Human Gait Recognition Using Topological Information

Javier Lamar León[1], Edel García Reyes[2] and Rocio Gonzalez Diaz[3]

[1,2] Patterns Recognition Department, Advanced Technologies Application Center (CENATAV), La Habana, Cuba.
[3] University of Sevilla, Dept, School of Computer Engineering, Sevilla, Spain.
jlamar@cenatav.co.cu, egarcia@cenatav.co.cu, rogodi@us.es

Abstract This paper shows an image/video application using topological invariants in human gait recognition. The 3D volume of a gait cycle is built stacking silhouettes extracted using a background substraction approach. Ideally, the border cell complex is obtained from the 3D volume with one connected component and one cavity. Then, it is necessary to apply a topological enrichment strategy in order to obtain a robust and discriminative representation for person recognition. Using a sliding cutter plane normal to some direction of view it is possible to divide the border cell complex in different parts. The incremental algorithm is used to compute the homology on each part. A vectorial representation is built ordering the number of connected components and tunnels obtained for each cut. In order to evaluate the robustness of this representation the silhouettes were diminished to a quarter of the original size. At the same time, this is considered a simulation of a human gait captured at long distance. Even, under these difficult conditions it was possible to get a 74% of correct classification rates on CASIA-B database.

Keyworks gait recognition, topology, cell complex, homology.

1 Introduction

Gait recognition is a challenging problem that gives the possibility to identify persons at a distance, without any interaction from the subjects, which is very important in real surveillance scenario [4, 7]. Methods based on feature extraction using contour of silhouettes have been usually used [2]. However, many silhouettes obtained are incomplete due to illumination changes, occlusions, and others. These factors severely affect recognition accuracy. Even though, a recent study [2] is aimed at suppressing the effect of silhouettes incompleteness to improve performance on previous approach, we do not pre process the silhouettes in this paper.

Topology has been previously used to match nonrigid shapes [5, 1]. In this paper, the changes of silhouettes induced by gait are considered as a moving nonrigid object. To the best of the authors knowledge this approach has never been applied to gait recognition.

The aim of this paper is to propose a novel topological representation for gait recognition built on the 3D volume gait and tested on CASIA-B database using a similar experiment set up for the Set A [7]. Furthermore, we reduce the sizes of silhouettes to simulate images obtained at long distance and to alleviate computational cost of the homological algorithm.

The rest of the paper is organized as follows. In section 2, we describe the new methods in detail. Experimental results are then reported in section 3. We conclude this paper and discuss some future works in section 4.

2 The new method

Fig. 1 shows the chain of processing to obtain the gait signature to carry out lateral view gait recognition. First, the moving object (person) is segmented for each frame applying background modeling and substraction [6]. The sequence of silhouettes is analyzed to extract the gait cycle. The 3D volume of a gait cycle is built stacking silhouettes aligned by the gravity centers. The border cell complex is created by triangles (2-cells) on surface of the 3D gait volume. Finally, the gait signature is obtained based on the topological invariants extracted from the border cell complex.

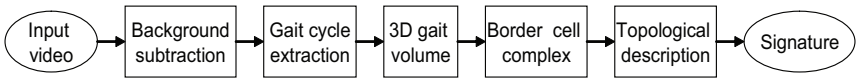


Figure 1: Extracting the gait topological signature.

In the gait cycle extraction the silhouette with the maximum length of the step is the one selected as the first image (with foot right or left) and the next silhouette of maximum length of the step with the same foot (right or left) is the last image (Fig. 2).

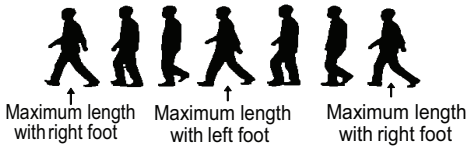


Figure 2: Gait cycle.

3D gait volume belonging to one gait cycle is built by aligning temporal silhouettes by its gravity center (gc) (Fig. 3(a)) and may be viewed as a 3D image (Fig. 3(b)), where each vertex can have at most 26 neighbors. Hereafter, we will use GC when we refer to the gravity center on 3D gait volume and border cell complex. In the 3D space t is defined as the frame number in the gait cycle, x and y are coordinates of the pixels on the image referred to gc of each silhouette.

Border cell complex is formed by triangles (2-cells) on bordered surface of the 3D gait volume. Triangles can only be built between vertexes of the same t, t and $t+1$ or t and $t-1$, i.e, vertexes of the same silhouette or between neighbor silhouettes. In this complex all 0-cell (vertex) and 1-cell (edges) belong, at least, to a 2-cell (triangle), which is the maximum dimension of the border cell complex, so we may store triangles and infer the existence of lower dimension simplices (0-cells and 1-cells). The border cell complex is not a manifold , that is, there are 1-cells (edges) that do not have only two 2-cells (triangles) as neighbors. An example of border cell complex is showed in Fig. 4. After having built the border cell complex belonging to one gait cycle, coordinates (x, y, t)

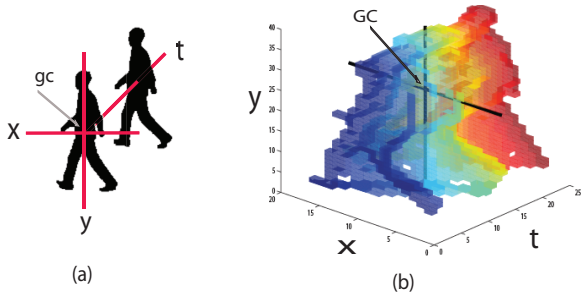


Figure 3: 3D space (x,y,t).

are normalized according to [4]. This defines a cube C, where axes x and y are between 0 and 1 and T is defined as the percentage of gait cycle (between 0 and 100) (Eq. 1).

$$T = [0, 1 * \frac{100}{G-1}, 2 * \frac{100}{G-1}, ..., (t-1) * \frac{100}{G-1}, ..., 100] \quad (1)$$

Where G is the number of silhouettes in a cycle and t is the number of the silhouette.

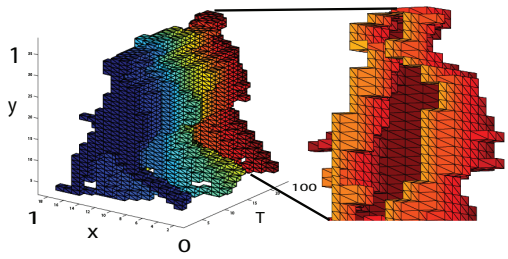


Figure 4: Border cell complex.

2.1 Topology enrichment

The topology of the border cell complex of a gait cycle, in general, is very poor, because it has one connected component and one cavity. In this section we present a strategy to increase the topological information of the border cell complex. The relations among the parts of the human body when walking are characterized by the number of connected components and tunnels, these are created by cuts of normal planes to the line defined by a viewing angle that goes through GC of the border cell complex. The intersection of the line with the cube (C) are two points a and b, which are the beginning of the cuts, i.e, n cuts from point a to GC and n cuts from point b to GC. The distance between two continuous planes for [a GC] and [b GC] is computed according

to Eq. 2 and Eq. 3 respectively.

$$for\ interval\ [a\ GC] \qquad \Delta_{[a\ GC]} = \frac{D_{(a,GC)}}{n} \tag{2}$$

$$for\ interval\ [b\ GC] \qquad \Delta_{[b\ GC]} = \frac{D_{(b,GC)}}{n} \tag{3}$$

where $\Delta_{[a\ GC]}$ is the distance between contiguous planes in the interval from point a to GC, $\Delta_{[b\ GC]}$ is the distance between contiguous planes in the interval from point b to GC, $D_{(a,GC)}$ is the distance from point a to GC, $D_{(b,GC)}$ is the distance from point b to GC, n is the number of cuts, the same to both intervals $[a\ GC]$ and $[b\ GC]$). At the same time 2 cuts are made, one in the interval $[a\ GC]$ and other $[b\ GC]$, where we get two features by cut (amount of connected components and tunnels) on two new cell complex generated between cut planes and points a and b. These features can be stored in a matrix $(n*m)$, where n is the number of cuts and m is the number of topological features. An incremental algorithm [3] is used to determine connected components and tunnels. This allows to obtain topological invariants using the information of the previous cut.

Let us now use an example according to Fig. 5. The border cell complex had been cut using normal planes to the line defined by points a and b. We made $n * 2$ cuts ($n = 5$) of plane, five in the interval $[a\ GC]$ and five in the interval $[b\ GC]$. Topological information for each cut is showed in the table.

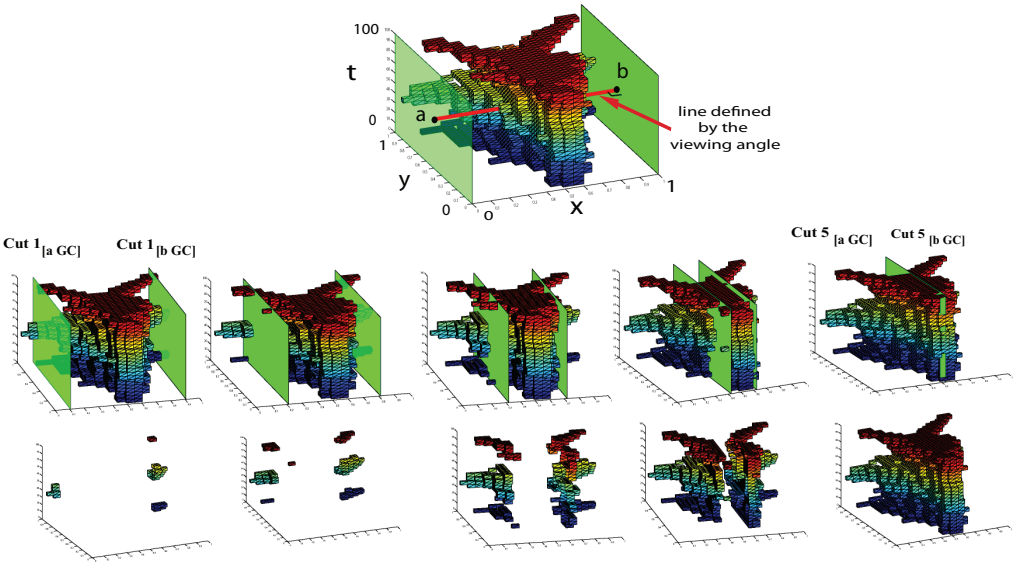
Where $V_{CC_{[a\ GC]}}$ is the vector of numbers of connected components for interval [a GC], $V_{T_{[a\ GC]}}$ is the vector of numbers of tunnels for interval [a GC], $V_{CC_{[b\ GC]}}$ is the vector of numbers of connected components for interval [b GC], $V_{T_{[b\ GC]}}$ is the vector of numbers of tunnels for interval [b GC].

The similarity between two vectors may be calculated using Eq. 4. In this approach, a vector is formed by the number of connected components or tunnels in each cut plane defined by a viewing angle for one of the intervals $[a\ \ GC]$ or $[b\ \ GC]$. In the above example, we have four 5-dimensional vectors $(V_{CC_{[a\ GC]}}, V_{T_{[a\ GC]}}, V_{CC_{[b\ GC]}}, V_{T_{[b\ GC]}})$ (see table (Fig. 5)), and the angle is computed as:

$$\alpha = \cos^{-1}\left(\frac{\sum_{i=1}^{n} v_i r_i}{\left(\sum_{i=1}^{n} v_i^2\right)^{1/2} \left(\sum_{i=1}^{n} r_i^2\right)^{1/2}}\right) \tag{4}$$

Where n is the number of cut numbers for one of the intervals $[a\ GC]$ or $[b\ GC]$ according to a viewing angle, v is a column of the table in Fig. 5 for a person and r is the same column v for another person. We computed four similarity measures s_i, i.e, four angles, between two persons. The total similarity value $S(P_i, P_j)$ is the weighted sum of these similarities (Eq. 5).

$$S(P_1, P_2) = w_1 s_1 + w_2 s_2 + w_3 s_3 + w_4 s_4 \tag{5}$$



Cuts	$V_{CC_{[a\ GC]}}$	$V_{T_{[a\ GC]}}$	$V_{CC_{[b\ GC]}}$	$V_{T_{[b\ GC]}}$
1	1	0	3	0
2	4	1	3	2
3	7	4	6	8
4	4	11	4	12
5	2	11	1	21

Figure 5: Cuts plane on a border cell complex.

3 Experimental results

In this section, we demonstrate the performance of the proposed method on the lateral view of the CASIA-B database, which contains 124 subjects. There are six normal walking sequences for each person. CASIA-B database provides image's sequences with background subtraction for each person as proposed in [6]. The cycle's silhouettes are scaled with factor 0.25 to simulate images obtained from a long distance (Fig. 6).

For topologically enriching the border cell complex, we used 4 viewing angles, with n cuts from the point a to GC and from the point b to GC. Each viewing angle has 4 feature vectors, then we have 16 feature vectors. The first viewing angle is the same as in the above example for $n = 30$, i.e, 30 cuts for $[a\ GC]$ and 30 cuts $[b\ GC]$, these cut planes can be called P_{yt} (Fig. 7a). The second viewing angle is orthogonal to the first viewing angle with $n = 30$ too and it is called P_{xt} (Fig. 7b). The third viewing angle (line (a, b)) forms a 45^0 angle with the axes x and y, 90^0 with t and goes through GC (Fig. 7c). We performed 60 cuts from point a to GC and 60 cuts from b to GC. We called this set of planes P_{ob1}. The planes generated by the fourth viewing angle are orthogonal to the planes of the third viewing angle and $n = 60$ too. We called this set of planes P_{ob2} (Fig. 7d).

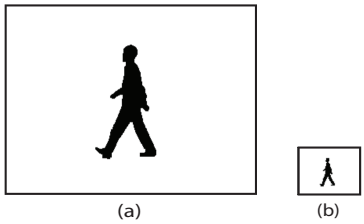


Figure 6: (a) size of the frame from the CASIA-B database (320x240), (b) scaled frame using factor 0.25 (80x60).

The features matrix for this experiment is showed in Fig. 8. The weights according to Eq. 5 are in value 1.

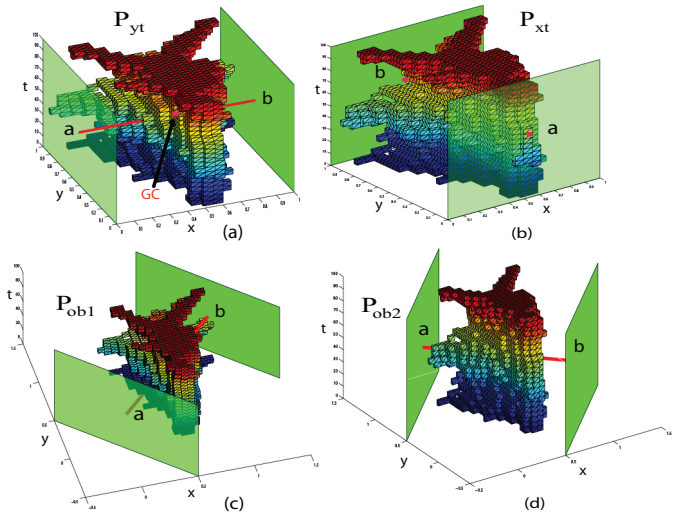


Figure 7: Viewing angles used in the experiments.

The experiment was carried out using the first four sequences for training, and the last two as testing set. Topological information is computed in each plane cut by incremental algorithms [3] using matlab [1]. The results are compared with paper [2]. Table 1 shows the correct classification rates at rank 1 (CCR), it is also considered the correct classification rates when at least one subject, of the two used as test is correctly classified (ALS). The results from paper [2] mentioned in table 1 were obtained using the original images without scaling to factor 0.25, therefore we cannot compare directly these values with our method.

[1] http://comptop.stanford.edu/programs/plex-2.0.1-windows.zip

Cut Times	P_{yt}				P_{xt}				P_{ob1}				P_{ob2}			
	$V_{CC[a\ GC]}$	$V_{T[a\ GC]}$	$V_{CC[b\ GC]}$	$V_{T[b\ GC]}$	$V_{CC[a\ GC]}$	$V_{T[a\ GC]}$	$V_{CC[b\ GC]}$	$V_{T[b\ GC]}$	$V_{CC[a\ GC]}$	$V_{T[a\ GC]}$	$V_{CC[b\ GC]}$	$V_{T[b\ GC]}$	$V_{CC[a\ GC]}$	$V_{T[a\ GC]}$	$V_{CC[b\ GC]}$	$V_{T[b\ GC]}$
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
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30	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
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60									-	-	-	-	-	-	-	-

Figure 8: Matrix of features.

Table 1: The average recognition rates.

Method	CCR	ALS
Frieze(BI) C. H. Chen (2009) [2]	79.8	
Frieze(FD) C. H. Chen (2009) [2]	91.1	
Wavelet(BI) C. H. Chen (2009) [2]	77.4	
Wavelet(FD) C. H. Chen (2009) [2]	90.3	
Our method (silhouettes reduced (Fig. 6b))	74.0	90

4 Conclusion and future works

In this paper, we propose a new representation based on topological invariants for human gait recognition. A new approach called topological enrichment is proposed to improve the discriminative capacity of the representation. The experimental results demonstrate that it is possible to obtain good classification rates even though the silhouettes are reduced to factor 0.25, simulating a video sequence captured at a long distance. It is important to notice that silhouettes incompleteness was not taken into account in this moment. In future works we will use other cut planes and we will study the influence of different weights to be used in Eq. 5.

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