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Recognition Using Gait

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Abstract

Gait or an individual's manner of walking, is one approach for recognizing people at a distance. Studies in psychophysics and medicine indicate that humans can recognize people by their gait and have found twenty-four different components to gait that taken together make it a unique signature. Besides not requiring close sensor contact, gait also does not necessarily require a cooperative subject.

Using video data of people walking in different scenarios and environmental conditions we develop and test an algorithm that uses shape and motion to identify people from their gait. The algorithm uses dynamic time warping to match stored templates against an unknown sequence of silhouettes extracted from a person walking. While results under similar constraints and conditions are very good, the algorithm quickly degrades with varying conditions such as surface and clothing.

ACKNOWLEDGMENTS

I would like to thank University of South Florida for supplying me with the gait data and Trina Russ for her support and encouragement.

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NOMENCLATURE

DTW	Dynamic Time Warping
CMC	Cumulative Match Characteristic

1. RECOGNITION USING GAIT

One approach for recognizing people from a distance (~300 m) is to use a gait biometric. Here, we use the shape and motion of a walking person to determine their identity. To design and test gait recognition algorithms, we use data from the HumanID Gait Challenge Problem [1]. The data contain multiple sequences of people walking under various scenarios and conditions. From these video sequences Sakar et. al. [1] have detected and extracted silhouettes of the people walking. The silhouettes are scaled to a standard size and centered in a chip (small image) of size 128 x 88. Figure 1 shows a subset of silhouettes from a video sequence. From the figure, one can see that the silhouettes are crude and extremely noisily with missing and extra information.

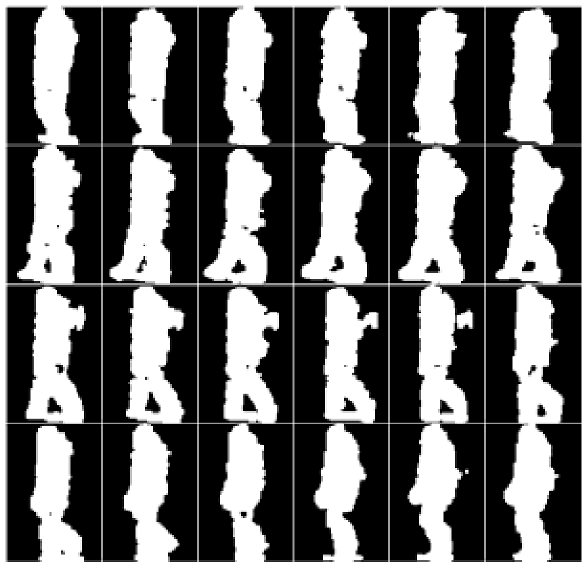


Figure 1. Example silhouettes of one gait cycle.

The gait challenge data set contains a gallery size of 122 people with 10 probe experiments. The probe experiments have only people from the gallery and do not necessarily have every gallery person. The probe sets have been designed to measure the performance of algorithms under various conditions such as camera angle (left or right), surface (grass or concrete), shoe type (shoe A or B), briefcase (yes or no), and time of collection (May or November). The gallery data set uses camera angle of right, surface of grass, shoe type A, no briefcase, and collection time of either May or November. The alternatives, concrete surface, shoe type B, direction from the left, carrying a briefcase, and collection time (6 months difference) are varied for the different probe experiments. Table 1 shows different probe experiments, and the x's indicate what has changed from the gallery to the probe. For example, probe G has data from a different camera angle (right), shoe (type B) and surface (concrete), but no briefcase and no change in collection time or clothing.

Table 1. The probe experiments and the differences from the gallery.

Exp	Camera Angle	Shoe	Surface	Briefcase	Time	Clothing
A	x					
B		x				
C	x	x				
D			x			
E		x				
F	x		x			
G	x	x	x			
H				x		
I		x		x		
J	x			x		
K		x		x	x	x
L		x	x	x	x	x

2. APPROACH

Our approach is to first create an ordered set of templates for each person. The templates represent the shape of the person at key points in the gait cycle and their order gives the sequential states that the person goes through for their gait sequence. Next, we match all templates to all the silhouettes using binary correlation. Finally, dynamic time warping is used to find the best set of template to silhouette matches (total smallest distance) while keeping the correct time ordering of the templates.

2.1 Template Creation

To create templates of each gallery sequence, we first determine the period of the gait sequence. The period is estimated by computing the area of the silhouette in the lower half of the image chip. Figure 2 shows an example of how the lower silhouette area changes with frame number (time). The figure shows that signal is periodic, but noisy.

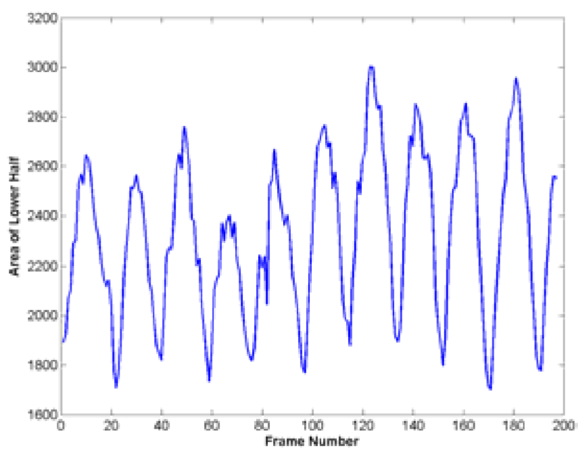


Figure 2. Estimating the gait period: lower silhouette area versus frame number.

Next, we band pass filter the lower silhouette area using short time Fourier transforms and use the median distance between the peaks and the valleys as an estimate of the period. Figure 3 shows the filtered signal from Figure 2. The algorithm estimates the period of the signal as 19 frames.

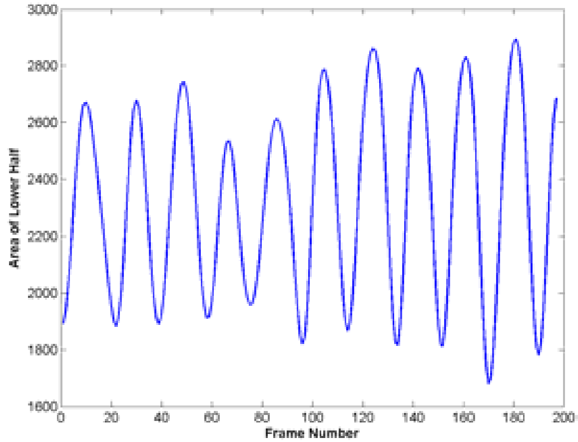


Figure 3. Band pass filtered lower-area signal. Gait period estimate is 19 frames.

Using the period estimate, we form an initial set of clusters for a gallery sequence. We use the period as a rough guide to determine which silhouette chips belong to which cluster, but it does not necessarily drive the number of clusters we create. Figure 4 shows an initial set of clusters found for a gallery sequence. Note that the clusters are smoother than the original silhouettes and are time ordered.

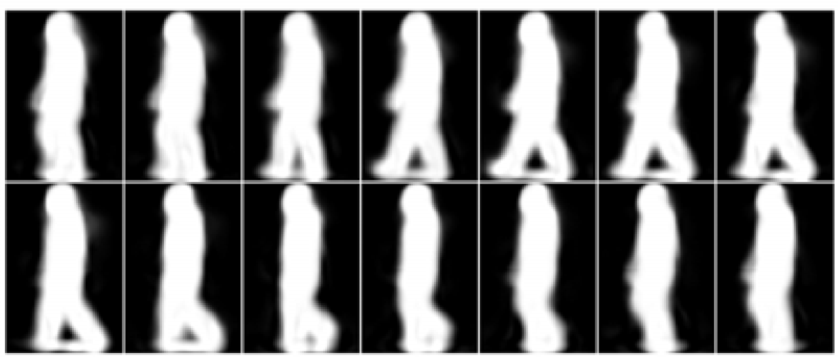
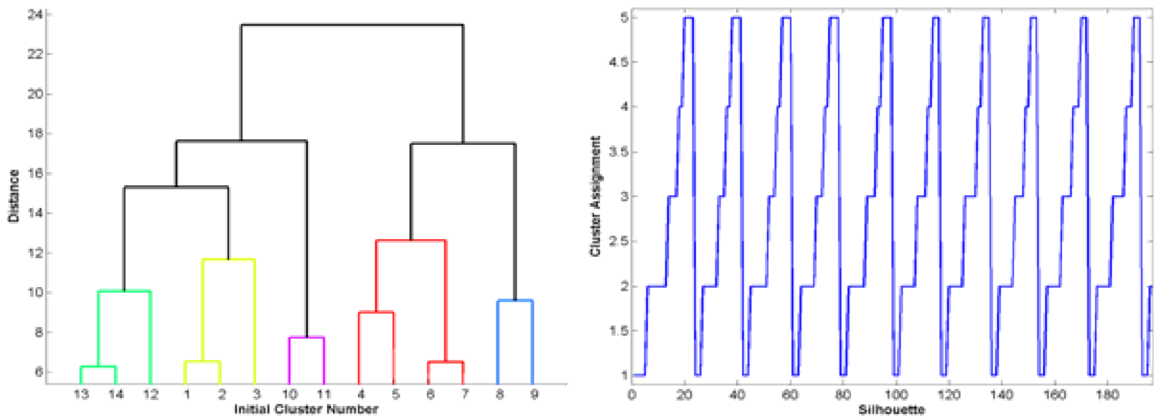


Figure 4. Initial set of clusters for a gallery sequence.

To get the final clusters, we use hierarchal clustering. Figure 5a shows the clustering tree. By cutting the tree at different spots, we can get the required number of final clusters. The assignment of the silhouettes to clusters is shown in Figure 5b. Figure 6 shows the final time ordered templates after averaging and applying a threshold.



a b

Figure 5. a) Hierarchical clustering tree for determining the final clustering. b) Assignment of silhouettes to final clusters.

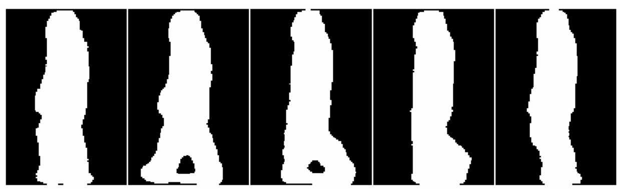


Figure 6. Final templates for a gallery sequence.

2.2 Template Matching

To match the templates to a sequence of silhouette chips we create a distance matrix. The distance matrix represents the distance between every template and all the silhouette chips in the probe sequence. To determine which silhouette chip matches which template, we use dynamic time warping (DTW) [2]. The DTW algorithm determines the smallest cost path through distance matrix using dynamic programming. Figure 7 shows a distance matrix represented as a gray level image. The probe chips are along the columns and the templates are along the rows. Here, the templates and probe come from the same person. The smaller costs are black and the larger costs are white. The green line shows the optimal path giving smallest total average cost. Note the standard DTW algorithm has been modified to account for the periodic nature of gait. Also, the DTW algorithms force each template to match in sequence. Thus, the templates account for the shape of a person, and DTW provides constraints for the person's motion.

Figure 8 shows a distance matrix where the templates and probe chips come from a different person. Here, DTW forces the matches of templates 3 and 4 even though they do not match very well. If we allowed the algorithm to match just templates 1 and 2, then we would not be correctly accounting for the motion of a gallery template sequence.

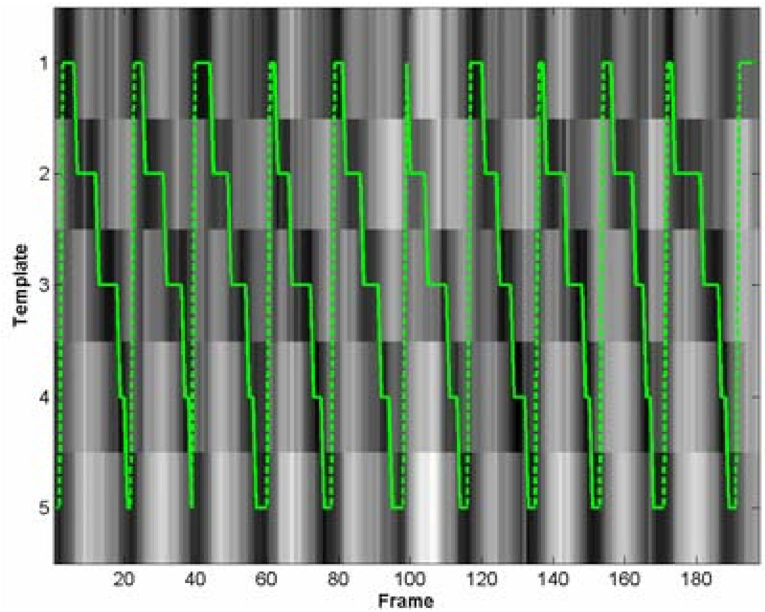


Figure 7. Image representation of a distance matrix that results from matching a set of templates to all the probe chips for the same person. The green line represents the optimal lowest cost path through the distance matrix using dynamic time warping.

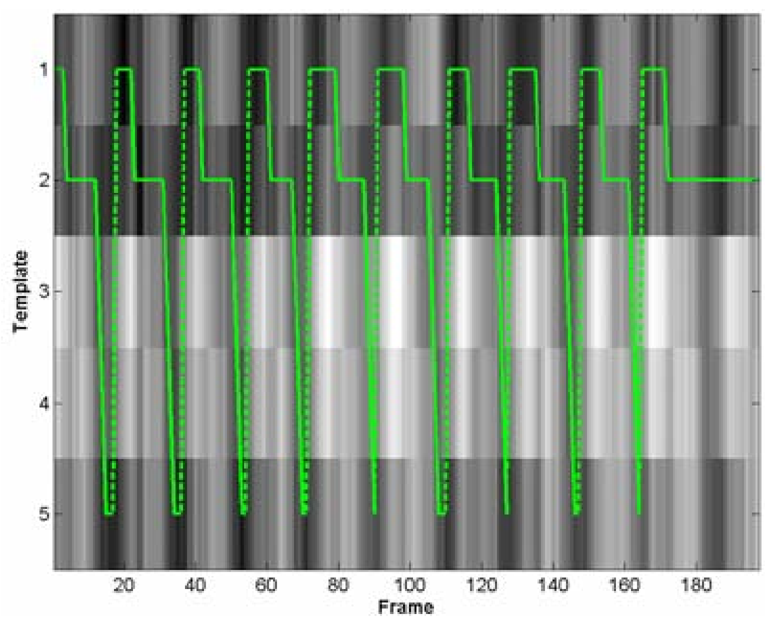


Figure 8. Distance matrix where the templates and chip sequence come from a different person.

3. RESULTS

To show our results, we create cumulative match characteristic (CMC) curves for the different probe experiments (Table 1). For CMC plots, the x-axis represents a rank threshold, and the yaxis shows the fraction of experiments that yield a correct match at ranks equal to or lower than the rank threshold. Figure 9 shows a CMC for the different probe experiments using 9 templates per gallery person. Camera angle and shoe have the smallest effect on the results (probe experiments A, B, and C). Surface has a significant effect (D-G, and L). This indicates people modified their gait for walking on difference surfaces. Time and clothing have the largest effect on the results.

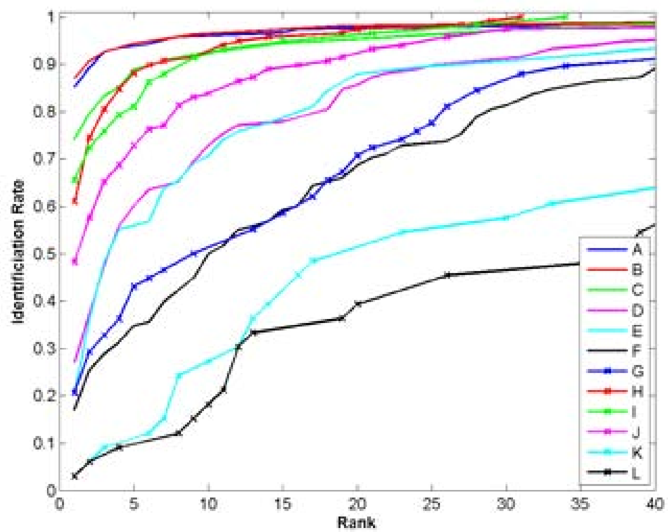


Figure 9. CMC plot for the different probe experiments.

4. CONCLUSIONS

We have developed algorithms to recognize a person by their gait. The algorithms are based on silhouette sequences extracted from video clips of people walking. The algorithms uses DTW to match stored templates against an unknown sequence of silhouettes extracted from a video clip. Here, the templates account for the shape of a person and DTW provides constraints for the person's motion.

We test our algorithms using video data of people walking in different scenarios and environmental conditions. While results under similar constraints and conditions are very good the algorithm quickly degrades with varying conditions such as walking surface and clothing.

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