Gait Recognition by Moment Based Descriptors

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Abstract

Gait receives increasing attention as a biometric. Given the requirement to process sequences, computational demands are high, motivating the development of basic approaches. Amongst these, change in area can be used as a recognition metric. We describe a new approach using moments, and its motivation from an area based approach. The technique derives from a spatial approach and is here extended to sequences. We show how it can be used to discriminate subjects by their gait. By its formulation, the new technique derives invariance advantages, but these can reduce performance.

Introduction

Recently, there has been much attention devoted to using gait as a biometric [1-6]. Approaches to automatic gait recognition can broadly be divided into two. Model based approaches aim to explicitly model gait [3, 7] as a series of equations. One of the main advantages of the model-based approaches is their handling of occlusion, which is of especial importance in gait as the walking human body is self-occluding. However, the model used to describe gait is often complicated, resulting in a high computational cost. Holistic / statistical approaches [2, 4, 6, 8] aim to process a gait sequence to find a set of measurements to distinguish between subjects. The disadvantage of traditional statistical approaches is they are not intimately related to gait and just produce raw numbers to distinguish between subjects. In addition, most current statistical techniques fail to take into account the temporal component of gait and instead focus on distinguishing between collection of silhouettes, rather than a sequence as a whole.

The holistic approaches do enjoy computational advantage: gait requires analysis of sequences of images, so computational demand is of much concern. Some of the approaches have aimed at simplicity, to provide "baseline" analysis [2, 4]. The penalty is that these approaches lose specificity to gait. In a similar approach, we included specificity by analysing gait from the changes in areas selected by masking functions [9]. Again, it is a generic approach to analysing periodic motion in image sequences. Our new approach enjoys similar computational advantage of other baseline approaches, with flexibility in deployment.

In order to capitalise further on these baseline approaches, we sought to determine a link between the area based approach and more conventional analysis. Unfortunately, there were no links other than basic, but it became apparent that we could deploy moments in a similar vein, to analyse gait with specificity and speed using moments to acquire invariant properties. We use a family of moment descriptors to describe a single shape, relating to work from Sluzek [10]. Then, Sluzek's approach has been extended to describe a sequence of images. We discuss the invariance properties of this new approach before comparing results with those of area masks, prior to further work and conclusions.

Recognition via Moment Based Descriptors

Previously, we have used area masks to describe the dynamics of area change through a gait sequence and this has formed the basis of description. Moments are an alternative approach that can provide much more information than a single measure of area. Essentially, moments can provide a geometric description of a shape. Lower order moments provide information similar to area masks, such as total area of the shape. We use moments to describe information for each image in the gait sequence and this forms our new basis of description. By using Hu invariant moments, the technique is invariant to rotation, translation and scaling of the silhouettes.

A gait sequence is represented as a collection of binary silhouettes. These binary silhouettes provide us with invariance to most lighting conditions and clothing colour, but do lose information. These silhouettes can be analysed singly (by current techniques) or as sequences, by new techniques.

Moment Based Descriptors for Single Images

Moments of order p, q of a discrete shape R are defined as

$$m_{pq} = \sum_{i,j \in R} i^p j^q \qquad \textbf{(1)}$$

Centralised moments are defined with co-ordinates translated to the center of a discrete shape R as:

$$M_{pq} = \sum_{i,j \in R} (i - a)^p (j - b)^q \qquad \textbf{(2)}$$

a and b are the centres of mass in the 2D co-ordinate system. The lower order moments are simple properties to describe the shape. Hu [11] derived moment expressions that are invariant to translation, rotation and scaling of shapes. Some examples are given below. The moments omitted, 3 to 7, are usually assigned to moment invariants of order 3.

$$I_1 = \frac{M_{20} + M_{02}}{(m_{00})^2} \qquad I_2 = \frac{(M_{20} - M_{02})^2 + 4M_{11}^2}{(m_{00})^2} \qquad I_8 = \frac{M_{20}M_{02} - M_{11}^2}{(m_{00})^4} \qquad \textbf{(3)}$$

Sluzek proposed a method to improve the quality of description by using a family of shape descriptors. By using additional descriptors, it is possible to improve the quality of descriptions. Let C_ζ be the circle defined as

$$C_\zeta = (x - a)^2 + (y - b)^2 = \zeta m_{00}/\pi \qquad \textbf{(4)}$$

The area of the circle is equal to the area of the shape multiplied by Ŭ The value of $\zeta_{\max}$ is chosen so the circle does not occlude the entire area of R and so a part of the shape R is visible. Let us denote the region R which is not occluded by the circle as *R(*Ŭ) which is defined as

$$R(\zeta) = \{(x,y) \in R \mid |(x,y) - (a,b)|^2 \geq \zeta m_{00}/\pi\} \qquad \textbf{(5)}$$

Thus for a given shape R we can create functions $I_k(\zeta)$ for each moment k which operates on the region *R(*Ŭ). These functions depend on both the region R and the value of Ŭ and are invariant to rotation, translation and scaling and are known as *m-invariant* functions. The function $I_k(\zeta)$ is the k-th Hu invariant on the region *R(*Ŭ). Note that when calculating $I_k(\zeta)$ that a and b must be recalculated on the new region *R(*Ŭ).

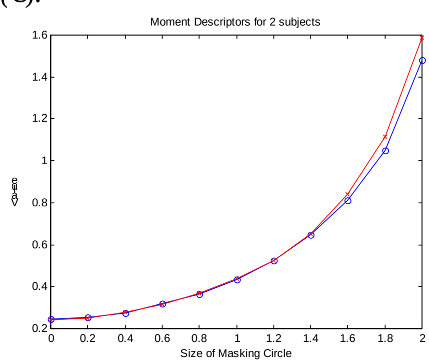

Figure 1 **Moment Descriptors for Two Subjects**

A given shape/image can now be represented by a family of shape descriptors. Adequate sampling should be chosen to give a detailed representation of the shape. $I_k(\zeta)$ is then the signature of the image for a given range of circles, ζ. These moment descriptors can be used to discriminate between two different images. Sluzek [10] showed that these shape descriptors are more reliable than traditional moment shape descriptors at identifying undamaged objects and/or to detect damaged ones. Sluzek analysed a database of 130 images and achieved a hundred percent accuracy both in the identification of objects and in the quality inspection. Figure 1 shows the moment descriptors for two single images from the walking sequence of different subjects. As can be seen from the graph, there is minimal visible difference between the two graphs when the value of ζ is low, but as the value of ζ rises the differences between the two becomes more apparent. Gait consists of a temporal, as well as spatial component, so over a sequence the differences between subjects should become even more apparent as the small differences will accumulate over an entire sequence.

Recognising Gait using Moment Based Descriptors

Gait recognition differs from traditional biometrics such as iris and finger print because it requires identification of a subject from a *sequence* of images. A gait sequence consists of a large amount of information, both spatial and temporal, and thus a technique is needed to represent the information in compact form. Let us consider a gait sequence as a collection of regions denoted by R_t where *t* labels the position of the region in the gait sequence. For each individual image R_t, we can once again define regions masked by circles as $R_t(\zeta)$. As the size of the masking circle increases, we describe areas on the periphery of the image, such as the subjects' feet. These are the areas of the image most likely to vary considerably over a gait sequence, but are not necessarily the areas that will allow us to distinguish between subjects.

Original Image ζ =0.5 ζ =1.0 ζ =1.5

Figure 2 Masking Circles for various values of Alpha

Figure 2 illustrates how the masking circle affects an image for various values of ζ. We can now define a complete signature set for a gait sequence thus

$$S \,|\, \{I_k(t,\zeta)\,|\,k\,|\,1,2,8;t\,|\,0,N,\zeta\,|\,\zeta_{\min},\zeta_{\min}\,2\,\zeta_{step},\ldots,\zeta_{\max}\} \quad \textbf{(6)}$$

t is chosen such that a full gait cycle was sampled at intervals of 1/*N* starting from a known start point. In the case of the SOTON database, all subjects start from a heel-strike and exactly one gait cycle is present. In other databases, key frames could be located using techniques developed by Collins' et al [2]. A spline curve was used to interpolate between values to provide exactly thirty samples for a full gait cycle. Thirty samples were chosen as, on average, a gait cycle consists of approximately 30 frames when filmed at 25 frames/second. Each sequence can therefore be described as a set as above for values of *k* and ζ. Figure 3 shows the sample output for a single subject using invariant functions for each frame in the sequence. The Hu1, Hu2 and Hu8 moments are illustrated and the size of the masking circle is zero (i.e. no masking circle is used).

A suitable ζ range must be chosen to give adequate image representation. In practise if the value of ζ is too large then no information about the image is obtained and this can lead to poor recognition performance. To ensure that all sequences are the same length we use a cubic spline curve to represent the data and take the same amount of samples (thirty) from each sequence $S_{\zeta,k}(t)$.

Invariant Properties

Invariant properties include invariance to: distance to the camera; height; clothing; colour; and lighting changes. By using Hu invariant moments, the moment descriptors for each silhouette are invariant to rotation, translation and scaling. Invariance to rotation could be of benefit if the subject is walking uphill or downhill, but this implies that gait stays constant when walking at an incline, which is certainly not true [12]. Scaling and translation invariance are important because they enable silhouette sequences from different databases to be compared easily. Scale invariance is of particular importance as gait can be filmed from a great distance and therefore the resolution of such images may be lower than those used in the SOTON database. In addition, scaling invariance gives us immunity to camera zoom. Translation invariance removes sensitivity to the centring of the silhouette, which can be a problem when area masks are used [5].

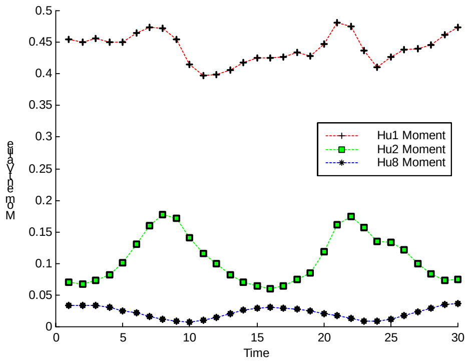

Figure 3 Hu Moments for a Subject with ζ =0

Results

We analyse our results on part of the SOTON database consisting of 114 subjects with at least eight samples of each subject. Subjects walk normal to the camera's plane of view and are filmed under laboratory conditions. These conditions allow us to concentrate on the basic properties of gait as a biometric, rather than the problem of extracting clean data. The background of the image is removed using chroma-key techniques, and the image is cropped and resized to a 64×64 silhouette with the subject centred in the image. We have chosen to use a simple *k* nearest neighbour classifier, rather than a more sophisticated classifier such as canonical analysis, and Euclidean distance for basic comparison, together with leave one out cross validation.

Person Identification using Moments

Table 1 shows the performance using a selection of Hu moment invariants (without using a family of masking circles). The feature vector from each moment was combined by simply concatenating the feature vectors of each individual moment invariant to form one large feature descriptor. Performance levels using a single moment invariant may appear poor, but the chance recognition rate is 1/114 and the results are substantially better than that. By combining the feature vectors, the performance level was raised, indicating independent information from each of the moment descriptors. The moments were combined simply by concatenating the feature vectors. Note that no normalisation took place when feature vectors were combined.

Moment Invariant	Recognition Rate
Hu1	44.7%
Hu2	35.9%
Hu8	22.7%
All 3 combined	51.4%

Table 1 Performance of Moment Invariants for Person Discrimination

By using a family of shape descriptors, we can describe the shape with more accuracy and thus increase the performance of the description and therefore the recognition rate. Table 2 demonstrates how we improve performance using a family of descriptors.

Values of ζ	Recognition Rate			
	Hu1	Hu2	Hu8	Combined
0	44.7%	35.9%	22.7%	51.4%
0 to 0.5 in steps of 0.05	63.3%	47.6%	29.1%	63.3%
0 to 1 in steps of 0.1	68.3%	44.5%	28.5%	56.7%
0 to 1.5 in steps of 0.25	65.9%	34.3%	28.8%	42.1%
0 to 2 in steps of 0.1	64.4%	39.4%	31.6%	44.7%

Table 2 Using a Family of Shape Descriptors for Person Discrimination

As can be seen from Table 2 the performance using a family of shape descriptors rises rapidly when low values of ζ are used but the performance falls away rapidly when large values of ζ are combined. This suggests that using large masking circles and thus describing information at the periphery of the silhouette can detract from recognition performance. The Hu1 moment performs consistently better than other moments at discriminating between subjects. Both the Hu2 and Hu8 moments perform poorly, achieving low recognition rates despite of the increased information present from using masking circles. The major difference between the Hu2 and Hu8 moments is the inclusion of the M_{11} term. We suggest from this that the M_{11} term is not very descriptive for discriminating between subjects because the moments that contain this term perform significantly worse than those that do not. The combined set of moments performs consistently poorly when a family of descriptors is used. This may be due to the poor performance on the Hu8 scheme that affects the overall recognition result heavily due to no normalisation of feature vectors.

Is Gait Symmetric?

Gait symmetry has been defined as the perfect agreement between actions of the lower limbs [13, 14]. Gabbard [15] has suggested using the term when no statistical differences are noted on parameters measured bilaterally. Historically, the psychologists' view is that gait is a symmetrical pattern of motion [16, 17]. We have assumed this true, and not taken into account the foot on which the subject starts, or their direction of travel. Does taking this information into account result in a significant difference in recognition rate? The SOTON database has labelled information including heel strikes and direction of walk. By using this information, we were able to undertake experiments where the direction of walk and the starting foot for the gait cycle were taken into account. As can be seen from Table 3 the performance gain when considering the starting leg is substantial. This suggests, once again, that there is an asymmetrical component of gait and by taking this into consideration performance can be improved.

In the following table the database is constrained so that only sequences where the direction of walk and starting foot are as indicated in the table are considered. As the table indicates, by constraining the database to specific starting foot and direction of walk we are able to dramatically increase the recognition rate. In application this indicates that if we could automatically determine the starting foot of the gait cycle and the direction of walk we could increase recognition rates.

Direction of Walk	Starting Foot	Recognition Rate using Hu1 Moments
Left	Left	83.2%
Left	Right	80.6%
Right	Left	81.9%
Right	Right	78.7%
Left	Both left and right	86.9%
Right	Both left and right	83.2%
Left and Right	Left	82.9%
Left and Right	Right	81.5%

Table 3 Recognition Rates when Considering Direction and Start Leg using Moment Based Descriptors

Conclusions

We have presented a new technique for recognition of gait sequences using moment based descriptors. A family of descriptors is formed for each silhouette in the sequence, by using a masking circle to define what areas of the image to describe. The technique uses Hu moments and is hence invariant to rotation, translation and scaling.

Results show that performance is dramatically improved if a family of masking circles is used, and we achieve a recognition rate of 68.3% on the SOTON database of 114 subjects, with eight samples each. We show that by considering the direction of travel and heel strike information performance can be substantially increased. By constraining the database to subjects using the same heel strike to start a gait cycle and walking in the same direction, performance is increased to over 80% on a databases of 114 subjects.

Future work will concentrate on evaluating the approach on a more varied database and examine the use of different ways of masking areas of the silhouettes. Further work will also analyse the affects of starting from a non-zero value of alpha (i.e. include only larger masking circles) and investigate the affects of using different moment descriptors.

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