NURBS: A NEW SHAPE DESCRIPTOR FOR SHAPE-BASED IMAGE RETRIEVAL

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ABSTRACT

The representation, matching and analysis of objects of interest are of prime importance in shape-based retrieval systems. In the large image repositories, there arises a problem to find a set of images that are relevant to the user's needs. This necessitates an effective retrieval approach that resembles the human capability to retrieving images that are relevant to a query from a database. Perceiving a shape is to capture prominent elements of an object. For the purpose of retrieval by shape similarity, representation is preferred such that the salient perceptual aspects of a shape are captured and are able to imitate the human perception in perceiving shapes. The representation method is important, because the effectiveness of the representation will determine the accuracy of the retrieval results. Thus, there is a need to have an effective and accurate representation method. The representation features are then used to compute the similarity score between two images. In this paper, we present a new shape descriptor to represent all possible shapes using Non-Uniform Rational B-Spline (NURBS). We also present NURBS-Warping method, which is similar to elastic matching, to obtain similarity score in the retrieval process. We run two sets of experiments to show the efficiency of NURBS shape representation and NURBS-Warping method over B-Spline representation.

Keywords: Shape descriptor, NURBS, Similarity matching, Shape retrieval system

1. INTRODUCTION

Shape is the most prominent visual feature of an image. Retrieval by shape is considered one of the most difficult and challenging aspects of image retrieval systems due to the dependence of shape on a variety of factors such as deformation, illumination, shadows and occlusions [1]. In shape-based image retrieval, the basic retrieval paradigm requires that, for each image, a set of distinguishing features that represent the shape of the objects in the image are extracted. These shape representation features are used to perform similarity comparison between two images.

Since the space of possible shape is varied, a method for representing it must be powerful enough to capture all the salient features. Global features [2], moment invariants [3], Fourier descriptors [4], wavelets [5] and B-Spline [6] are among the several approaches proposed for this purpose. All these representation methods use feature-based matching to compute the similarity score between two images. In order to obtain an accurate shape representation, these methods need high dimensionality feature vectors. This high dimensionality results in an increase in the complexity and processing time of the similarity matching process. Thus, in order to increase the effectiveness of the similarity matching procedure by reducing the selected number of features, a well-established feature selection method needs to be developed. However, there is a risk of loss information, which will give impact on the retrieval result, if the selection method is not accurate. In addition, each image may have different number of prominent features, which makes the task of finding relevant corresponding features between two images, non trivial. Although Haudoff and Frechet distance function are introduced to solve this correspondence problem, these distance functions are dependent on a threshold parameter specifying the minimal fraction of matching points, which must be known a priori. Furthermore, the efficiency and robustness of feature-based methods is reduced in the presence of noise and distortion in the image.

B-Spline stands as one of the most efficient shape representation method for use in signal and image processing [7]. Although B-Spline provides a compact representation and has high robustness against the presence of noise in the image, little work has been done for its use in shape similarity matching. It is partly due to the non-uniqueness of the B-Spline descriptors, in which a given shape may be represented by different sets of B-Spline parameters. Furthermore, each image may be represented by a different number of B-Spline parameters to be compared. Therefore, it is a difficult task to find relevant corresponding B-Spline parameters in order to perform similarity matching between two images. Few researchers tried to solve this correspondence problem: Huang and Cohen [8] introduced a residual error-based matching to solve the correspondence, by finding the best transformation parameters in a noiseless image. With these transformation parameters, the data points are retransformed, and the similarity matching is performed by using knot matching method [6]. In order to determine the transformation parameters accurately in a noisy image, Yang and Cohen [9] presented an improved method by computing a cross-weighted moment, which is invariant to noise, missing data, and perspective effects of the image. However this work requires two separate stages for classifying objects and estimating the transformation parameters. Furthermore, the knot matching method uses the point where a curve crosses the positive horizontal x-axis, which is arbitrary for affine curves as the starting point. This will result in a lack of good correspondences between curve segments and hence increases the error in curve matching.

Gu [10] introduces a gradient-based algorithm, which simultaneously computes the minimum mean square error (MMSE) distance between two object curves and estimates the transformation parameters. The feature correspondence between the two curves that are matched is solved by ensuring that same number of features are detected on each curve. For each curve, these features include: initial B-Spline knot points, points interpolated at the corresponding positions of the knot points from another curve to be compared and extra points by uniform interpolation. This extra assignment of comparison features does not adequately capture the appearance of an object, and hence there is a risk that these features are not the salient perceptual features.

In this paper, we introduce Non-Uniform Rational B-Spline (NURBS), as a better spline representation compared to B-spline. In order to solve the perceptual correspondence problem, we present an elastic matching method to compute the similarity score between two images. In the elastic matching method, similarity score is computed based on local comparisons of the contours of shapes. The elastic matching is related to the physical energy that is obtained by measuring the amount of deformation needed to explain the difference in two contours. This paper is organised as follows: In Section 2, an overview of our proposed method is presented. Section 3 presents the advantages of using NURBS as a shape representation method for use in shape-based similarity retrieval strategy. Section 4 shows the effectiveness of NURBS-Warping method in order to compute the similarity score between two images. Section 5 presents the experiments to evaluate the proposed NURBS representation compared to B-Spline and the effectiveness of the NURBS-Warping method in deriving a meaningful similarity score for retrieval purpose. Section 6 concludes the approach presented in this paper and discusses the future directions of our research.

2. PROPOSED METHOD

The proposed method is inspired by the manner in which humans perceive objects and compare them. In the elastic matching approach, the query image is represented by NURBS, with position of the control points and their weights as variable parameters, in a manner that the query image is regarded as a deformable template. Then, the NURBS-based template is deformed by an external force in order to improve its match with the database image, by adjusting the NURBS control points. The position of the control points will not change if all the deformed control points have converged and locked themselves on the boundary of the database image. The smoothness of the deformed template is maintained throughout the warping process. Thus, this process is referred to as NURBS-Warping method. The similarity between two images is determined by measuring the effort spent in the warping process. At the end of the warping process, two similarity scores are computed: Total Cumulative Change in the Position of the Control Points (TCCPCP) and Degree of Matching (DOM). These two similarity scores are used to retrieve a set of highly similar database images that are relevant to the query image.

3. NURBS AS A SHAPE DESCRIPTOR

Non-Uniform Rational B-Spline (NURBS) are chosen as a shape descriptor to model all the various forms of shape compared to the B-Spline. NURBS inherits all the advantages of the B-spline properties such as follows :

- represents free form shape with remarkably little data and well defined in the mathematic form.
- local controllability, which implies that local changes in shape are confined to the NURBS parameters local to that change.
- ability to control smoothness and curvature continuity.
- characteristic of shape invariance under affine transformation, which means that the affine transformed curve is still a NURBS curve whose control points and weights are related to the original curve control points and weights through this transformation.

The choice of NURBS as a shape descriptor, not only offers a common mathematical form for representing free-form shapes but also geometric shapes. The difference between NURBS and B-spline is that it includes a non-uniform knot vector and an additional parameter, which is the weight. The details of B-Spline and NURBS are explained in [11]. Inclusion of weight as an additional parameter adds an extra degree of freedom to NURBS and facilitates the representation of a wide variety of shapes. Furthermore, the use of non-uniform knot vectors allows better shape control and the modelling of a much larger class of shapes than the uniform knot vector used in B-spline. With these additional parameters, NURBS allows a higher compact representation, which effectively reduces the original number of the boundary points required to represent the query image. Therefore, we strongly believe that NURBS is a good and accurate shape descriptor. In our previous work, a new method for defining NURBS parameters from the boundary of the shape is presented [12].

In the similarity matching process, NURBS representation faces the same correspondence problem as the B-Spline representation, as discussed in Section 1. In this paper, we proposed NURBS-Warping method as a similarity matching method. In this method, we are not trying to match a set of NURBS parameters from the query image with another set of NURBS parameters from the database image. In this, the query image's NURBS control points are adjusted at each warping iteration, under an external attraction force until the shape of the deformed query image is similar to the shape of the database image. The weights of the corresponding control points are fixed throughout the warping process in order to make this process simple and fast. The external attraction force is computed from the edge map of the database image itself. When the optimum matching is achieved between the deformed query image and the database image, the final adjusted set of NURBS control points are able to model the database image. At each warping iteration, the number of the adjusted control points is the same with the number of control points at previous warping iteration and guarantee to be in correspondence.

In order to ensure that the similarity score reflects the effort spent throughout the warping process, the Cumulative Change in the Positions of the Control Points (CCPCP) is computed after each iteration of the warping process. At each iteration of the warping process, the adjusted set of control points is in correspondence with the set of control points at the previous iteration and both sets are of same size. With this correspondence property, the CCPCP is computed by using Euclidean distance function. The Total Cumulative Change in the Positions of the Control Points (TCCPCP), which is the sum of the CCPCP at each iteration up to the completion of the warping process, is used as a measure of the similarity between the query and database image. The warping process is continued until the CCPCP value is equal to or less than a prespecified threshold value. With this warping method, we take full advantages of the underlying NURBS representation to measure the similarity score, for use in the retrieval process.

4. SIMILARITY MEASURE DETERMINATION

Before the warping process is carried out, the query image is normalized with a transformation matrix, (T), based on the orientation of the database image. This normalization step is important to ensure the similarity score is solely determined from the warping process without being affected by the orientation differences between the query and database images. NURBS representation has an important characteristic; the NURBS parameters of the normalized image are obtained by simply subjecting the original parameters by the same transformation matrix, (T). The query image is then warped to match the shape of the database image by adjusting the normalized NURBS control points. The TCCPCP value is computed at the end of the warping process.

The accuracy of the similarity score is solely determined by the TCCPCP value. However, the TCCPCP value is a meaningful similarity score only if the warping process has effectively warped the query image to the shape of the database image. The effectiveness of the warping process is determined by :

- its ability to control the smoothness and continuity of the deformed query image in the warping process.
- the strength of the external force to attract NURBS control points to the database image, regardless of initial orientation of the query image in relation to the database image.

In NURBS representation, the smoothness and continuity is dependent mainly by the NURBS basis functions that are determined by the Cox-deBoor algorithm [11]. Thus, movement of control points does not significantly influence the smoothness and continuity. In order to increase the capture range of its external forces and guide the query shape towards the boundary of the desired database image, we choose gradient vector flow (GVF) field as an external force. GVF is insensitive to initialisation and has the ability to move into boundary concavities. The details of the definition of the GVF are given in the [13].

However, the query image is hardly warped to the shape of the database image if the shape of the query image is far different from the shape of the database image. The failure of the warping process will make the computation of the TCCPCP value meaningless. Thus, another similarity score, Degree Of Matching (DOM) is introduced as a measure of the closeness of the deformed query image to the database images upon completion of the warping process. With this extra parameter, only selective TCCPCP values are considered in the retrieval process if their DOM value is equal to or more than a desired threshold value. Thus, our method is reliable in computing a meaningful similarity score in the retrieval process by having NURBS as a shape descriptor and GVF as an external force.

5. EXPERIMENTS

In this work, we run two sets of experiments to show that the NURBS is a better shape representation compared to B-spline representation and to illustrate effectiveness of the NURBS-Warping method in computing the similarity score between the query image and the highly similar database images. The methodology of each experiment is presented and the results of the experiments are discussed.

Methodology

The aim of the first set of experiments is to verify the effectiveness of NURBS representation over the B-Spline representation. In these experiments, four silhouette images consisting of geometric and free form shapes are used, and are shown in the Fig. 1.

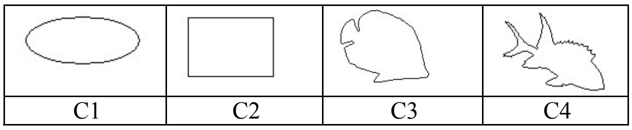

Figure 1: C1 and C2 are geometric shapes; while C3 and C4 are free form shapes

In order to verify the effectiveness of the NURBS representation under fair test conditions, the B-Spline algorithm is developed from the algorithm that is used by NURBS representation. This is possible because B-Spline is a subset of NURBS. B-Spline algorithm is generated by setting all the weight parameters value equal to 1 and by uniform spacing interval of the knot vector value. The centroid-radii method is used to measure the error between the reconstructed images generated by these two representations, with the original image. This error measures the dissimilarity of the reconstructed image and the original image. In this method, both images are superimposed at their centroid point. Radii lines are projected from the centroid point to the boundary of the original image and the reconstructed image at regular interval. For each radii line, distance between the intersection points by the radii line on the boundary of the original image and the reconstructed image is cumulated. In these experiments, a sampling interval of 5^0 is used. The error is the cumulative distance difference between the original image and the reconstructed image at the sampled points.

In the spline representation method, different images need different Number of Control Points (NCP) to generate the reconstructed image that is similar to the original image. However, for the purpose of comparison in our experiments, the four silhouette images are represented by a set of incremental number of NURBS or B-Spline control points. Thus, we choose the initial NCP equal to 4, and increment with a step size value of 2 until the NCP equal to 50.

The second set of experiments are aimed at proving that the similarity score computed from the NURBS-Warping method are used in retrieving a set of database images at the same order in the original set of database image. In this experiments, a collection of highly similar silhouette images are used. The first image in the database itself is used as a query image and the database images are ranked manually according to human judgement in the order, based on the similarity of the query image.

In this experiment, the query image is represented by using NURBS parameters. The query image is superimposed on the database image, and the normalized NURBS control points are adjusted toward the database image under the attraction of GVF force generated from the boundary of the database image itself. The warping process is continued until the CCPCP value is equal to or less than a prespecified threshold value. The prespecified threshold value used here is 5 units. At the end of the warping process, the TCCPCP and DOM are computed. The above experimental process is repeated for each database image. Fig. 2 illustrates the query image Q1 and the ranked database images D1 – D6 with decreasing order of similarity. The similarity between D1 and Q1 is the highest, while D6 and Q1 are least similar to each other as compared to other images in the database.

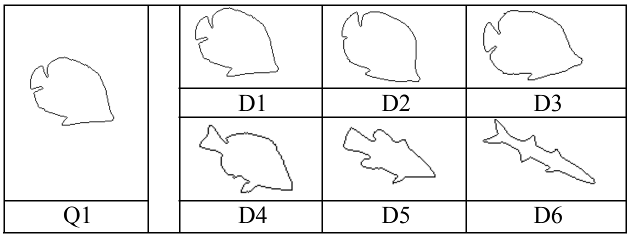

Figure 2: Q1 is a selected query image and D1-D6, are ranked database images.

Experiment Results And Discussion

In the first set of experiments, the effectiveness of NURBS representation compared to the B-Spline representation is successfully investigated. Fig. 3 shows the error of the reconstructed image compared to the original image using different incremental number of NURBS and B-Spline control points. A good representation technique has low error with smallest number of control points used for representation.

Fig. 3 illustrates the error of reconstruction, of images C1-C4, using NURBS and B-Spline representation, for different number of control points. From this, it may be seen that the reconstructed images using NURBS representation converge to the shape of the original images by using a smaller number of NURBS parameters compared to the B-Spline. It may also be noted that, the error for the reconstructed image, C2, using NURBS representation, is extremely low as compared to B-Spline representation. This illustrates that the NURBS representation is able to represent effectively, any geometric shape that has sharp corners.

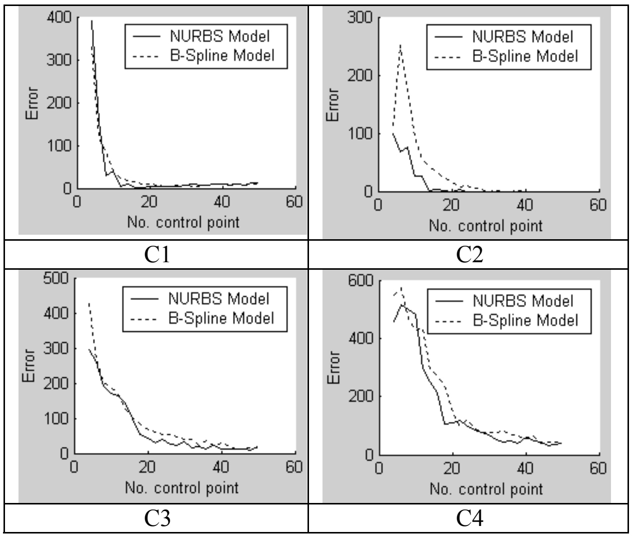

Figure 3: The error versus the number of control points for images C1-C4

Fig. 4 illustrates the shape of the reconstructed image in relation to the original image, C4, using different number of NURBS and B-Spline control points. From this, it may be seen that, with 12 control points, curve approximation with NURBS is superior to that with B-Spline. With 32 control points, NURBS representation converges more closely to the high curvature points as compared to the B-spline representation. Therefore, it may be concluded that NURBS is a suitable representation method to describe any free form shape that may contain numerous convex and concave portions.

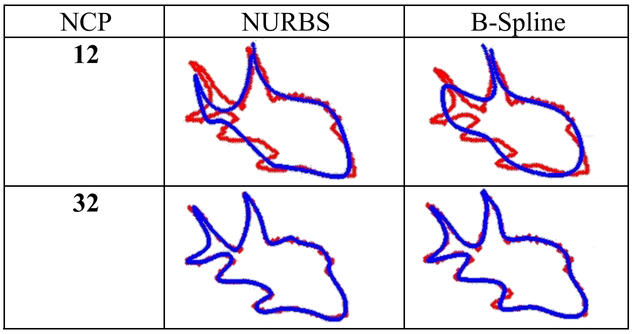

Figure 4: The reconstructed image using NURBS and B-Spline representation is displayed using NCP equal to 12 and 32 respectively

In the second set of experiments, the computed TCCPCP values are used to derive similarity scores of the database images to the query image, Q1. Fig. 5(a) shows the TCCPCP value, while Fig. 5(b) displays the DOM value computed for each highly similar database images, D1-D6 respectively. The TCCPCP value is used to rank the retrieved images. The most similar database image to the requested query image will have the lowest TCCPCP value.

In Fig. 5(a), the most similar database image, which is D1, has the lowest TCCPCP value compared to the other database images. The TCCPCP value for D2 to D6 is increasing as their similarity to Q1 is decreasing. Although D2 and D3 are very similar to Q1, the similarity score based on the TCCPCP value is able to differentiate the similarity between them to Q1. Thus, D2 and D3 are displayed in the correct ranking according to the sequence of images in the database that are predefined manually.

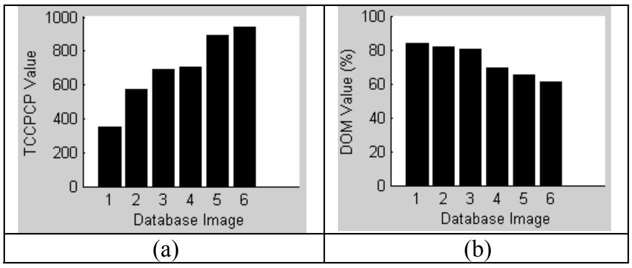

Figure 5(a) and 5(b) show the TCCPCP value and DOM value computed for each database image respectively

In Fig. 5(b), the DOM value computed for each database image is very high. All the DOM values computed are higher than 60%. The high DOM values achieved in the NURBS-Warping method show that the GVF is a powerful force to attract the query image, which is represented by NURBS descriptors, towards the shape of the database image. The result of the ranking of the retrieved images is displayed in Fig. 6. In Fig. 6, the retrieval results show that the similarity score computed in the NURBS-Warping method has a potential for use in a highly similar database.

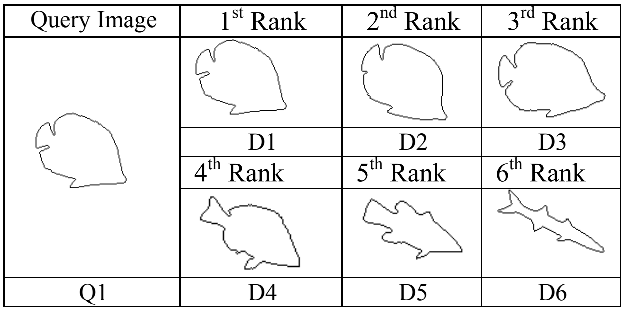

Figure 6: The ranking of the retrieval results requested by query Image, Q1

6. CONCLUSION AND FUTURE WORK

From the results and discussions presented in Section 5, it is clear that NURBS is an accurate shape descriptor for use in highly similar database retrieval systems. We have proposed a new elastic matching method, which we refer to as NURBS-Warping, to take the full advantages of the underlying NURBS representation to measure the similarity score for use in the retrieval process. This method is able to solve the correspondence issue that arises in the B-Spline representation. Our future work involves investigation of alternative similarity scores that improve the retrieval results.

7. REFERENCES

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