MULTIVARIATE ANGLE SCALE DESCRIPTOR FOR SHAPE RETRIEVAL

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ABSTRACT

Boundary based shape descriptors have been widely used in image retrieval problems. A plethora of contour-based descriptors regarding the shape as a 1-D signal sequences, can be found in literature. Centroid Contour Distance –CCD- as well as Angle Code Histogram (ACH) are well known and extensively used descriptors. In this paper the Angle Scale Descriptor -ASD- is introduced which is based on the angle sequences as they are computed at different scales. It is a multivariate approach where each feature vector consists of angle values produced across by the different scales and includes information from fine to coarser scales. This descriptor provides information for shape boundary which could be efficiently combined with other descriptors.

In the present paper, improvement of the Angle Code when using the multi-scale representation will be shown, as well as the enhancement of the overall retrieval process when fusing the ASD with CCD descriptors that provide complementary shape information.

Keywords: multi-scale representation, multivariate descriptor, shape retrieval, fusion.

1. INTRODUCTION

Regarding the progress made in computer storing, image databases are becoming bigger so the necessity of efficient algorithms is obvious. The image retrieval problem is a common issue when dealing with database organization. Although text-based image retrieval is very fast, CBIR is preferred instead, as it captures more information than a plain textual description.

There can be found many methods in literature for shape recognition [1,2]. Shape context descriptor [3] is one of them and has a significant impact to the feature extraction and shape matching research. An improvement of [3] is introduced in [4], well suited for articulated objects. Existing methods, such as [5] which is the state of art, achieve high retrieval performance scores, having however the problem of high computational cost.

An alternative way to extract information is the idea of capturing different scales of the image [6]. Most multi-scale techniques make use of the Scale Space theory. Scale Space theory stems from the computer vision literature [7] and has been used in terms either of signal smoothing or image filtering. In Curvature Scale Space (CSS) [8,9] the signals of x,y coordinates are smoothed successively and a CSS image is composed where the curvature zero crossings are counted at different scales. A main disadvantage of the CSS representation is the sensitivity of the curvature to noise. In [10] an improvement of the CSS method is proposed. The Curvature Scale Image (CSI) is constructed using Fourier Descriptors so in that way information from the whole image is available.

Motivated from the original implementation of Scale Space theory a novel approach of multi-scale representation is introduced. It is based on the Angle Code descriptor [11] but uses the sequence of angles instead of the encoded scheme. The angles' sequence forms a descriptor that captures information about the shape's contour orientation. The information provided by the angles has not been extensively exploited. Hence, it is in the authors' intention to make a contribution to the above literature gap. Existence of noise influences the angle calculation. However, the proposed consecutive angle's scaling results in a family of multi-scale signals. Therefore, except from the computation of angles at varying levels of detail, elimination of noise influence is achieved as moving to coarser scales. The "across" Angle's sequence Scales that leads to a set of multidimensional vectors, is the core of the new Angle Scale Descriptor (ASD). By dropping the time index, the set of the extracted multi-scale signals does not get influenced by any possible rotated versions of the object. Therefore, comparison of shapes is rotation invariant while translation invariance is given. Scaling invariance can be easily achieved by an appropriate downsampling to the shapes' contours. The method is tested on the MPEG-7 shape database, achieving promising results. While this feature extracts essential information from shapes, combined use with other complementary features is more challenging. In that spirit, and in order to enhance the overall retrieval performance, combination of the Angle Scale Descriptor with the Centroid Contour Distance (CCD) [12] feature is accomplished at a late fusion stage. The idea of calculating the distances between the contour points and the centre point of a closed curve, is a feature commonly used [13], as it captures information of the shape's contour in a quite informative way.

The rest of the paper is organized as follows. In section 2 the feature extraction, as well as the matching stage are described. In section 3, the fusion of CCD and ASD is provided. Experimental results are shown in section 4 and finally the paper concludes in section 5.

2. THE ANGLE SCALE DESCRIPTOR (ASD)

Representing a sequence at different scales originates from the well known Scale Space representation [7], which handles the signal as a one-parameter family of smoothed signals. However in the present work multi-scale representation Gaussian smoothing or any other convolution process is not involved. Description of an angle sequence at multiple scales captures both global and local information of it. As moving to coarser scales, information at different levels of scales is revealed.

The proposed descriptor lays in the category of multivariate feature extraction, so an appropriate multidimensional matching stage is adopted.

The well studied Angle Code descriptor [11] will serve as the basis of the introduced feature extraction. In addition, the Centroid Contour Distance descriptor [12] will be used in next section for fusion purposes.

2.1 The angle sequence

The Angle Code (AC) descriptor [11] has been widely used by means of its histogram [14]. The AC sequence descriptor is defined by the sequence of consecutive angles formed by the boundary points. Appropriate quantization of the angles leads to an AC scheme, which can be easily expressed by a 9-bins histogram. Assuming that the original data consists of N points, the angle at a boundary point i, i=1:N, is formed by two successive vectors connecting the point i with the boundary points i-r and i+r. Let x_i, y_i be the coordinates of point i. Then the angle at point i is defined by the cosine's law, where $\vec{v}_{ic} = (x_{i+r} - x_i, y_{i+r} - y_i)$ and $\vec{v}_{i\ell} = (x_{i+r} - x_i, y_{i+r} - y_i)$ stand for the vectors coming to and *l*eaving from the point i respectively.

$$a_i = \cos^{-1}\left(\frac{\vec{v}_{ic} \bullet \vec{v}_{i\ell}}{|\vec{v}_{ic}| \cdot |\vec{v}_{i\ell}|}\right) \in [0^o, 180^o] \tag{1}$$

In the present work, the consecutive angles are not quantized, so the respective angle sequence (**as**) of angle a is considered instead:

$\mathbf{as}(a) = [a_1\ a_2\ \ldots\ a_i \ldots a_N]$, where a_i is defined at (1).

2.2 The multi-scale angle sequence - ASD

As it is obvious, the parameter r defines the 'locality' in which the angle a_i is calculated. Therefore **as** is greatly influenced by the selection of the parameter r. Adopting different values of r results in creating different scales of the original **as** (Figure 1). More specifically , by augmenting the parameter r the **as** becomes more coarse, as details are removed. Small values of r capture small changes in the angles of the boundary, while increasing values of r represent the global behaviour of the signal. In that way, r can be regarded as the scaling factor. Thus the whole procedure of angle-scaling is considered to imitate the well known Scale Space representation. Implementing the above procedure k times, a family of angle sequences (**f-as**), representing the discussed scaled signals is acquired:

$\mathbf{f\text{-}as}(r_j) = [\mathbf{as}(a,r_1);\ \mathbf{as}(a,r_2);\ \ldots\ \mathbf{as}(a,r_j);\ \ldots\ \mathbf{as}(a,r_k)]$, j=1:k
where $\mathbf{as}(a,r_j)$ is of length N.

The proposed descriptor handles the above scale space representation as a set of N, k-dimensional vectors. The Angle Scale Descriptor (ASD) is the 'across' Angle's sequence Scales (Figure 2) implementation of $\mathbf{f\text{-}as}(r_j)$:

$$\mathbf{ASD} = \{\mathbf{f\text{-}as}(1{:}k,1),\ \mathbf{f\text{-}as}(1{:}k,2),\ \ldots\ ,\mathbf{f\text{-}as}(1{:}k,N)\} \tag{2}$$

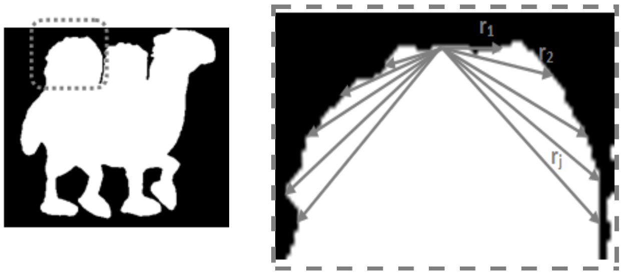

Figure 1: A*ngle computation at a boundary point using different scales.*

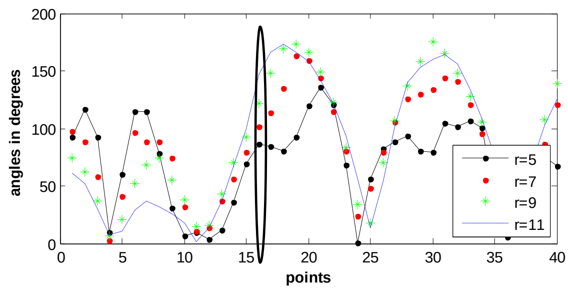

Figure 2: P*art of a camel shape with N=40 points is shown. The points selected across at different scales in the encircled area, formulate a vector point of the ASD.*

2.3 Matching Method

The introduced Angle Scale Descriptor (2), resulted in a set of N k-dimensional points. Provided that each shape is represented by a certain number of sub-vectors, a multivariate test is needed in order to quantify (dis)similarity among two shapes. In this paper the Mutual Nearest Point Distance (MNPD) measure is adopted [15]. Given two sets of n_1 and n_2 k-dimensional points,

$H=\{h_i\}$, $i=1{:}n_1$ and $G=\{g_j\}$, $j=1{:}n_2$

the MNPD is calculated as follows:

$$MNPD(H,G)=\frac{\sum_{i=1}^{n_1} d^{min}(h_i - g_{j=1:n_2}) + \sum_{j=1}^{n_2} d^{min}(g_j - h_{i=1:n_1})}{n_1 + n_2} \in [0,1] \quad (3)$$

For each k-dimensional h point the distances to all the g_j points are computed. Summation of the nearest distances leads to the first term of the numerator of (3). The same procedure is repeated in a bi-directional manner, in order to avoid circumstances where the sets of vectors share small distances in one-direction calculation, while they are not similar. The whole aggregation is normalized according to the number of points that each set of vectors owns. In the present work all shapes are represented by N points, so $n_1 = n_2 = N$. A small value of MNPD means similarity of the compared sets. Other alternative to the MNPD is the WW-test [16], which is more accurate but with higher computational complexity.

3. FUSION FOR SHAPE RETRIEVAL

As it is known, a shape descriptor well-suited for shape retrieval should contain sufficient information concerning the shape. The proposed Angle Scale Descriptor reveals information about the angles of the shape's contour; therefore its combination to a feature of complementary information would improve the retrieval performance. The Centroid Contour Distance (CCD) descriptor is employed in this paper.

The (CCD) descriptor [12] is formed by the consecutive boundary-to-centroid distances. Let i be a shape contour point having (x_i, y_i) coordinates. Assuming that the shape centroid has coordinates (x_c, y_c), the CCD curve is computed for all N boundary points:

$$CCD(d)=[d_1\ d_2 \ldots d_i \ldots d_N], \quad d_i = \| x_i - x_c, y_i - y_c \|_2 \in [0,1]$$

The distance between two shapes represented by CCD sequences is acquired by calculating the minimum Euclidean distance of all the rotated versions.

Combination of the ASD and the CCD is accomplished at a late fusion stage, by averaging the different scores. An obvious advantage of late fusion is that combining descriptors of different feature extraction methods is feasible. Moreover, the percentage at which a descriptor would participate to the overall performance can be regulated by a weighted average.

Let D_{CCD} and D_{ASD} are the matching scores when comparing two shapes, using the CCD and the ASD representation respectively. For the ASD dissimilarity score, the MNPD distance is used. Fusion is easily deduced by calculating a weighted average of the dissimilarity values. Retrieval process will proceed with the new dissimilarity measure. In the evaluation section the enhancement of the retrieval process when fusing the descriptors will be shown.

4. EVALUATION

The introduced method was evaluated using the set B of the MPEG-7 shape database. This database consists of 1400 images, equally classified into 70 classes. Set B is used to test similarity-based retrieval methods and to examine shape descriptors' robustness to several distortions. A sample of the MPEG-7 part B database is shown in Figure 3.

Figure 3: *Sample of the MPEG-7 database.*

4.1 Pre-processing

An initial step of the pre-processing stage is the boundary coordinates extraction. As shapes are stored in a binary form, implementing a contour tracing algorithm does not pose any difficulties. Next, all shapes' boundaries are downsampled so as to obtain the same length N. In the experiments that follow, N was set to nearly 180 points.

4.2 Experimental Results

Evaluation of the retrieval process was implemented using precision and recall diagrams and the so-called bullseye test. Precision measures the correct hits over the total number of retrieved images. Each image of the database serves as a query image, and the average value of the whole procedure is calculated. Recall is defined as the ratio of the correct hits to the correct database's hits. In the bullseye test, each shape in the database is taken as a query and matched to all shapes in the database (including itself). Correct hits among the first 40 matches are counted.

In Figure 4, the improvement of the ASD over the AC is depicted. Implementation of the ASD used k=15 different values of r, r=5:2:24. Determination of the adopted parameters was set experimentally. In Figure 5, fusion of the ASD & CCD results in higher precision-to-recall rates, as it merges different kinds of information. The CCD sequence was normalized according to max value. The weight was set to 0.6 for the ASD and to 0.4 for the CCD.

Finally, in Table 1 a summary of the experimental results is given, using the bullseye score. In addition, a comparison with the Curvature Scale Space method [8] is made.

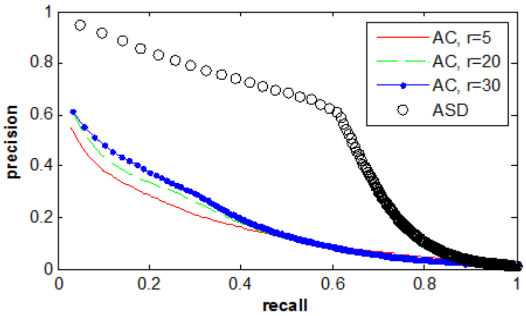

Figure 4: *A noticeable improvement of the AC is achieved when adopting the ASD, using k=15, r_1=5, r_k=34.*

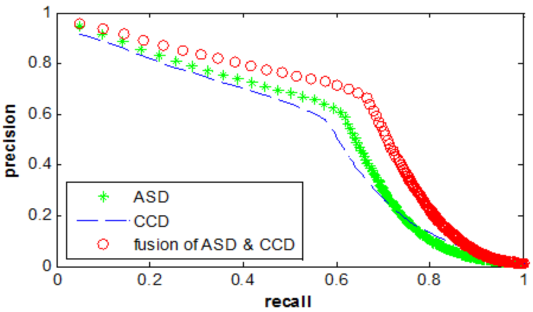

Figure 5: *Fusion of ASD & CCD enhances the single descriptors' performance.*

Table 1: *Retrieval score for the MPEG-7 database*	
Method	Bullseye score (%)
CSS	75.44
AC (r=30)	43.14
ASD	**70.51**
CCD	68.67
Fusion of ASD&CCD	**76.20**

5. CONCLUSIONS

This paper introduces a new way to extract features at different scales. The 'across' angle scales implementation of the multi-scale signals as well as late fusion of different features are the contributions of the present work. The proposed descriptor captures both global and local information of the shape's contour and explains the outperformance of the ASD against AC. The weighted score's average of the ASD and the CCD proved very promising, while fusion with several other descriptors is straight forward. Combination with some global descriptors (eccentricity, solidity etc) is expected to lead to higher retrieval scores. Furthermore, the parameters selection is an issue that needs further research. Identification of convex or concave angles is also possible and would improve the overall performance of ASD. The introduced method was applied in the set of 1400 shape MPEG-7 database, however application to other sequences-such as handwriting, biometrics etc is almost straightforward.

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