JOURNAL OF APPLIED
COMPUTER SCIENCE
Vol. 26 No. 2 (2018), pp. 73-98

The Perspectives in Gait Recognition

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Abstract. *In this paper we provide a detailed information on classical and recent research results in gait recognition. We provide classification of leading concepts, representations, experiments and available datasets. The most promising algorithms are provided with more details and in the end we provide some predictions on future research. Paper contains also summary on methods used in a variety of papers on gait recognition published after 2002.*
Keywords: *gait recognition, baseline algorithm, gait energy image, biometry, gait biometry.*

1. Early gait analysis

The beginning of 21 century is extremely intense period in biometric methods. It is due to both development of faster processing units and number of application and toolboxes that can efficiently process data coming from sensors and cameras. Among others, gait analysis is one of most inspiring digital pattern matching problem. Yet still scientists could not agree on a proper way to define gait. Usually it is understood as "the manner of walking" [1, 2]. It is known that human body and its movement has a lot of distinctive properties such as:

- different sizes of bones,

- different strength of muscles,
- rhythm embedded into one's movement.

Moreover all of those properties can be observed, both by a human and a computer camera. This provide supposition that a successfully recognition could be performed.

Recognizing individualities by one's gait is equally interesting and frightening. As our actions and movement is more and more monitored by cameras, this particular biometry could cause our privacy to be reduced almost to zero. World cinematography used this concept extensively, that a hero or villain could be located within a minutes at a distant camera. Nowadays audience is willing to believe this is actually possible, as similar problems already have been solved (like recognizing person at a photography). Also many people had recognized someone they knew, from a large distance, without seeing his/hers face.

The origin of this biometry is a research in psychology led by Gunnar Johansson from the University of Uppsala in early 70s. In those experiments [3, 4] observers were shown a man or a woman wearing single coloured clothes, covering any possible individual features, with background in contrasting colour. In the other experiment only some joints were marked. The observer's task was to identify individuals based on their movement. The experiment proved that a successful recognition can be achieved, especially in a case when observer is a close friend with the individual. This also introduced first representation of gait by using Moving Light Display (MLD), which is white pixels for silhouette and black pixels for background.

In 21 century the demand for biometric recognition is constantly increasing. The most popular authentication methods - the password - will soon be replaced with more secure methods. Gait recognition belongs to the second generation biometry - that is, methods which became possible to implement because of creation of more advanced machinery. The researchers suppose that apart from gait, it is possible also to recognize individual's sex [5, 2], current state of health, rush, or mood [2].

The most relevant advantages of those recognition methods are [6, 2, 7]:

- They could perform recognition at large distances,
- Also they could be applied to a low-resolution images, and
- They did not require ones approval to extract his/hers gait features.

Yet, even early implementations have shown that achieving low-error-rate shall be a demanding task. Most algorithms proved to be strongly dependent on following factors [8, 6] :

- Carried items,
- Camera angle,
- Artefacts in background,
- Clothing and changes in silhouette,
- Shoe type, ground type,
- Time passed since the pattern extraction,
- Indoor - outdoor environment.

Research have shown that correct-recognition-rate decreases from $91-95\%$ to $30-45\%$ as the time difference changes from minutes to months. Also any carried items seems to have huge, and very unpredictable impact on gait's rhythm[6].

Gait recognition, based on its advantages and disadvantages, can be a successful early detection methods. It could provide filtering prior to application of a different recognition [1, 6]. Current threat of terrorism acts, also encourage scientists to enhance theirs implementations.

2. Baseline algorithm

Although first research on computer gait recognition was conducted in 80s, not much progress have been done there. It lacked in technology, funding, and ways to compare achieved results. Low recognition rates did not seem promising for this type of research. Yet the huge importance of advantages of this recognition kept the research ongoing. Demand caused several institutions to provide funding for this research. One of them were "Human identification at distance" funding program held by US Department of Defence[9].

In the 2002 there was a breakthrough as the result of this support. At that year "Human ID Gait Challenge Problem" was formulated [6]. It was the first wide research in this area, which concluded with

- definition of the most important obstacles to a successful recognition,

- summary of key-relevant questions in this recognition,
- description of basic experiments,
- pointing out the most promising concepts at that time,
- publishing of dataset[1], which could be applied to test other approaches,
- and the "Baseline algorithm" - the first algorithm that was able to perform successful recognition at some of scenarios.

Thanks to both dataset and the algorithm, other scientists could test and compare their own implementations. Creation of "Human ID Gait Challenge Problem" and publication of Baseline algorithm became a symbol when computer gait recognition truly had starter. Since then more datasets appeared on the internet, and many changes have been applied to improve performance of the Baseline Algorithm.

Baseline Algorithm was designed to handle gait analysis in experiment with a single camera. It follows from supposition that a single camera should be able to record all the important features of gait. Simplest experiment assume that:

1. There is a static camera that can observe the whole scene,[2]
2. We observe single individual at a time,
3. The experiments can vary by change of following factors:
   - Movement direction,
   - Shoe type,
   - Carried items,
   - Camera placing,
   - Indoor or outdoor environment.

At the moment of publishing, by Phillips, Sarkar, Robledo, Grother and Bowyer in [10] (and later in [5]), Baseline Algorithm was better from any other competing algorithm. Currently there are much better solutions to compete with, but this algorithm is still used for comparison. Baseline consisted of three step performed in semi-automated manner. Those steps were [10]:

[1]Examples from the database presented at Figure 1.
[2]Camera can be moved in between experiments.

1. **Bounding boxes** - first stage requires finding the silhouette at each image in sequence. That particular part was semi-automated. Frames that bounds individual are interpolated from a few frames that where placed manually by the user. This method is very simple, and actually quite accurate if individual is walking uniformly and perpendicularly to the camera.

2. **Silhouette extraction** - in this algorithm extraction of silhouette is performed by means of background subtraction. Background is simply defined as an average pixel colour. As a foreground are chosen such pixels that has a Mahalanobis distance greater than a certain value (in [10] referral value was set to 4 or 7) from the background. Mahalanobis distance [11] is defined by means of the following formula

$$M_d(X,Y) = \sqrt{(X-Y)^T S^{-1}(X-Y)}, \tag{1}$$

   where X, Y are two vectors (two images in sequence) and S is covariance matrix (of the whole sequence). As the result each pixel is assigned either to foreground or background, thus it is a binary image. The last step is to extract silhouette with the bounding box and scale it into fixed resolution.

3. **Similarity measurement** - at this stage we compute similarity measure based on median-maximization of correlation of sequences of silhouettes. It is noticeable that algorithm only compares two sequences. There are several obstacles to overcome at that stage. The sequence may consist of a several cycles of walking, the sequence may begin at different stage in each sample. The algorithm is based on the following Tanimoto measure - counting percentage of common pixels in two images, i.e.

$$T_s(X,Y) = \frac{\sum_{i\in I} X_i \wedge Y_i}{\sum_{i\in I} X_i \vee Y_i}, \tag{2}$$

   with I being a set of all pixels, X, Y being two vectors of $\{0, 1\}$ values representing, 1 if pixel belongs to foreground and 0 otherwise. Based on this measure the following distance function might be used [12]:

$$T_d(X,Y) = -\log_2 T_s(X,Y). \tag{3}$$

   To properly compare two gait cycles its length, N_{Gait}, must be determined. In [10] N_{Gait} was fixed to 30. Nowadays this parameter is usually estimated,

Figure 1: USF database gait samples for Baseline Algorithm[13]

by computing the number of frames in between the widest consecutive leg positions. [6].

$$Cor(S_X, S_Y) = \sum_{j=1}^{N_{Gait}} T_s(S_X(j), S_Y(j)), \tag{4}$$

where S_X, S_Y are two sequences of silhouette images. Two overcome different phases algorithm counts median of different shifts [6]:

$$Sim(S_X, S_Y) := median_k(\max_j Cor(Shift(S_X, k), Shift(S_Y, j))). \tag{5}$$

Authors claimed that if the more accurate silhouettes are extracted, the better performance is expected. Results of Baseline Algorithm in different scenarios are presented in Table 1. One can conclude that:

- Baseline algorithm is almost insensitive for camera placement. However, it is important that in both placements of camera, it was able to observe all the features of movement (movement was almost perpendicular to the camera).
- Algorithm appeared to be sensitive to change of shoe type, and
- Be a failure in case of ground type change.

3. Leading research models

After the publication of Baseline Algorithm, many possible ways of improving the performance were investigated. It concluded in four main approaches to gait analysis[7], but eventually first and second took most of researchers' attention [8, 1, 2].

Floor	Shoe	Camera position	Top 1	Top 5
Grass	Shoe A	Left	79%	96%
Grass	Shoe B	Right	66%	81%
Grass	Shoe B	Left	56%	76%
Solid	Shoe A	Right	29%	61%
Solid	Shoe B	Right	24%	55%
Solid	Shoe A	Left	30%	46%
Solid	Shoe B	Left	10%	33%

Table 1: Baseline Algorithm performance in different scenarios [10]. Recognition was successful if top k element contains the same object.

- Model based or Silhoutte Model approach - In this approach the role of the algorithm is to locate the key points of human body from perspective of gait, or to cover the silhouette with simple mathematical shapes like circle, rectangles, ellipses. Then to monitor its changes in time which will define a set of functions. A collection of such functions shall be the gait pattern. The relevant characteristics will be e.g.
  - Angles during the motion,
  - Distances in between the joints,
  - Motion frequencies and differences in phase in legs movement,
  - Distance in between joint and foundation.
- Model-free, or Motion Based, or Appearance Based Models approach - In this approach one extract pattern without analysing the underlying model. Mostly this means that every of its pixels in used in pattern extraction. The simplest one would be a centroid of silhouette, but nowadays more sophisticated representations are used. Each representation's main task is to reduce the dimensionality of the problem.
- Stochastic models approach - in this approach pattern is understood by means of probabilities of different shapes of silhouettes following one another (transition matrix estimation). As those model uses raw silhouettes, such models where separated from Model-free Approach which uses gait compression.
- Biomechanical methods - This approach is very unique, it originates from

Model-free approach, but in this model we estimate only parameters that are related to gait biomechanical models (for more please see [14]).

Currently the experiments focus on 4 scenarios, based on the way the gait is recorded:

- Gait is recorded through the devices located on individual [15, 16],
- Gait is recorded by a single camera,
- Gait is recorder by two cameras and 3D contour is extracted,
- Multi-gate, the gait is recorded simultaneously by multiple cameras from different angles and perspectives.

Experiments 2-4 usually share the same approach, with differences in used algorithms. That approach can be summarized by following 3 points:

1. Locating the individual in the sequence, including estimation of the direction of movement or its angle to the camera.
2. Computing the gait representation (in model based methods - placing key points of silhouette, in model-free methods - reducing the dimensionality).
3. Classify the pattern - finding one or many top matching patterns or comparing against true value.

3.1. Model-free approach

Model-free approach is direct descendant of Baseline Algorithm. Its three steps are still fundamental in good recognition. The performance of each of them has be significantly enhanced. At first it was the location of the individual and its silhouette, that was targeted to be improved. Yet, the research proved decorrelation of the silhouettes sequence (which was the main tool in sharpening the silhouettes) actually causes the drop of recognition rate. It appeared that almost the same amount gait information is stored in low resolution and high resolution images [6, 17].

Currently to extract silhouettes the following operations are performed:

1. Application of EM algorithm to separate foreground and background. Mostly used together with Mahalanobis metric.

2. Applying mathematical morphology methods to smooth, and fill holes in the silhouette.

3. In some implementations, we try to remove shadows of foreground objects.

4. The biggest connected set of pixels is interpreted as an individual. Al smaller object are being dropped.

5. We fit the frame that can bound the individual.

6. Finally, we scale to a selected resolution.

After the result of Liu and Sarkar[18] was published, proving that low resolution contain almost the same amount of gait information, interest in further improvement of those algorithms decreased.

The most researches focused on improving recognition rate by using different extraction or classification methods. The first classification method, that proved to be very useful, was build on PCA transformation [6, 19]. The gait images compressed by this transformation is known as eigen-stance representation. Also linear discriminant analysis (LDA) appeared to have similar information of one's gait[20]. Many of those approaches were inspired by results in face recognition research. Also combination of two : PCA and LDA proved to be even better combination. As both PCA and LDA are algorithms that are applicable to vectors, in [21] authors suggested to use similar concept which use the matrix representation. They used coupled subspace analysis (CSA) with DATER algorithm (discriminant analysis with tensor representation)[8] which lead to one of best recognition rates achieved by a single algorithm in gait analysis. (See Table 2).

Lately most of the interesting results comes from introducing a new intermediate representation. Till CSA-DATER algorithm, starting gait representation was the sequence of MLD images, being reduced by the recognition algorithm to final representation for classification. Since publishing "Simplest representation yet for gait recognitions: averaged silhouette"[17], we observe a number of different intermediate representations. Authors suggested not to classify the whole sequence of silhouettes, but to compute a different representation. Averaged silhouettes, otherwise called as GEI (Gait Energy Image), are images which have average pixel colors computed from whole sequence. That representation was proved to be very usefull and to hold most of the information of one's gait. It also have some remarkable properties f.ex. we no longer have to split the sequence in gait cycles,

Experi-ment	Ground	Shoe	Camera	Baseline (Top1/5)	DATER	CSA-DATER
A	Grass	A	Left	79% / 96%	87% / 96%	89% / 96%
B	Grass	B	Right	66% / 81%	93% / 96%	93% / 96%
C	Grass	B	Left	56% / 76%	78% / 93%	80% / 94%
D	Solid	A	Right	29% / 61%	42% / 69%	44% / 74%
E	Solid	B	Right	24% / 55%	42% / 69%	45% / 79%
F	Solid	A	Left	30% / 46%	23% / 51%	25% / 53%
G	Solid	B	Left	10% / 33%	28% / 52%	33% / 57%

Table 2: Compare CSA+Dater against Baseline Algorithm (2006) [21]

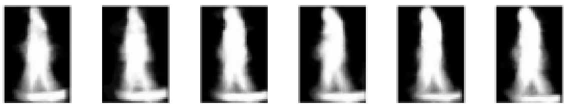

Figure 2: Examples of Gait Energy Images [17]

and any difference on gait phase is no longer an obstacle. Currently most of the experiments uses GEI as its intermediate representation[8, 21, 22, 23, 24].

Another example of intermediate representation is MSI - Motion Silhuette Image. Similar to GEI is an images create on the basis of gait sequence. MSI is computed by the following formula[25]:

$$MSI(x, y, t) = \begin{cases} 255 & , I(x, y, t) = 1, \\ \max\{0, MSI(x, y, t-1) - 1\} & , I(x, y, t) = 0, \end{cases} \tag{6}$$

where x, y are pixels coordinates and t is number of image in a sequence. MSI example is presented on Figure 3. Currently there is a plenty of different representations like: CGI - Chrono-gait image[26]; GEnI - Gait entrophy image[27]; GII - Gait individual image [28]. Different representations seem to handle different problems related to gait analysis, f. ex. to handle unknown movement direction.

The advantage that comes from any intermediate representation is a big reduction in the number of dimensions. Yet all the previously successful methods might still be used for recognition, like PCA in [29, 25], LDA and MDA [30, 29, 31, 32], CCA [33]. Since number of dimensions has been significantly reduced, also more types of classifiers could be applied, like SVM [34, 26, 32]. As the deep learning methods becomes so popular also classification by artificial neural networks

Figure 3: MSI image and samples from its source squence [25].

(ANN) [35] and deep convolutional neural networks (CNN) [36, 37] is an ongoing research.

3.2. Model-based approach

The other main approach in gait analysis is based on human body model. Therefore before extracting the gait one should obtain an approximation of such model. In this approach that model can be described by a various types of shapes, like: centroid, ellipses, rectangles or else simple mathematical structures. Once the model is retrieved, there is no need to observe all the silhouette's pixels, just the parameters of the model, consisting of some important points of the human body[19]. Model-based gait analysis has a solid foundations. Yet apart from information coming from the experiments one cannot exclude that a big payload of gait data was lost due to model creation. Definitely this approach provide a lot of gait information with just a few dimensions.

In paper by Lee and Grimson [38] a model of 7 ellipses is considered. To describe the position of ellipses, thier location in relation to silhouette's centroid is considered. The role of ellipses is to cover different parts of body, 4 of them to cover upper and lower parts of legs, other 3 to cover the torso, arms and head. This leads to creation of 56 variables that change in time. Classification uses Fourier transformation and application of ANOVA. In paper by Lu, Plataniotis and Venetsanopoulos [39] authors introduce full biomechanical model - so called LDM (Layered Deformable Model). This model is presented on Figure 4. It uses layers, as one layer can overlap the other one. Another model is ASM (Active Shape Model) suggested in paper [40].

Model-based solutions are less popular than model-free. Yet it is expected that such solution will be also appearing in the future. There are many differences in between both models. Some experts suggest that model-free approach includes

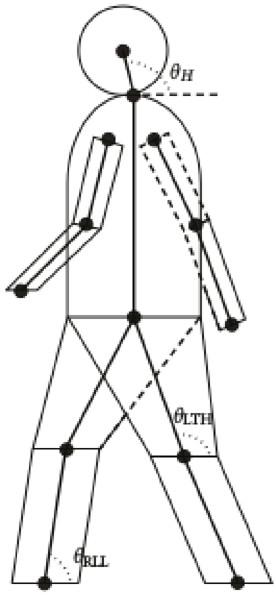

Figure 4: LDM model example. [39]

two different types of information, which improves recognition rate:

- Information on dynamic - coming from individual's gait,
- Information on static - coming from individual's silhouette.

Model based solutions are focused on dynamics, thus the recognition in this case comes directly from information of one's gait.

3.3. Hybrid approaches

In order to improve recognition rate a hybrid approach may be considered. It means to use a two types of biometrics simultaneously. In most gait recognition algorithms there is a big impacts on movement direction, carried items, ground type. Also it appears that human gait changes in time[41]. It may be the case that actually almost perfect recognition of individual, based on gait alone, is actually impossible. Then a hybrid approach, that merges the results coming from gait and other recognition algorithm could improve recognition rate[42]. In paper [41] authors suggest to merge gait analysis with face recognition. Obviously the best candidates for being merged with gait are those that allows feature extraction at distance. In hybrid solution one must decide on algorithm to merge results. Usually the results are computed as averages. In some implementations authors decide on voting of different classifiers.

4. Multi-gait analysis

There is a separated branch in gait research which is trying to obtain gait pattern by using multiple camera images. Those method use extensively algorithms designed for a single camera. When a gait is observed from many perspectives it is less probable that some significant features will not be recorded. We recognize two types of recognitions which uses more than one camera:

- 3D gait recognition, and
- multi-gait recognition.

4.1. 3D gait recognition

In 3D gait recognition a pattern is extracted from 3D model of silhouette. In order to create such a model, a system of two parallel cameras is created. In most cases it is sufficient to create an accurate 3D model of individual. Algorithms used for such cases are very alike to those applied for a single camera. There is however a big difference in between those two cases. In case of 3D model, there is much more data to be analysed. Thus a proper reduction is required. An example of algorithm that could perform such recognition is the following one[43]:

1. Create 3D model based on system of two cameras.
2. Silhouette extraction:
   (a) Background subtraction method,
   (b) Mathematical morphology methods, for silhouette gaps removal,
   (c) Choosing the biggest connected set of pixel as individual's silhouette.
3. Applying Canny filter, 3D contour detection.

4. Creating single dimensional signal for gait pattern:
    (a) Creation of SSV (Stereo Silhouette Vector), by subtraction of centroid location from every pixel in contour.
    (b) Computing a norm of SSV for every frame.
5. Classifying the gait pattern. Authors of [43] suggested to use kNN classifier for this purpose.

4.2. Multi-gait recognition

Recognizing gait patterns using multiple cameras is one of the newest approaches in this area. It is intuitive that fusing information obtained by multiple cameras should provide higher recognition rate. In the case of single camera there is a treat that due to bad angle, not all necessary features of gait shall be observed. The most important task in this area is to make gait pattern invariant on movement direction. The simplest algorithm perform the recognition separately to each camera, and then merge obtained result based on a chosen rule. We can distinguish two different approaches:

1. Voting on best candidate - in this approach each camera will be paired with its best match. The final result will be selected based on results from each camera.
2. Joint result on each sample - in this approach each camera creates a percentage matching of a given item with all of the samples. Then results of each camera are merged into joint percentage. Based on those result - top matching is returned by the algorithm. [44]

In [44] authors considered several ways to create joint percentage, f. ex:

1. Sum
$$x = \sum_{i=1}^{N} x_i. \tag{7}$$
2. Weighted average
$$x = \sum_{i=1}^{N} w_i \cdot x_i, \tag{8}$$
   for vector of weights - w.

3. Product
$$x = \prod_{i=1}^{N} x_i. \tag{9}$$
4. Dempster - Shafer Theory - an extension of Bayes rule. It replaces probability function with belief function of log-likelihood. Belief function returns 1 if argument is above upper threshold, 0 if argument is below lower threshold, and preserves monotonicity in between. There is an issue with using pure Bayes rule in real applications. Even if we obtain a strong premise that a sample is well matched, the probability is decreasing. Details on this theory can be found in [45].

In all of the above formulas x is a joint result and x_i is result of recognition based on i-th (out of N) camera. In paper [44], authors summarized the efficiency of using different type of joint percentage, and recommended to use Dempster-Shaffer Theory as in the experiments it reduced error rate from 9.08% for sum to 3.81%.

In paper [27] author achieved also very good insensitivity to unknown walking direction (98%), as well as remarkable performance in case of carrying items or big silhouette changes (over 90%).

4.3. Other tasks in gait analysis

Apart from model-based and model-free recognition, or multi-gait recognition - there are also several open problems in this area, that researchers are currently exploring, like:

- Gait recognition in outdoor environments,
- Walking direction recognition[31],
- Silhouette changes recognition [31],
- Multiple objects recognition [26].

5. Available datasets

Although first experiments with gait analysis were performed in late 70s, no bigger progress was made until the beginning of 21st century. Among main reason for that, experts point out that before there wasn't any available dataset that could be used for researching purposes. To create such a dataset actually generate quite a big cost, both in equipment and wages for experiment participants. For such type of experiments the datasets should have over 100 distinguished samples, so the results will be reliable. Currently there are two datasets offered to researchers. The first one was made available to others by the by University of South Florida (USF) all together with Baseline Algorithm. The other one was provided by CASIA (Chinese Academy of Sciences). Although both datasets have been created over 15 years ago, most papers uses one of them to provide comparable results.

The dataset from USF [13] provide the results of the experiments which took place on 20-21 May and 15-16 October 2001. This datasets contains:

- 122 individuals, and 33 of them participated in both experiments - May and October,
- data are parametrized by 5 factors:
  - Shoe type,
  - Carried item,
  - Ground type,
  - Two camera positions (on the left, or on the right),
  - Date for some objects.
- The dataset uses 1.2 TB as a video sequences.

It is important to notice that the web page[13] was not updated since 2007. Yet still many of the researchers use this database to compare their results. On the other hand CASIA database[46, 47] provide different scenarios for experiments. Dataset is divided into 4 subsets, ordered from A to D. Subset A consist of 12 sequences each of 20 subjects that took part in the experiment, taken in 3 different positions of camera. Experiment took place on 10 December 2001, it consists of 19139 photographs and 2.2 GB memory. Subset B consist of records of 153 subjects walks, in one out of four scenarios:

1. Normal walk,
2. Slow walk,
3. Fast walk,

4. Carrying a briefcase.

Each sequence was recorded simultaneously by 11 cameras from different angles (uniformly distributed).

Subset C and D are slightly different in type of records. Subset C consist of infra-red images of walking individuals. It consist of 153 subjects, in one out of four scenarios:

1. Normal walk,
2. Slow walk,
3. Fast walk,
4. Carrying a briefcase.

The experiment took place on night. Subset D consist of images of subjects, taken by CCTV cameras outside of the place of experiment. It consist of 88 subjects, but precise description of dataset was not provided. The subset is considered to be reserved for future behavioral analysis.

Among other datasets with gait data, SOTON[48] database should be mentioned. The dataset is prepared by University of Southampton. It consist of gait sample of around 100 subjects movement: indoor, out-door and on treadmill. There was a recent discussion whether one's gait will not be impacted by treadmill, which causes researchers to avoid such experiment. Many experts supposed that individuals shorten their gait on treadmill and behave in more relaxed manner. We should mention that ground type was recognized as an important factor of gait. Recent research [49] proved, however, that there is no relevant difference in gait on treadmill as along as the speed is constant. Thus it is expected that more datasets including gait sample on treadmill will be considered in the future.

In Tables 3 and 4 we present summary on investigated configurations and papers that contains them. However, the symbols used require some clarification.

Type 1 - experiment that uses accelerometer or other tool different to camera.

Type 2 - single camera experiment

[3] Gabar Tensor Discriminant Analysis

[4] ANN - artificial neural net, PNN - probabilistic neural net

[5] Gait individuality image

Paper	Year	Type	Dataset	Gait repr.	Classifier/algorithm	remarks
[10]	02	2	USF	-	Baseline	
[17]	04	2	USF	GEI	other	
[50]	04	2	USF	-	PCA + HMM	
[51]	05	2	CASIA	-	DCT + SVM	
[18]	05	2	USF	-	PCA + HMM	
[21]	06	2	USF	-	CSA+DATER	
[25]	06	2	SOTON	MSI	PCA + kNN	
[20]	06	2	USF + other	-	LDA + HMM + kNN	
[44]	06	4	CASIA	-	FFT	
[2]	07	2	USF	GEI	GTDA[3]+LDA	
[52]	07	2	CASIA	other	DWT + SVM	
[53]	11	2	CASIA	-	DWT + PCA + LDA	
[54]	12	2	CASIA	GEI	DCT + PCA + ANN/PNN[4]	
[55]	12	2	CASIA	-	DWT, Haar Wavelet	
[54]	12	2	CASIA	GEI	DCT + PCA + ANN	
[56]	12	2	CASIA	-	PCA +LDA + C4.5 + Naive Bayes	
[29]	15	2	CASIA	GEI	PCA + LDA + kNN	
[8]	15	2	USF	GEI / GABOR	PCA + LDA, RSM-MV	
[57]	15	2	CASIA	GEI	DWT + t-SNE + SVM	
[34]	15	2	CASIA	GEI / GABOR - Filters	SVM	
[37]	16	2	other	GEI	CNN	
[30]	16	2	CASIA	GEI	DCT + LDA + kNN	
[36]	16	2	CASIA	GEI + Heat-Map	CNN + LSTM	
[33]	16	4	USF, CASIA	GEI	CCA + PCA	
[31]	16	2	CASIA	GEI + PHash	PCA + LDA + kNN	
[47]	16	2	CASIA	-	Latent Dirichlet Allocation	
[26]	17	4	CASIA	GEI	SVM	recognition for more than one object
[28]	17	4	CASIA	GII[5]	DPLCR	extensive research on angle impact
[27]	17	2	CASIA	GA	PCA+LDA+Naive Bayes	
[35]	18	2	CASIA	-	TGLSTM	

Table 3: Model Free - solutions

Paper	Year	Type	Dataset	Gait repr.	Classifier/algorithm	remarks
[38]	02	2	other	Ellipses	SVM	Model-based
[19]	03	2	USF	centroid	PCA-kNN	Model-based
[58]	06	2	other	-	PCA	Model-based - using 17 cylinders
[41]	07	2	USF	-	PCA-HMM	Hybrid approach
[15]	07	1	-	-	-	using an accelerometer
[39]	08	2	USF	LDM	KSF-DTW	Model-based
[43]	09	3	other	SSV	kNN	
[40]	10	2	USF	ASM	Kalman Filter	Model-based
[59]	11	1	-	other	DWT+kNN/ANN	
[32]	18	2	CASIA + SOTON	Triangle	LDA+SVM	Model-based
[16]	18	1	-	-	PCA	creating 3D trajectories - fusing with accelerometer

Table 4: Other - solutions

Type 3 - 3D model creation

Type 4 - multi-gait experiment.

6. Summary

Gait recognition is a unique, even among other second generation biometrics. Many problems in this area have been recognized, yet even more there is to be discovered. Baseline Algorithm, first successful approach, was published in 2002. It allows to achieve recognition rate over 90% in best case scenarios, yet it fails against many factors, like: ground type, carried items and time difference. Since 2002 the algorithm have been enhanced in many ways. First of all - it was automated. Many space dimensionality reduction algorithms were found applicable like PCA, LDA, CSA and DATER, and variety of intermediate representations, like GEI, was created.

Still impact of many factors could not be removed, like big difference in angle, large changes in silhouette shape, ground type, indoor - outdoor differences. Also so far recognition could be performed of just a single individual at a time. Recognition in case of multiple objects, with possible overlaps, seems to be much harder problem. There are some interesting ideas that could lead to another breakthrough. New intermediate representations and application of classifiers, like deep convolution neural networks, have first promising results. Also multi-gait recognition is expected to provide a better recognition rate.

The most probable scenario is that scientist would focus their research on improvement in both model-based and model-free algorithms, and simultaneously multi-gait will be explored. Whether, and when the obtained results will be applicable in production system, is an open problem, as there is no ongoing research on medium and large scale databases. Monitoring hundreds of people simultaneously, using different cameras, resolutions, different lights - more and more factors can appear as we reduce control on environment of experiment. Currently best algorithm, can perform relatively successful recognition of just a single individual at a time. Also research dataset are much smaller than production datasets. Whether classification algorithms will preserve convergence and recognition rate - once the number of subjects will increase, is also an open problem.

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