor of a smartphone can be used to quantify the gait parameters with accuracy comparable to that of a 3-axis accelerometer [14].

### 3.3. Data analysis

Next, we investigated whether this arm acceleration data in the x, y, and z directions could be used as feature quantities to classify gait patterns. Correct answers were labeled as feature quantities at each data point. Accuracy, precision, recall, and F-measure were used as indices of classification performance using 10-fold cross-validation.

In the cross-validation method, the dataset is divided and the evaluation is repeated while switching between learning data and evaluation data. As cross-validation can evaluate the classification of novel data, it is widely used in the field of pattern recognition [15].
For cross-validation (Figure 6), the dataset was randomly partitioned into 10 subsamples of equal size [15]. A single subsample was used as test data, and the remaining subsamples were used as training data. The process was repeated 10 times, and each subsample was used in turn as the test data. The evaluation indices were calculated as the average of the 10 results.

These indices were calculated by substituting the values from Table 2 into Equations (1)-(4) [16]. Accuracy was judged by the correctness of the classifier on all gait patterns. Precision was judged from the positive predictive value of the classifier for each gait pattern. Recall was judged by the sensitivity of the classifier for each gait pattern. The F-measure was calculated from the harmonic mean of precision and recall and used as a measure of overall performance.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (2)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (3)
\]

\[
\text{F-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)
\]

4. Results and Discussion

The six classifiers were shown to classify the three gait patterns with accuracy greater than 0.6 for seven of the participants (A, C, D, E, F, I, and J). Classification with accuracy greater than 0.7 was achieved for three participants (A, F, and G). For a fall prevention system, an accuracy of 0.6 was insufficient. However, the accuracies for the seven participants were above chance, thus suggesting that the proposed method was able to achieve basic gait classification. To increase the classification accuracy, the factors that generate individual differences and the identification of an optimum classifier for each user are required. In addition, it is considered that gait classification of the proposed method needs definite changes kind of arm acceleration data. This suggested that the use of time-series data is needed in place of specific timing data.

A previous study [17] found no significant difference between the gait parameters (step length, stride length, velocity, ankle range of motion, and pelvic obliquity) of old men and young men. This suggested that the gait patterns identified in the present study could be applied with equivalent accuracy to the case of old men. However, another study suggested that significant differences exist between the same gait parameters while comparing old women and young women [18]. Therefore, it is necessary to examine the classification of gait patterns in young women and elderly women.

Next, we explored which classifiers were the most accurate when applied to each participant. The neural network classifier had the highest accuracy for four participants (C, F, H, and J), and the highest average accuracy across all participants. Therefore, the neural network classifier was identified as the optimal classifier. In the F-measure comparison of total performance, the neural network classifier had the highest value when applied to the long step gait (Figure 7). It also produced the smallest difference between the normal step and the long step gaits (Figure 7). Therefore, the neural network classifier was judged to produce the most well-balanced
classification of the three gait patterns. These results suggested that the neural network classifier was the most capable of the six classifiers for gait classification while using arm acceleration data. Future studies should also consider processing time and implementation in real applications. Other advantages of the different classifiers should also be considered. For example, the rules in the tree structure of the decision tree are known to be readable by humans [12].

For all classifiers, the F-measure was higher when applied to normal step than the long step or high step gaits (Figure 7). Recall was also higher when applied to normal step gait than to other gait patterns (Figure 8). Therefore, the normal step gait was the most frequently identified of the three gait patterns. This was attributed to the normal step gait requiring a smaller arm swing to maintain dynamic stability, reflected in the arm acceleration data.

In terms of precision, the high step gait produced higher values than the normal step or long step gaits for five of the six classifiers (Figure 9). This suggested that the high step gait is identified with greater accuracy than the other gaits. The long step gait was lower in precision, recall, and F-measure than the normal step and high step gaits. This suggested that the long step gait was the most difficult gait to identify.

5. Conclusions

In this study, we evaluated a proposed gait classification method that applies machine learning to arm acceleration data. The method was tested on three gait patterns performed by ten participants. We compared the accuracy, precision, recall, and F-measure of six different classifiers on the three gait patterns.

Accuracy evaluations confirmed that the gait patterns of seven participants could be classified with an accuracy greater than 0.6. This demonstrated that the proposed method is capable of gait classification. F-measure evaluation showed that the neural network classifier was the most well-balanced classifier in classifying the three gait patterns. The recall and F-measure results also showed the normal step gait to be the most consistently identified of the three gait patterns. The precision evaluation showed that the high step gait was the most accurately identified. Overall, the results suggested that the proposed gait classification method is an effective approach to help elderly people avoid falls.

Table 3. Accuracy of each participant

<table>
<thead>
<tr>
<th>Participant</th>
<th>Classifier</th>
<th>Accuracy</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>SVM</td>
</tr>
<tr>
<td>A</td>
<td>0.806</td>
<td>0.733</td>
</tr>
<tr>
<td>B</td>
<td>0.478</td>
<td>0.450</td>
</tr>
<tr>
<td>C</td>
<td>0.706</td>
<td>0.667</td>
</tr>
<tr>
<td>D</td>
<td>0.622</td>
<td>0.656</td>
</tr>
<tr>
<td>E</td>
<td>0.583</td>
<td>0.589</td>
</tr>
<tr>
<td>F</td>
<td>0.750</td>
<td>0.744</td>
</tr>
<tr>
<td>G</td>
<td>0.817</td>
<td>0.817</td>
</tr>
<tr>
<td>H</td>
<td>0.356</td>
<td>0.400</td>
</tr>
<tr>
<td>I</td>
<td>0.711</td>
<td>0.628</td>
</tr>
<tr>
<td>J</td>
<td>0.694</td>
<td>0.544</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.652</td>
<td>0.623</td>
</tr>
</tbody>
</table>
Figure 7. F-measure for each classifier

Figure 8. Recall for each classifier
In future work, we will test the performance of the proposed method when it is applied to the gait patterns of elderly people.

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References


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