An Approach Making the Shape Matching Techniques Robust to Noise

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ABSTRACT: *Computer vision has been an active research area for the past few decades. It is being used in many fields of industries for example digit recognition and handwriting recognition in banks, industrial parts recognition etc. Shape matching is an important sub-domain of Computer Vision, and relies on effective shape representation techniques. These techniques must be developed in order to effectively estimate similarity between the shapes. Major similarity estimation results correspond to effective shape matching techniques. These shape matching techniques or shape descriptors must be invariant to variances or noise in the shape for accurate shape matching results. But, unfortunately, these descriptors are not invariant to noise like small cracks or slits present in the contour of the image. These cracks changes the shape boundary which changes the shape altogether. In this paper, we propose a noise removal approach that significantly improves the performance of sophisticated shape matching techniques. Existing shape matching techniques focus on complex algorithms without giving much consideration to the noise removing preprocessing techniques. These preprocessing techniques can reasonably improve the accuracy where the shapes are affected by cracks. We present a preprocessing approach to identify and remove small cracks and slits in the shape contour. It has been observed that these cracks or slits introduce changes in a manner which makes classification of shapes difficult. This technique is simple and effective and may be used to preprocess the images before applying sophisticated shape representation techniques to improve their accuracies. The effectiveness of proposed pre-processing approach is verified using publicly available shape datasets.*

Keywords: Preprocessing Shape, Shape Matching, Contour-BAsed Approaches, Cracks, Noise, MPEG-7

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1. Introduction

A huge range of digital images are used in applications of image processing. Different properties of these digital images are being drawn out by a lot of studies. These studies are aimed at the correct matching of images using the properties of an image. These properties include shape, color and texture amongst which shape is considered to be able to describe an image alone. Thus shape matching is an active study these days which largely depends upon shape representation techniques and methods to measure similarities between shape. These shape representation techniques and similarity measuring methods need to be effective enough to produce accurate shape matching results.

Accurate shape matching relies on shape representation techniques representing the shape accurately in the presence of false alterations or distortions. Previous studies have provided many of the shape representation procedures which were intended to deal with the distortions present in the content of the image like rotation, articulation, scaling and jag etc. But unfortunately, these representation techniques failed to address the problem of shape contour alterations. The false alterations present in the contour of an image cause shape misrepresentation.

Most of the earlier studies focused only on developing complex systems, in shape matching and recognition, to increase the accuracy of shape matching and retrieval systems. Many Sophisticated shape representation and matching techniques have been presented which produce excellent matching results in the presence of variety of distortions such as noise, affine deformations, occlusion and articulation. These techniques usually engage sophisticated shape descriptors, complex distance measures and computationally complex matching techniques to achieve good shape matching results in the presence of these shape alterations. Consequently, they consume substantial amount of time for shape matching and retrieval. Little attention has been given to the efficiency issue.

Thus there is a significant need of a quick identification technique for these false alterations or distortions. These quick identification techniques must beless complex and less time consuming. Thus they will be an aid to preprocess the images of the dataset leading to less number of false hits. Moreover, the results of the already available shape matching techniques will become better.

In this paper, our goal is to provide a novel pre-processing technique to reduce the effect of shape alterations which occur at the shape contour. These variations are small slits and cracks. In figure 1, these variations are represented by few samples of the shapes affected by noise. Although it does not change the visual perception of the shape but exhibits a few obvious slits which changes the boundary of the shape by adding some extra boundary points making up cracks. Our approach will remove these extra boundary points. Thus, the proposed approach will preprocess the shape by removing noise from the boundary.

The rest of the paper is organized as follows: section II gives a brief review of existing shape matching techniques. Section III describes the importance of preprocessing technique while our proposed methodology is discussed in detail in section IV. Experiments are reported in section V. The last section gives the conclusion of the paper.

2. Background and Related work

Content-based Image Retrieval (CBIR) is one of the processes of extracting and representing image contents in terms of important *properties* or *features* like shape. Shape is considered to be the most important propoerty of an image for humans as they majorly employ the contour information to determine an image.

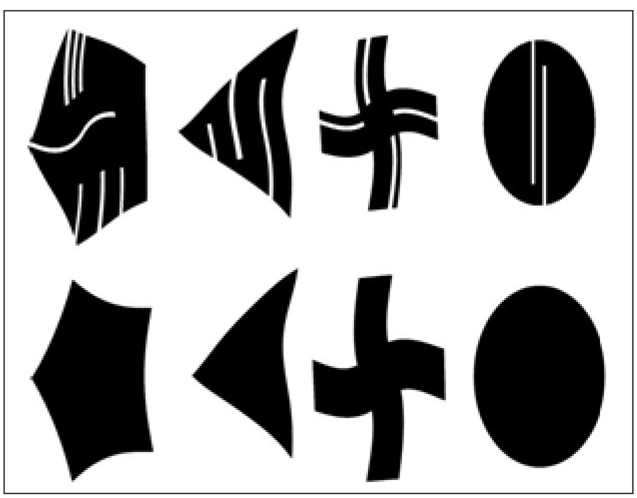

Figure 1. The upper row shows images with cracks in MPEG-7 dataset classes
while the bottom row the images without cracks from the same classes

Shape matching looks for precise and perceptually important shape representation techniques and distance measures which are essentially not sensitive to many variations or alterations including articulations and affine deformations. Past researches have delivered many sophisticated shape representation and matching techniques such as shape context, shape signature, symbolic representation, integral invariants, curvature moments etc.

These shape representation techniques are called shape descriptors which can be broadly classified as contour-based and region-based descriptors. Contour-based approaches use only the boundary information of an image as the boundary information includes only the pixels on contributing to the contour of the shape. Contour based approaches are widely used for understanding a shape. Region-based techniques use all the shape pixels to create the shape descriptor. However, both contour-based and region-based shape descriptors are sensitive to noise which resultantly affects the performance of content based image retrieval. The noise also includes cracks. These noise factors are somewhat minimized by using various shape representation methods.

Much of the contour-based shape representation generates a global representation of contour. Some of them include shape signature [10], integral invariants [1], differential invariants [2] [3], shape context (SC) [4] [5] [6] and shape context with inner distances (IDSC) [7]. Belongie et al. [5] introduced SC descriptor based on histogram of contour points generated in log-polar coordinates. Belongie et al. [5] use chi-square distance as a distance measure to compute distance between SC descriptors whereas Mori et. al [4] employees-norm. Ling et. al. [7] enhanced the SC descriptor by employing inner distance instead of euclidean distance as it is considered to be insensitive to considerable articulations. Chi-square distance is employed to compute distance between IDSC descriptors and the final correspondence between the IDSC descriptors of two shapes are determined using dynamic- programming [8] [9] to cater for the temporal relationship between the IDSC descriptors.

The overall system yields superior retrieval accuracies as compared to SC [10] and other competitors but at the cost of high computational cost. Daliri et al. [11] defined a symbolic descriptor based on Shape Contexts. To cater for the presence of occlusions and articulations, they employee edit distance for final matching of string based descriptor.

On contrary to global shape matching, there are certain approaches that divide the contour into sub-contour segments, the piecewise approaches [12] [13], other than global approach. Some of them include polygon decomposition [12], smooth curve decomposition [13] and curvature decomposition [14]. Sub-contours are represented by generating descriptors which are then modeled in a combined format defined in every representation above. Their advantage is that they deal with the problem of very significant occlusion but at the cost of high computational complexity and failing to capture global structure. Some of these techniques are [17] [12] [11], which divide the contour into segments. They use an iterative procedure. At every iteration, they sample a segment of different length and compute similarity through complex descriptors. Attala et al. [12] uses SAD (Sum of Absolute differences) while Daliri et al. [11] uses shape context. They combine the results of iterations to achieve a global matching result. Alajlan et al. [16] proposed a multi-scale representation of triangle areas, to capture local and global shape information, for shape matching.

In this paper, we propose a simple but effective preprocessing technique to handle noise. Preprocessing techniques helps to reduce noise in images or performing some changes in the input data to achieving more accurate results. These techniques have been used in the past to achieve good results by either extracting the required part of the shape to be processed or by focusing on the required part and removing all unnecessary areas. Moreover, preprocessing may be achieved by changing the input data according to some specific requirements. Some preprocessing techniques have been used in a vast range of research work done, although nature or working of these techniques varies. This makes it difficult to generalize any categorical system for these techniques.

The proposed method preprocesses the shapes and enhances the performance of above mentioned shape representation and matching techniques. Our approach is simple so it may be employed to increase the accuracy of any of the shape representation algorithm. By removing small cracks or slits present in the contour of the images the images are processed before applying the sophisticated shape representation techniques. Being a simple approach it is not computationally extensive. Also it reduces the time complexity of the applied complex shape matching approach by changing the dataset images and removing expected false hits. The changes are done by removing the noise from the contour of the image. This noise correspond to variations or false alterations introduced in the boundary of the shapes of images in the dataset.

Our approach is based on the observation that these variations are in the form of small cracks or slits. These slits are not being too wide, but contribute much to the overall change in the contour.

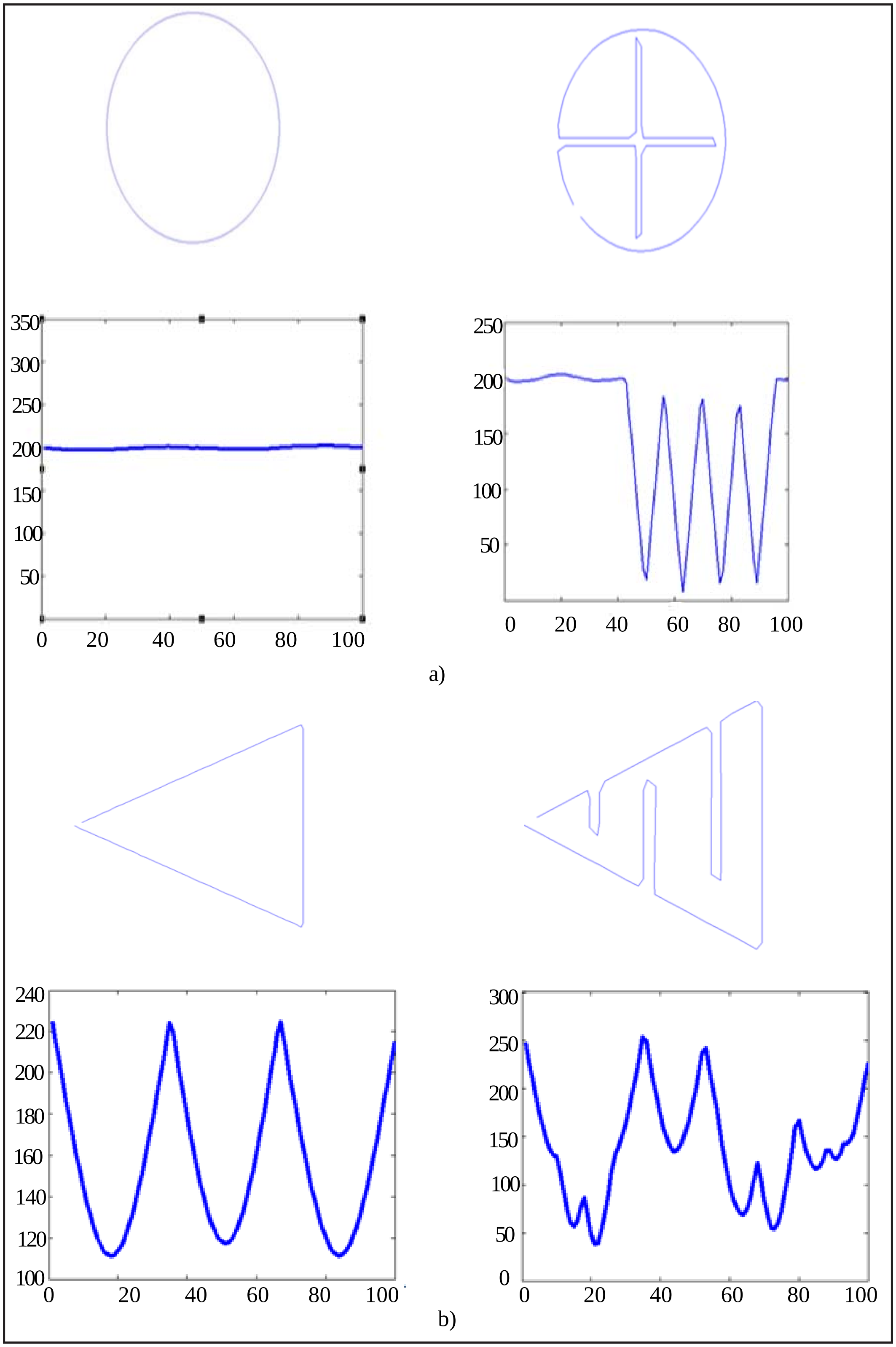

Figure 1.Changed Time Series Depicted due to Slits an cracks in the contour , one image is without any slits or cracks in the contour while the one on right with Slits and their respective time series are beneath them. a) shows two images from the class of circles b) shows two images from the class of triangles.

3. Importance of Crack Identification and Removal

In the field of Image Recognition, the matter of identifying or matching an image accurately highly depends on the quality of the input images provided. This in turn is affected by the fact that how accurately we get these inputs. This issue depends on *image acquisition* techniques and other factors such as camera limitations, image capturing and human errors which results in scale variations. A major cause of noise is the conversion of a 3D image into 2D which results a lot of significant information loss. Moreover, capturing images from scenes results in inaccurate images or destroyed images which introduce a lot of noise in the shape.

Accurate classification of images using contour-based shape matching depends upon the contour matching between the images of a given class. But there are a lot of input shapes in real time systems which have small cracks or slits in their contours. As Figure 1 depicted, cracks in images are not too wide and does not change the visual perception of shape but it adds extra points on boundary. In this way, it affects the 1D representation of the contour. This type of cracks or slits change the contour of the image altogether which results in large dissimilarity between the shapes and the accuracy of the given shape matching methodology is influenced. This idea is illustrated in figure 2.

Here, it is obvious that the contour of the images belonging to the same class is changed and it exhibits additional contour points which are actually not part of shape. Computing shape descriptors for these extra contour slits and the boundary points in them increases the computational effort and the distance calculated between two shapes. This reduces the overall accuracy of the proposed technique. So, we propose preprocessing to handle this type of cracks and distortions in image in the next section.

4. Proposed preprocessing Algorithm

In this section, we present our proposed approach for the preprocessing of shapes to handle the distortions that are present in them. All of the shapes have these distortions due to their scale variations and presence of cracks in them. So to meet this challenge, we present the idea to do preprocessing of these shapes. By doing so, all the shapes will have the same area of minimum bounded rectangle (MBR) of a shape.

Let A_{actual} represent the area of MBR of shape and $A_{desired}$ is the area of MBR which is desired. So, we have rescaled the shape by the factor which is equivalent to $A_{actual} / A_{desired}$. By performing this preprocessing step, we will be able to make our shape matching approach invariant to scale changes in shapes. In literature, there are some contour-based methodologies present, which are considerably affected by the presence of cracks in the image. The presence of cracks in these images significantly distorts the information of contour as a result.

So, effectiveness of contour-based shape matching approaches can be increased in a way, if we perform the step of preprocessing in order to remove the cracks that are present in shapes. We have proposed our crack-identification approach on the basis of an observation that crack is usually not wide and it is represented by the significant number of points on the contour that are between two entry points on the surface of the shape. Our proposed preprocessing algorithm is for the identification of cracks and also for the filtering of subcontours that represents these cracks. It is made up of the following steps:

1. Extract the contour of the shape which can be formally represented as:

$$C = \{c_1, c_2, c_3, .. c_n\} \tag{1}$$

where $c_i(x_i, y_i)$ represents a point on the contour at a given location i and n is the total number of points on the contour. We will use $C(i, j)$ to represent a sub-contour between contour points indexed by i and j respectively.

2. Identify the corner points on the contour by employing corner detection technique as presented in [15]. Let Υ represents represents the indexes of all the detected corner points on the contour C.

3. Identify a set of pair of corner points indices Φ from Υ that are likely to represent the entry point of crack as:

$$\Phi = \{(\Upsilon_i, \Upsilon_j) \mid \| C_{\Upsilon_i}, C_{\Upsilon_j} \| \le J \wedge | C(_{\Upsilon_i}, _{\Upsilon_j}) | \ge l \;\; \forall \Upsilon_i, \Upsilon_j \in \Upsilon \wedge \Upsilon_i \ne \Upsilon_j\} \tag{2}$$

where ||..,..|| represents a euclidean distance function, | . | represents number of points on a given sub-contour, j is the threshold on the allowable distance between the given pair of corner points to represent the entry point of a crack and l is the threshold the minimum number of contour points that can represent the crack. As we have normalized the images with respect to the area of shape, it is relatively easy to specify the values of *j* and *l* which have been determined empirically as 15 and 60 respectively.

4. Identify closest pair of candidate corner points from Ö, indexed by (Υ_q, Υ_r) , as:

$$(\Upsilon_q, \Upsilon_r) = argmin_{(\Upsilon_i, \Upsilon_j)} \| C_{\Upsilon_i}, C_{\Upsilon_j} \| \ \forall (\Upsilon_i, \Upsilon_j) \in \Phi \tag{3}$$

5. Divide the sub-contour $C_{(\Upsilon_q, \Upsilon_r)}$ into two equal halves represented by sub-contours *A* and *B* where $A = C_{(\Upsilon_q, \lfloor \frac{\Upsilon}{2} \rfloor)}$ and $B = C_{(\lfloor \frac{\Upsilon}{2} \rfloor, \Upsilon_q)}$

6. Compute the distance of each point on sub-contour *A* to its closest point on sub-contour *B* and compute its variance as:

$$\sigma_A = STD\,(min_{b \in B} \| a, b \| \ \forall\, a \in A) \tag{4}$$

7. Similarly compute the distance of each point on sub-contour *B* to its closest point on sub-contour *A* and compute its variance as:

$$\sigma_B = STD\,(min_{a \in A} \| a, b \| \ \forall\, b \in B) \tag{5}$$

8. The standard deviation of distance between the closest points on two sub-contours *A* and *B* σ_{AB} isthen computed as:

$$\sigma_{AB} = min\,(\sigma_A, \sigma_B) \tag{6}$$

9. Sub-contour $C_{\Upsilon_q}, C_{\Upsilon_r}$ is considered to be representing the contour of a crack in the shape if

$$\sigma_{AB} \le \wp \tag{7}$$

where the value of $\wp$ = 0.6 has been assigned empirically so that it selects only cracks and not the useful features in the shape.

10. If the condition specified in equation (7) is satisfied, prune the sub-contour $C_{\Upsilon_q}, C_{\Upsilon_r}$ from contour *C*. Filter all the corner points indices from Υ which lies on the sub-contour $C_{\Upsilon_q}, C_{\Upsilon_r}$ and remove corresponding corner points indices pairs from Φ.

11. If the condition specified in equation (7) is not satisfied, $C_{\Upsilon_q}, C_{\Upsilon_r}$ is considered to be representing a useful feature in the shape. In this case, we filter the corner point indices pair (Υ_q, Υ_r) from Φ.

12. Repeat step 4-9 till $\Phi = \{\}$.

Figure 3 shows the steps of proposed preprocessing approach in visual form. Part (a) shows the actual shape from which the contour is extracted shown in figure 3 part (b). The corner points are then identified using the Harris corner detection algorithm to find the pints of interest. As depicted in the figure, these are the main points that exhibit an obvious change in the contour. The set of points obtained include the corner points of the slits and cracks. This set of points is taken into consideration as the *candidate point list* from which we accurately identify the crack entry points using equation (3) to equation (7). Once the points are correctly extracted, they will be removed from the contour representing a gap depicted in figure 3 part (*e*). The next section shows the effectiveness of our proposed approach using image datasets.

5. Experimental Studies

In this section, results are presented to evaluate the performance of proposed pre-processing technique. Experiments are conducted to investigate how the proposed noise removal approach enhances the effectiveness of existing sophisticated shape matching techniques

5.1 Experiment 1: Evaluation of proposed pre-processing technique using MPEG-7

This experiment has been conducted on publicly available dataset MPEG-7 [18] which has been widely used to evaluate shape matching methods using bulls eye score. A numerous variety of shapes are available in this dataset with common noise parameters like articulation, occlusions and affine deformations. In total, 1400 images are available in MPEG-7comprising of 70 classes. Every class contains 20 images of a same thing or animal for example lamps, moon, dog, goat etc. Bulls-eye score is computed as the ratio of the total

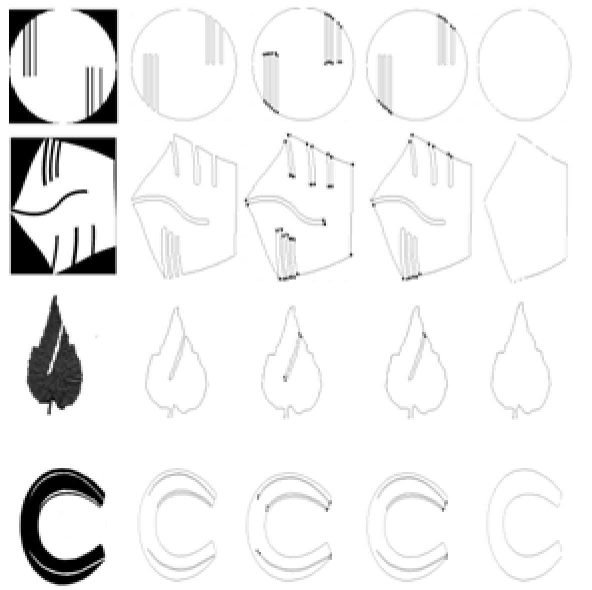

Figure 3. Demonstration of different phases of crack identification and removal algorithm. (a) Original shape (b) 2D representation of contours

Method	% Score	Improved %Score using the Proposed Methodology
Fourier Descriptors	70.52	75.31
Shape Contexts	76.51	80.47
IDSC [7]	85.54	87.3

Table 1. Accuracy Comparison of Proposed Method With Previous Shape Matching Techniques Using Mpeg7 Dataset

number of shapes retrieved from the same class w.r.t. query and the maximum number of correct retrieval (20×1400).

We have used some of the existing shape matching techniques to compute shape matching on the preprocessed dataset using the proposed approach. The results in Table 1 show a considerable increase in the accuracy of the given shape matching techniques.

6. Conclusion

Shape matching is an active study these days which largely depends upon shape representation techniques and methods to measure similarities between shape.

These shape representation techniques and similarity measuring methods need to be effective enough to produce accurate shape matching results. Accurate shape matching relies on shape representation techniques representing the shape accurately in the presence of false alterations or distortions. Most of the earlier studies focused only on developing complex systems, in shape matching and recognition, to increase the accuracy of shape matching and retrieval systems. Many sophisticated shape representation and matching techniques have been presented which produce excellent matching results in the presence of variety of distortions such as noise, affine deformations, occlusion and articulation. These techniques usually engage sophisticated shape descriptors, complex distance measures and computationally complex matching techniques to achieve good shape matching results in the presence of these shape alterations. Past researches have delivered many shape representation and matching techniques such as shape context, shape signature, symbolic representation, integral invariants, curvature moments etc.

These shape representation techniques are called shape descriptors which can be broadly classified as contour-based and region-based descriptors. Some of them include shape signature [10], integral invariants [1], differential invariants [2] [3], shape context (SC) [4] [5] [6] and shape context with inner distances (IDSC) [7].

In this paper, we introduce a noise removal preprocessing approach to improve the accuracy and efficiency of sophisticated shape matching techniques. The proposed approach works on the concept of identifying and removing cracks or slits which change the contour of the shape. These cracks are generated by the addition of extra points on the contour as a result of noise parameters like occlusion. By removing small cracks or slits present in the contour of the images the images are processed before applying the sophisticated shape representation techniques. This type of cracks or slits change the contour of the image altogether which results in large dissimilarity between the shapes and the accuracy of the given shape matching methodology is influenced. Computing shape descriptors for these extra contour slits and the boundary points in them increases the computational effort and the distance calculated between two shapes. The proposed method preprocesses the shapes and enhances the performance of above mentioned shape representation and matching techniques. By performing this preprocessing step, we will be able to make our shape matching approach invariant to scale changes in shapes. So, effectiveness of contour-based shape matching approaches can be increased in a way, if we perform the step of preprocessing in order to remove the cracks that are present in shapes. The proposed approach enhances the accuracy of the sophisticated shape matching techniques reported in literature. IDSC has been used as it is being used as a state of the art technique for shape matching these days. Experiments have been conducted using publicly available datasets to preprocess the shapes containing slits and cracks before applying complex shape matching techniques.

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