Age Classification Based on Gait Using HMM

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Abstract

In this paper we propose a new framework for age classification based on human gait using Hidden Markov Model (HMM). A gait database including young people and elderly people is built. To extract appropriate gait features, we consider a contour related method in terms of shape variations during human walking. Then the image feature is transformed to a lower-dimensional space by using the Frame to Exemplar (FED) distance. A HMM is trained on the FED vector sequences. Thus, the framework provides flexibility in the selection of gait feature representation. In addition, the framework is robust for classification due to the statistical nature of HMM. The experimental results show that video-based automatic age classification from human gait is feasible and reliable.

1. Introduction

Gait is actually characterized by walking of an individual. Walking is one of the most common of all human activities. Over the years there have been many research projects for investigating the effects of aging on human movement or walking [1-4]. The aims of these studies are to identify gait variables that reflect gait degeneration with increasing age, so that more diagnostic measures can be found to provide better physical therapy services to elderly people. At the same time, these studies also tell the truth that there exist differences in gait between the elderly and the young. So, it is reasonable to study the age classification based on gait using computer vision and pattern recognition techniques.

The velocity of gait and the length of stride are significantly different among different age populations according to previous studies. In [1] it is suggested that there is a definite reduction in the stride length beyond the age of sixty. The examination from [2] reconfirms the above conclusion with a 17-20% reduction in the velocity of gait and length of stride exhibited by the elderly group aged greater than 65 when comparing with the young adults from a range of 20-39 years. The cause of such a reduction is associated with the decrease in muscle strength and the change in motor control with increasing age [3]. In [4] the effects of aging on the gait pattern are presented.

Referring to these studies and the existing gait recognition techniques, we consider a framework for automatic age classification based on gait. It will play an important role in surveillance applications. Our objective is to recognize whether an individual is young or old from a video sequence of the individual walking in a fronto-parallel pose. Since gait is a kind of cyclic activity across different stances, it is suitable to employ exemplar-based HMM to characterize an individual's gait. HMM has been applied to human identification in [5-9]. In the literature, different feature extraction methods are used before HMM training. In [7] a framework that is independent of the selection of features is proposed. For the issue of age classification, it is important to extract appropriate features that will effectively capture the aging characteristics. According to previous studies, there should be both structural and dynamic differences in shape changes over time between the young and the elderly. Therefore, the discriminative traits can be found in the contour of a silhouette. In [9] a FED vector is proposed for the improved performance by the exemplar-based HMM. We use this approach in our framework.

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The rest of the paper is organized as follows. In Section 2, the issue of feature extraction is explored. Section 3 describes the FED and HMM. In Section 4, we present the database and experimental results. Section 5 concludes the paper.

2. Feature extraction

It has been observed that the elderly walk more slowly because of the age related degeneration in the nervous system and muscle strength [4]. The extracted features should reflect the decline of walking performance for the issue of age classification. In an overall view, most of the differentiation of gait between the young and the elderly can be captured by the shape of stances and shape changes over time in a gait cycle. Hence, we take the contour of silhouette into consideration. We can model the contour variations during a walking period using HMM.

At the preprocessing stage, each image sequence is converted into a binary silhouette sequence using background subtraction and morphological operators. We then extract the contour of each silhouette by means of a border following algorithm based on connectivity. In [10], the author computes all distances between contour pixels and its associated centroid so as to obtain a one-dimensional distance signal. However, the signal lengths are not the same for different contours and they require normalization. To avoid these problems, our method is to select a fixed number of pixels from the contour, as shown in Figure 1.

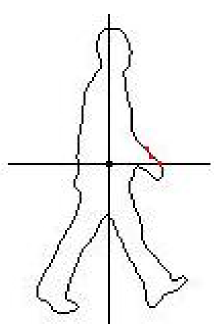

Figure 1. Contour points selection

The central black point denotes the centroid of the silhouette. Since the degree of a circle is a constant 360, we could choose the same number of points from any contour if an interval of angle was fixed. Starting from 0 degree, the right horizontal line in Figure 1, we select pixels one by one in an anti-clockwise direction according to the fixed interval of angel. In this work, it is 6 degree. The three red points in Figure 1 illustrate a part of these selected pixels. The total number of pixels obtained from a contour is 360/6=60. Of course, there is the issue of picking the interval value of angle. This is related to the total number of pixels on a contour and the final experimental results. We set it as 6 degree empirically for our gait database.

Now the length of distance signal will be 60. A two-dimensional contour can be expressed by a vector as follows:

$$C_{ij} = [D_1, D_2, ..., D_k, ..., D_{60}] \tag{1}$$

where C_{ij} denotes the j_{th} contour of the i_{th} individual in a gait cycle and D_k is the Euclidean distance between the k_{th} pixel and its corresponding centroid.

3. The HMM framework

3.1. Exemplar extraction

In this framework, we extract N exemplars from the stances in a gait cycle for a person as analogues to the states of HMM. The HMM for person i is given by $\lambda_i = (\pi_i, A_i, B_i)$ with N number of states, where π_i is the initial probability vector, A_i is the transition probability matrix, and B_i is the output probability distribution which we model as a continuous probability distribution in this paper.

The selection of the exemplars should make the overall average distortion minimized. Our method is to divide each gait cycle into N equal segments. These gait cycles are normalized to contain the same number of frames first. Using the feature vectors described in last Section, we then compute the mean vector of each part and take it as the exemplar of that part. The exemplar set is denoted as $\varepsilon = \{e_1, ..., e_N\}$. In order to choose N we compute the average distortion as a function of N according to the following measurement:

$$\min_{f_1,...,f_l} d(e_i, I(f_1, ..., f_l)) \tag{2}$$

where d is Euclidean distance, e_i is the i_{th} exemplar in ε and $I(f_1, ..., f_l)$ denotes the set of feature vectors in the i_{th} part. The rate distortion curve for our gait database is shown in Figure 2. It can be found that the average distortion does not decrease appreciably beyond $N = 5$.

To compactly encode the observations, we build the FED as proposed in [9]. Thus, the distance signal C_{ij} can be transformed into a lower dimensional representation. The FED vector for the j_{th} contour of person i is computed as follows:

$$F_{ij} = [d(C_{ij}, e_1), ..., d(C_{ij}, e_N)] \tag{3}$$

where d is Euclidean distance. Note that the dimension of F_{ij} is only N. For the i_{th} person, each frame in a gait cycle is converted into a FED vector now. The FED vector sequence is taken as an observed manifestation of the transition across exemplars (a hidden process).

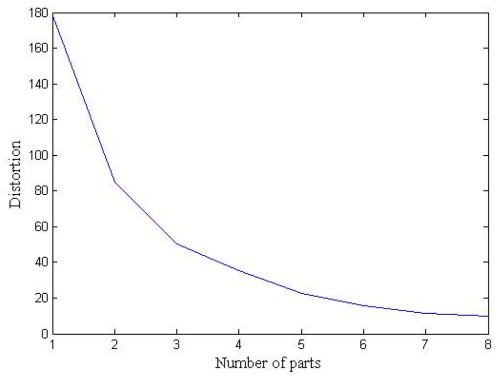

Figure 2. Rate-distortion curve for number of exemplars vs distortion

3.2. HMM-based age classification

For HMM training, we need to estimate the initial value of HMM parameters $\lambda = (\pi, A, B)$. As the HMM states are exemplars from gait sequence which has the property of period and irreversibility of time, we use the left-right loop model for HMM in this work. We obtain N exemplars as described above and therefore, the initial probabilities $\pi_n^{(0)}$ are set to be equal to $1/N$. The initial estimate of transition matrix $A^{(0)}$ can also be obtained easily associated with the characteristic of left-right loop model. For the i_{th} row of this matrix, we set $A_{i,i}^{(0)} = A_{i,i+1}^{(0)} = 0.5$ and for the last row, we set $A_{i,i}^{(0)} = A_{i,1}^{(0)} = 0.5$. All other elements are set to 0. The observation probability B is represented by a mixture of Gaussians. The initial estimate of Gaussian parameters is from the training samples and it is refined iteratively using Expectation-Maximization algorithm.

We train a HMM for every age group. The larger the number of training samples, the more reliable the estimate of B. The HMM is trained iteratively. In each iteration, the probability distribution B is re-estimated and the Baum-Welch algorithm is used to update π^i and A^i.

Given the HMM generated by an age group, we can compute the likelihood that an observation belongs to this age group using the forward algorithm. Generally, the log probability is used as the similarity score.

4. Experiments

4.1. Database

None of the existing public gait databases includes data from elderly people. As the first attempt on gait-based automatic age classification, we build a database consisting of two age groups. From [1] we learn that the age of 60 is a separation point for the performance of walking. Hence, we regulate the range as 60~65 for the old group and as 25~30 for the young group. Both of the groups have the same difference of five years. We also wish that there are similar number of males and females in each group in order to eliminate sexual effects on the experimental results.

According to these settings, we tried to find the appropriate subjects. Fourteen volunteers in good health were accepted as subjects in our database. There are 7 people (4 male, 3 female) for each age group. Note that all of the subjects must be free of disabling physical conditions and without neurological disease that could influence locomotion based on a medical review. In the data collection process, each person was asked to walk along a straight line for three times while a static camera was recording his/her walking from a side view. As a result, each subject has three video sequences in our gait database.

From the extracted silhouette and contour, some differences can be observed with our eyes between the young and the elderly, as is shown in Figure 3. An old subject is on the upper row and a young one is below it. Two points of difference can be found between them. One is the bending degree of the back and the other is the stance of the front supporting leg.

4.2. Experimental results

The objective of our experiments was to evaluate the classification performance of the HMM-based framework for distinguishing the young and the elderly from gait. To make the best use of the subjects in our database, we adopted the leave-one-out approach for performing experiments. Each subject was taken as the test data in turn and the rest were used to train two HMMs for the young class and the elderly class respectively. The determination of the test subject to be young or old depended on the value of log probability generated by corresponding HMM.

We also conducted other experiments to make a comparison among implementations and classifiers. Since the generation of FED didn't rely on the gait representation, we used the silhouette image instead of contour as the original feature in another experiment. PCA was employed to obtain feature vectors from silhouettes before computing FED vector. Another consideration was to choose a different classifier. Because we didn't have a large amount of training data, naive Bayes classifier was a better choice.

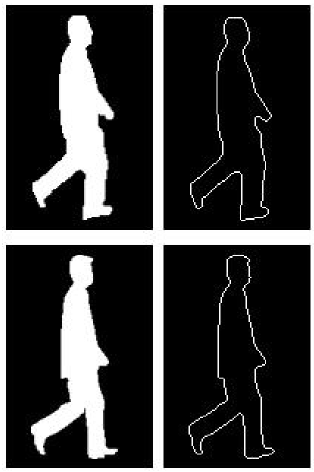

Figure 3. Samples from our database

The results are listed in Table 1. Two kinds of gait features were used as the input to naive Bayes classifier. One was the sixty-points contour feature proposed in this paper and the other was the averaged silhouette of a gait cycle.

Table 1. Results from different methods

Methods	Correct classification rate
Contour + HMM	83.33%
Silhouette + HMM	76.24%
Contour + naive Bayes	65.85%
Silhouette + naive Bayes	63.28%

It can be seen from Table 1 that HMM based approaches perform better. Gait itself is a kind of movement that changes across time periodically. Using HMM we can make more appropriate simulation in a statistical way than using naive Bayes classifier. The results also show that contour feature is more appropriate than silhouette feature for age classification. It is because the contour representation discards more redundant information as compared to the silhouette-based representation.

5. Conclusions

In this paper, we have presented a general HMM-based framework for the task of age classification based on human gait. We built a database of two age groups and considered the contour feature extraction of gait in a new way. Though the framework is independent of feature selection, the output classification rate relies on the features. We obtain a significant result due to the accurate modeling of gait by HMM and the appropriate contour feature that reflects the difference of walking between the young and the elderly. The correct classification rate is over 80%. In spite of the small number of our samples, it is reliable in the meaning that we have made the comparison with other feature selections and classifiers. In future, we will enlarge the database to increase the amount of both subjects and age groups.

6. Acknowledgement

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