ACCURATE SIMILARITY MEASURES FOR SILHOUETTES RECOGNITION

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Abstract: In this paper, we propose a new method to recognize silhouettes of objects. Models of silhouettes are stored in the database using their textual descriptors. Textual Descriptors are written following the part-based method published in (Larabi et al, 2003). The main issue with the textual description is its sensitiveness to noise, in order to overcome this issue, we have applied (Aouat and Larabi, 2010) a convolution to initial outline shape with a Gaussian filter at different scales. The approach was very interesting for shape matching and indexing (Aouat and Larabi, 2009), but unfortunately it is not appropriate to the recognition process because there is no use of similarity measures in order to select the best model for a query silhouette.

In this paper, we compute parts areas and geometric quasi-invariants to find the best model for the given query; they are efficient similarity measures to perform the recognition process.

1 INTRODUCTION

There are two general methods for image matching, retrieval and recognition: intensity-based (color and texture) and geometry-based (shape), (Alvarado et al, 2002; Arandjelovic and Zisserman, 2010; Chang and Kimia, 2011; Keysers et al, 2007; Latecki et al, 2005; Ma and Latecki, 2011; Mokhtarian, 1995).

Our method is a geometry-based since we use parts of 2D silhouettes, and an appearance-based method, because we use different views of 3D objects.

In this paper, we propose a new approach to recognize descriptors of 2D silhouettes. The silhouette is represented with a single closed contour (Larabi et al, 2003). We used textual descriptors of silhouettes for the matching and the indexing processes (Aouat and Larabi, 2009). Due to noise, the descriptors may be very different even though the silhouettes look alike. Comparing such silhouettes descriptors will result in a mismatch, for this reason an algorithm was developed to smooth the outline shapes (Aouat and Larabi, 2010).

In this paper, we assume that the smoothing and the indexing processes were already performed (Aouat and Larabi, 2010; Aouat and Larabi, 2009), and we compute efficient similarity measures to complete the recognition process.

The paper is structured as follows:

In the second section, we give an overview of the outline shapes part-based method (Larabi et al, 2003). In the third section, we will explain the necessity to compute similarity measures after the indexing process. In the fourth section however, the first similarity measure based on parts areas will be presented, followed, in the fifth section, by the second similarity measure based on Geometric quasi-invariants, we will also validate the quasi-invariants values we maintain for the recognition process. In the last experimental section, we use real images of two well known databases and discuss the descriptors matching and recognition after applying both similarity measures on textual descriptors of used silhouettes.

2 TEXTUAL DESCRIPTION OF SILHOUETTES

The part based method (Larabi et al, 2003) builds shape descriptors by using the minimum rectangle (MR) that encloses the outline shape (Graham, 1972). (OXY) is the referential attached to MR chosen such as the origin O is the left top edge of MR (see Figure 1).

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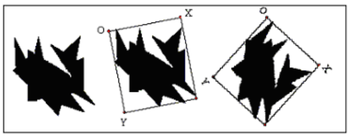

Figure 1: Initial silhouette, the minimum rectangle MR, and the rotated silhouette

From this geometric description, the outline shape may be drawn without ambiguity implying the propriety of uniqueness and preservation of perceptual structure. The invariance of this description to rotation is guaranteed by the sweep up of the silhouette following one of the directions of the minimum rectangle encompassing the silhouette. For more details refer to (Larabi et al, 2003).

Textual descriptors of silhouettes are sensitive to noise; indeed noise may modify and distorts the outlines and their descriptors such as shown in Figures 2 and 3.

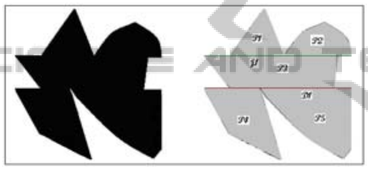

Figure 2: A non-noisy silhouette and its decomposition.

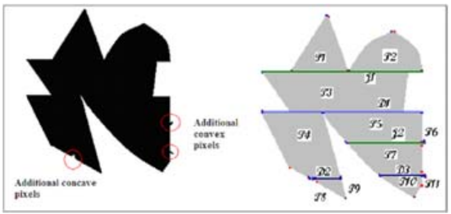

Figure 3: A noisy silhouette and its decomposition.

The coarse descriptor of the silhouette in Figure 2 is: <CP><CP>P1 P2 J1 P3</CP> D1 <CP>P4 D2 P8 P9</CP> <CP> <CP>P5 P6 J2 P7</CP> D3 P10 P11</CP></CP> while the coarse descriptor of the silhouette in Figure 3 was: <CP><CP>P1 P2 J1 P3 </CP> D1 P4 P5</CP>.

3 INDEXING PROCESS

The database of shapes models, represented by their textual descriptors, is indexed using the following data as shown in Figure 4:

The index is: (5, 1, 1, 01, 3, 3, wjjh&wjjw) where: (**5** is the number of parts, **1** is the number of junction lines, **1** is the number of disjunction lines, **01** indicates that there is a junction line followed by a disjunction line, **3, 3** indicate respectively that there are three parts in relation with the first and the second separating lines. The set of characters **wjjh&wjjw** indicates that in the first separating line, there are four segments with attributes w, j, j, h and in the second separating line, there are four segments with attributes w, j, j, w.)

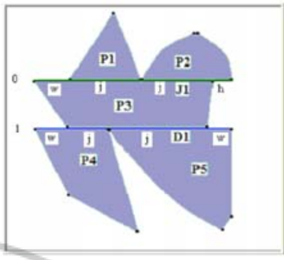

Figure 4: Indexing a shape.

Different shapes may have the same index, the difference between them is in the geometry of their parts. In order to perform the full matching for the recognition process, two similarity measures will be used: the Parts Areas and the Geometric Quasi-invariants.

4 PARTS AREAS

Let us consider the two curves f and g shown in Figure 5. If f tends towards g (f ~ g) then the area between f and the (OX) axis will be approximately the same area as that between g and the (OX) axis. In this case the difference between the two areas is close to zero. As the shape is included into the Minimum Rectangle (MR) which is the referential OXY (see Figure 1), so all (OX) and (OY) coordinates are positive therefore we can write:

$$\left| \int_a^b f(x)\,dx - \int_a^b g(x)\,dx \right| \sim 0$$

All selected models after the indexing process, will have the same index as the query, so they will evidently have the same number of parts. The query silhouette will be compared with all models of its class that have the same index and the same number of parts. The recognition aims to select the best model which is close to the query.

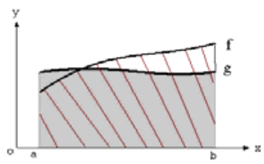

Figure 5: Difference of areas between two curves.

The first step consists in reconstructing silhouettes from their descriptors. In the second step, we use the same referential for both query and model silhouettes, this is possible due to the use of the minimum rectangle as the referential. The last step is the computation of the areas:

Let us consider two vectors Vq (Sq1,Sq2 ,…Sqn) and Vm (Sm1,Sm2 ,…Smn) containing respectively parts areas of the query and those of the model.

The first similarity measure between two silhouettes is given by:

$$\sum_{i=1}^{n} (Smi-Sqi)^2$$

where n is the number of parts of both silhouettes. The best selected model is that which minimizes this similarity measure.

5 QUASI-INVARIANTS

The Geometric quasi-invariants (ρ, θ) are defined as the angle θ between the intersecting segments, and the segments length ratio ρ, (see Figure 6).

$$\rho = \frac{\overrightarrow{a_0a_1}}{\overrightarrow{a_0a_2}} \qquad \theta = \arccos\frac{\overrightarrow{a_0a_1}.\overrightarrow{a_0a_2}}{\|\overrightarrow{a_0a_1}\|.\|\overrightarrow{a_0a_2}\|}$$

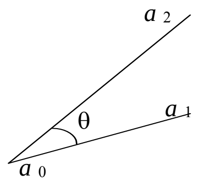

Figure 6: Geometric quasi-invariants (ρ , θ).

The (ρ, θ) pairs found in each image vary slightly with a small change in the viewpoint, and are invariant under similarity transform of the image (Gros, 1994; Lamiroy and Gros, 1996).

In order to study the variation of the pair (ρ, θ) between successive segments, we considered, in an offline study, 28 polyhydric objects and several images (856 images) of each object taken under different points of view (average object rotation is 20^0). Identical views have been eliminated of the image base to avoid redundancy. We then extract the geometric features: that are the intersecting segments and we analyze the similarities to determine the similarities values. We use ln(ρ) instead of ρ because ln(ρ) follows a uniform distribution. For each two successive images of the rotated object, we analyze identical geometric configurations and evaluate the difference between the quasi-invariants we extracted from. 90% of configurations show (see Figure 7) a quasi invariant distance less than: $(\ln(\rho) = 0{,}23\ ;\ \theta = 18{,}61°)$

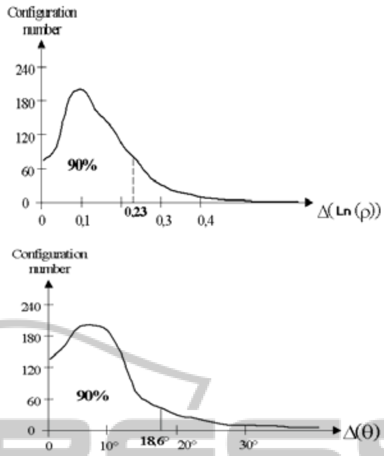

Figure 7: Similarity of quasi-invariants.

6 EXPERIMENTATION

Experiments are done on two known databases (Mokhtarian et al, 1996; Leibe and Schiele, 2003).

First we apply the smoothing process on the outline shapes (Aouat and Larabi, 2010), then we apply the part based method to obtain their textual descriptors (Larabi et al, 2003). The second step is to perform the indexing process which leads to determine many classes; all objects of the same class have the same index.

The first similarity measure is computed for each model of each class (see examples in Figures 8 and 9). “Dif” is the difference of areas between the model and the query. (Dif = |the area of the model- the area of the query |). The symbol “R” means that the model is recognized, so it verifies, also, the second similarity measure. In case of many recognized models, we sort them following parts areas, in order to find the best model for the query.

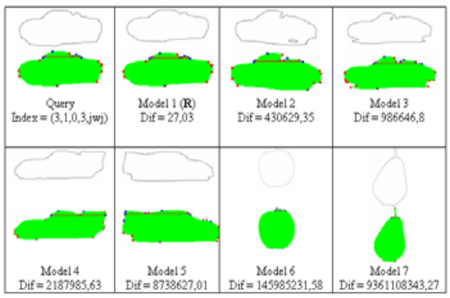

Figure 8: Recognition of a car (from Leibe and Schiele database).

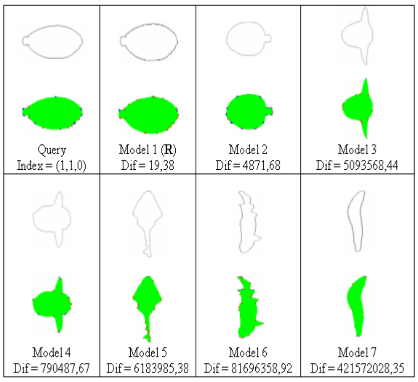

Figure 9: Second example in Mokhtarian database for the recognition process.

7 CONCLUSIONS

In this paper, we proposed a new method for silhouettes recognition. Textual description, smoothing and indexing were previously performed (Larabi et al, 2003; Aouat and Larabi, 2010; Aouat and Larabi, 2009).

We have seen the importance of applying efficient similarity measures to achieve the recognition process.

Two similarity measures have been proposed:

- The use of parts areas: indeed when two objects are almost similar, the difference between their areas is close to zero. The use of this measure is not sufficient because different parts may have the same area.
- The computation of geometric quasi-invariants in order to efficiently compare the query silhouettes geometry with the models geometry.

Conducted experiments, performed on two known databases, showed the method efficiency and its usefulness to resolve the problem of the recognition process.

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