Boundary Shape Recognition Using Accumulated Length and Angle Information

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Abstract. In this paper we present a method to recognize shapes by analyzing a polygonal approximation of their boundaries. The method is independent of the used approximation method since its recognition strategy does not rely on the number of segments composing the shape. Length and turning angle information are extracted from the chain of segments. The comparison method is invariant to scale, translation and some occlusions of the extracted contour. A simple pre-processing method, also based on arc-length features, is presented to be used as a coarse fitting method to determine angle rotation and as a first filter to eliminate non pertinent candidates.

1 Introduction

Content based image retrieval is one of the topics of interest in the computer vision field which nowadays is at its very peak, due to the growth in the last years of the amount of stored graphical information. For this kind of data, underlying analysis processes mainly lie on graphics recognition, allowing then classification of the images, typically in terms of available symbols. From a general viewpoint, several kind of recognition approaches can be involved, according to data representation. Bitmap images are usually analyzed with statistical methods, which are time-consuming and quite accurate, but can also be analyzed with structural methods, faster but requiring a pre-vectorization step. In the context of content based image retrieval, the last approach is usually preferred, as the amount of considered data implies the use of efficient processes.

One of the most important visual features when classifying images is shape of the represented objects and subsequently a lot of literature deal with object recognition by shape. Zhang and Lu review in [9] shape representation and description techniques. A great part of the existing methods focus on the contour to represent the shape. Those contour-based descriptors are usually classified as statistical or structural approaches. Focusing in structural descriptors, for reasons explained above, a prior polygonal approximation of the contour is required, yielding a description of the shape in terms of segments and structural relationship between them. From these data, Stein and Medioni in [5] extract a feature vector achieving a more global viewpoint than a pairwise segment comparison.

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But, since in the literature we can find many strategies to perform a raster-to-vector conversion, and by now it does not exist any "perfect" algorithm, as argue Tombre *et al.* in [6], it is interesting to define a method to discriminate shapes between them, independently of the used approximation method, robust with respect to the numbers of resulting segments and with respect to the generated artifacts.

To give an example, Rosin and West method [3], has the advantage that it does not use any parameter to compute the approximation. This generality has its negative part, since in the high curvature points, the method tend to over-segment the shape. On the other hand, Wall and Danielsson method [7], use a threshold to determine at which points the curvature of the shape is high enough to cut the pixel list into several segments. But this method has to be well tuned to provide accurate results. Even if both strategies perform good approximations, they can result in very different segment chains, in particular for the number of segments of these chains. A method which aim to be independent of the approximation strategy has to be independent of the number of segments composing the shape. Most of methods try to counteract the effect of the cardinality of the segment chain by re-sampling the polygonal approximation at extremal points, as in [2,8]. Our presented method aims to be invariant to the number of segments and consequently of the approximation method.

The key idea of the proposed method is that two shapes are similar if, starting from a reference segment, and covering a certain length, we have turned the same angle in both shapes. Thus, accumulated lengths and accumulated turning angles are used as feature vectors to describe a shape, which aims to achieve cardinality independence of the analyzed segment chains.

The remainder of this paper is organized as follows: we will introduce in the next section how we compute a coarse matching between two shapes. This first step will be used as a pre-processing method to determine angle rotations between shapes and as a first filter if the two shapes are found too different. In section 3, the matching method is presented, using accumulated length and turning angle as features to describe a given shape. We provide the experimental results in section 4. Finally a summary and discussion of extensions and future work is presented in section 5.

2 Coarse Shape Fitting: Undoing Rotation

Given a closed contour of a shape $S = \{s_1, ..., s_n\}$ polygonally approximated with n segments and total perimeter length $|S|$, we encode all the segments by a tuple of numbers (l_i, ϕ_i), where l_i denotes the length of the segment s_i and ϕ_i denotes the angle between s_i and s_{i-1} in the counterclockwise direction.

We compute a vector of accumulated lengths, normalized with the total perimeter of the shape.

$$\ell(i) = \frac{1}{|S|} \times \sum_{k=1}^{i} l_k \quad where\ 1 \leq i \leq n \tag{1}$$

We then define a mapping function f which assign the corresponding turned angle ϕ_i at each value of $\ell(i)$.

$$f(\ell(i)) = \phi_i \tag{2}$$

Sudden direction changes in the analyzed shape result in pulses in f arc-length function which act as discriminative key points to fit two shapes. As the number of segments of two shapes to compare can be completely different, we need to define a method which is independent of the number of segments. An equally sampling of $\ell(i) \in [0, 1]$ is done to compare a couple of vectors of the same size.

However, since we compute a vector of accumulated length, f values has to be shifted in the x axis depending on the reference segment choice. Given two shapes to compare, a normalized cross correlation can be used as a fast method for template matching of the two vectors, and then find the correct shift between two segment lists where the maximum correlation value has been reached. Experimentally we find that using only a 75% of the number of segments composing a shape as sample rate is enough to find correct shift between two shapes. We can find an example of shape fitting to determine angle rotation in Fig. 1.

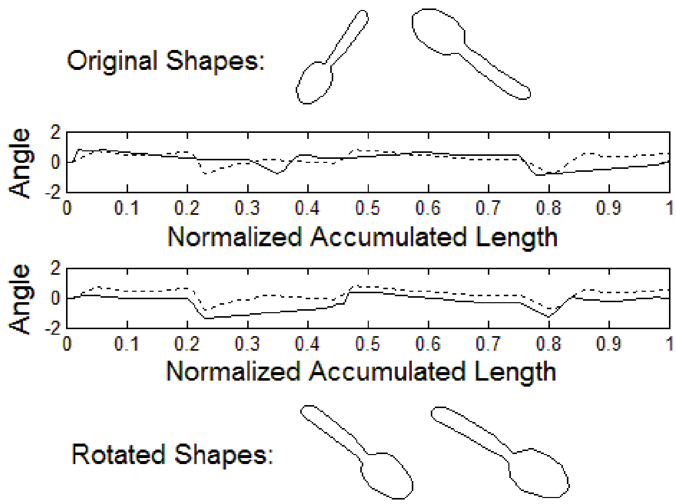


Fig. 1. Shapes and arc-length plots before and after the fitting process. A normalized cross correlation is computed between the two functions to determine the shift between them, thus normalizing the shapes to a certain rotation.

But polygonal approximation methods usually introduce some small noisy segments, which may not seem very important since they have small lengths, but may have important turned angle values. The presence of these small segments results in pulses of elevated values in the f function. Even though this possible presence of noise, the method could be used as a pre-processing step to identify a rotation parameter to correctly choice a reference starting segment, thus determining the rotation between two shapes. The method is also used as a first filter when compared shapes have completely different representations. Let us further detail in the next section how can we improve the presented method to be used for boundary shape recognition.

3 Shape Matching

Following the same idea than the presented coarse fitting method, we describe shapes in terms of accumulated length and turning angles. To avoid the influence of the noise introduced by the presence of small segments, we use accumulated turning angles instead of the mapping function to guarantee more stability.

$$\Theta(i) = \sum_{k=1}^{i} \phi_k \tag{3}$$

Now, the idea of this shape comparison is to use the ℓ values to know how many segments are necessary in both shapes to achieve a certain covered length and then look if the turned angles Θ are close or not. Let us further detail how these shape matching is performed.

Given two shapes to compare $S_1 = \{s_{11}, ..., s_{1n}\}$ and $S_2 = \{s_{21}, ..., s_{2m}\}$, having $n <= m$, we compute their ℓ and Θ feature vectors. For all the segments of S_1 we check how many segments of S_2 are necessary to achieve a similar length.

$$L(i) = arg \min_{1 \leq j \leq m} (abs(\ell_1(i) - \ell_2(j))) \tag{4}$$

Given a certain number i of segments of the shape S_1, $\ell_1(i)$ is the total covered length from the starting segment up to the ith segment, $L(i)$ is then defined as the number of segments of S_2 required to achieve the closest covered length. To be more tolerant to the presence of small segments which can distort the distance between accumulated angles in a given accumulated length, we denote as $\widetilde{L(i)}$ the segment set containing $L(i)$ and its two adjacent segments, accumulating only the minimum distance between $\Theta_1(k)$ and $\Theta_2(L(k-1))$, $\Theta_2(L(k))$ and $\Theta_2(L(k+1))$. To give a distance between the two shapes, we look if at similar lengths, we have a similar turned angle. The distance $d(S_1, S_2)$ between the two shapes S_1 and S_2 is computed as follows

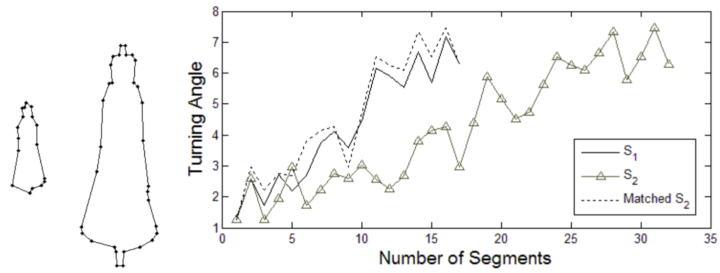
$$d(S_1, S_2) = \sum_{k=1}^{n} \min \left(\delta(\Theta_1(k), \Theta_2(\widetilde{L(k)})) \right) \tag{5}$$

Being $\delta(\phi, \theta)$ the difference between two turned angles considering that angles close to 0 and 2π must have very low difference, and thus computed as a distance in the trigonometric circle

$$\delta(\phi, \theta) = \sqrt{(\cos \phi - \cos \theta)^2 + (\sin \phi - \sin \theta)^2} \tag{6}$$

We can appreciate in Fig. 2 how the turned angles plots are matched between the two shapes of different scale and number of segments. Even if the distance between the two resulting angle vectors $\Theta_1(k)$ and $\Theta_2(\widetilde{L(k)})$ is elevated, we can see that the trend of both of them is almost the same.

Better recognition results are reached when the distance is formulated more accurately. DTW (Dynamic Time Warping) is a well-known method used in speech recognition field that measures similarity between two sequences which may be shifted in time, involving the alignment between two sequences with minimum edit cost. The use of this kind of edit distances [4], can fix the remaining shifts between angles giving better results than a bin to bin comparison of sequences. But a simple analysis of the slope and variations of the resulting functions yields acceptable results.



a) b)

Fig. 2. Angle fitting. (a) S_1 and S_2. (b) Turning angle plots. The influence of the number of segments composing the shape has been avoided, and the resulting turning angle plots are comparable.

We can see that the presented method can find a matching between close shapes undergoing some noise, scaling and different number of segments, since the used features are based on the accumulation of lengths and angles. The invariance to rotation is not guaranteed by the matching method itself because as all the used features are accumulated metrics, the method is very dependent on the first segment choice. But the previous coarse fitting method which use almost the same computed features makes possible the use of the presented method with no significant complexity addition.

4 Experimental Results

To test the method, we use the MPEG silhouette database consisting of 1400 images grouped in 70 different shape classes. In Table 1, we show the resulting ten most similar images when querying a given shape against the whole database. As we can appreciate, the retrieved images are usually components of the queried class, or at least, for the false positives, are quite visually similar. The number of segments composing the queries and the results are also shown, and we can

Table 1. Sorted ten similar symbols. (Number of segments composing the shape approximation).

Query	1*st*	2*nd*	3*rd*	4*th*	5*th*	6*th*	7*th*	8*th*	9*th*	10*th*
(87)	(114)	(90)	(10)	(93)	(18)	(101)	(14)	(109)	(109)	(100)
(22)	(22)	(28)	(22)	(40)	(21)	(14)	(16)	(34)	(20)	(24)
(34)	(34)	(33)	(23)	(30)	(32)	(28)	(27)	(29)	(32)	(28)
(34)	(39)	(38)	(36)	(37)	(39)	(37)	(36)	(35)	(40)	(33)

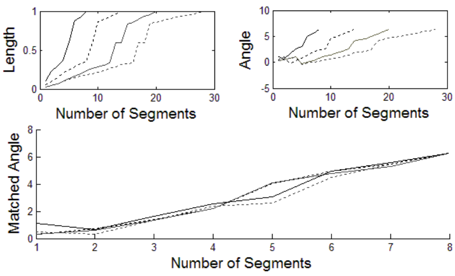


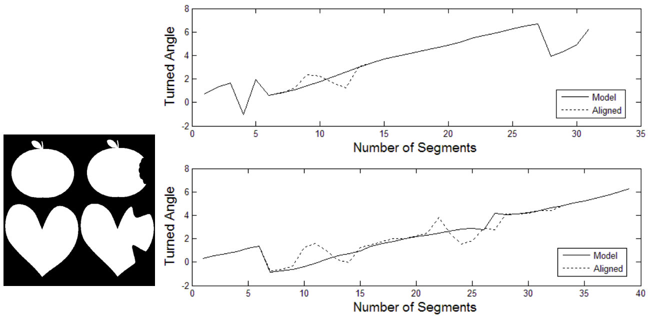
Fig. 3. Shape matching depending on the number of segments. The matched angles have the same trend independently of the number of segments composing the shape (8, 14, 20 and 28).

appreciate that similar shapes with a significant difference of segments can be matched. In [1] different shape descriptors as CSS, wavelet representations of contours, Zernike moments, etc. are tested against this database, performing good recognition tasks. All these descriptors are pixel-based, and thus can not be compared with the presented method which aims to discriminate polygonal approximations of graphical symbols by a fast and simple representation.

To see if the method is really tolerant to changes in the number of segments composing a shape, we compute polygonal approximations of a heart shape at different scales, resulting thus in a different number of segments, going from 8 to 28 segments. In Fig. 3 we can appreciate that the resulting turning angle functions are matched in an acceptable way. Notice that the shape with less segments is always the one taken as model, thus introducing some noisy results if the approximation is too rough.

a) b) c) d)

Fig. 4. Couples of shapes belonging to the same class but unable to match. (a) Beetle class. (b) Deer class. (c) Squared-device class. (d) Circular-device class. Even if these shapes belong to the same class, their boundaries are too different to allow a match.



a) b)

Fig. 5. Matching partially occluded shapes. (a) Model and occluded shapes. (b) Turning angle plots. Even if there is an interval where the turning angle does not fit,the method is able to recover the tend between the two turning angles giving acceptable distances between model and occluded shape.

However, the presented method has its limitations. With some classes which can seem similar, but which are composed of shapes having important local distortions of length and angles of their contour segments, the method is unable to find the similarity between objects of these classes as most of contour-based approaches. Some examples are shown in Fig. 4. But the method is still tolerant to slight changes in the contour due to occlusions, as shown in Fig. 5 were we can appreciate that the resulting turned angles are totally matched in the part of contour not affected by the occlusion.

5 Conclusion

In this paper we presented a method for shape recognition based on accumulated length and angular information. Having a polygonal approximation of the contours, two shapes are considered similar if starting from a reference segment and covering a certain length, the accumulated turned angle is also similar. A method based on a similar idea is also presented as a pre-processing step to act as a first filter when shapes are found completely different, and to determine the correct reference segment guaranteeing invariance to rotation.

Even if a lot of shape descriptors based on an approximation of the contour exist in the literature achieving great recognition rates, we consider that is very important to define description techniques able to maintain its performance in despite of the approximation method used. Most existing methods seem to be designed *ad hoc* for an approximation method in particular, or at least need a tuning of parameters depending on the number of segments which composes a shape. The use of accumulated metrics allow to be invariant of the cardinality of the segment chains encoding a shape. However, the use of accumulated length and angle has its drawback, since the method is dependent on a good reference segment choice. It would be interesting to further investigate how to provide rotation invariance without the need of a pre-processing step.

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