An Efficient and elastic approach for partial shape matching using DTW

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Abstract

We present the Partial shape matching for scale invariant and deformation tolerant 2D images. Scale invariance means a feature of objects that do not change if scale or length of objects changes. Deformation tolerance means tolerating a change in the volume and/or shape of object.

We propose to transform shapes into sequences and utilize an algorithm that determines a subsequence of a target sequence that best matches a query.

The proposed scheme lies a novel shape descriptor that also permits the quantification of local scale. Shape descriptors are computed along open or closed contours in a spatially non-uniform manner. The resulting ordered collections of shape descriptors constitute the global shape representation.

A variant of an existing Dynamic Time Warping (DTW) matching technique is proposed to handle the matching of shape representations. Due to the properties of the employed shape descriptor, sampling scheme and matching procedure, the proposed approach performs partial shape matching that is invariant to Euclidean transformations, starting point as well as to considerable shape deformations.

Additionally, the problem of matching closed-to-closed contours is naturally treated as a special case. Algorithm outperforms the commonly used techniques in retrieval accuracy.

Keywords: DTW(dynamic time warping technique), shape descriptor.

1.1 Introduction

Shape matching is a fundamental problem in computer vision and pattern recognition. It deals with the problem of describing a shape and calculating its similarity to others.

In general, the performance of existing shape matching techniques tends to drop significantly when too much noise exists in the shape. Due to occlusion or segmentation errors, it may be the case that only parts of objects in a given image have correct contours. Therefore, a shape similarity measure based on parts of objects is needed. However, the identification of shapes given their parts is still an unsolved problem in shape similarity.

Shape matching is a well investigated problem in computer vision and has versatile applications as e. g. in object detection or image retrieval. The most important part of designing a shape matcher is the choice of the shape representation which has a significant effect on the matching step.

Basically, Shape matching deals with transforming a shape, and measuring the resemblance with another one, using some similarity measure. So, shape similarity measures are an essential ingredient in shape matching. Shape matching is of central importance in a number of computer vision problems such as shape classification, retrieval, recognition, and simplification. This system deals with the partial shape matching of binary images only. [1] [2]

In most of the cases, arbitrary differences in scale and Orientation should not affect the matching process. Due to viewpoint dependencies and shape articulations and deformations, different 2D image projections of the shape of the same 3D object may differ considerably. Further complications are caused by occlusions which force shape matching to be based on partial evidence.

In some case, the best matching of an open contour with part of a closed contour needs to be established [1] but all of the above complicating factors contribute collectively to increasing the complexity of the matching problem.

Shape matching including wide range of applications such as, object detection and recognition, content based retrieval of images and image registration.To perform shape matching, most of the existing methods [2] define shape representations and descriptors which are then compared through appropriately selected methods and metrics.

It may arise some serious problems as, length problem, scale problem, and distortion problem.None of current shape matching techniques provides solutions to all problems listed above. Even feature-based approaches, although potentially being based on local features, require the presence of most of the object to compute the statistics of the features.

The existing partial shape similarity measures (e.g., Ref. [6]) require that the query part is nearly identical to the corresponding part of the target contour, which is clearly an unrealistic assumption due to noise distortions and due to (even small) perspective projection changes. Veltkamp and Tanase [7] proposed to use an extended dynamic programming approach directly on the turn angle function representation of object contours. Since their matching of a single part is not elastic, their approach is not scale invariant.

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In the context of this work, we are interested in addressing the 2D shape matching problem by simultaneously considering all the above complicating factors. Shapes are represented as binary images depicting foreground objects over their background. Based matching technique [10] that accomplishes global 2D shape matching based on the computed shape descriptors. The key novelty in this variant is its ability to handle partial matching. Although primarily developed for matching open to closed contours, the proposed scheme treats the

Matching of two closed contours as a special case. This can be effectively achieved by treating one of the two closed contours as an open one that starts and ends at the same point.

A variety of shape matching algorithms/techniques/model are available to address the 2D shape matching problem such as, Smith Waterman Algorithm**,** object morphing model, Dynamic Time Warping technique, wedge wave feature extraction algorithm, Dynamic alignment matching algorithm, genetic algorithm etc. So, from the above, we used Dynamic Time Warping technique to implement this system. Efficiency of this technique is discussed later in this report.

Shape matching is a well investigated problem in computer vision and has versatile applications which include industrial inspection, fingerprint matching, object detection and recognition, ECG pattern matching, stereo matching and content based image retrieval.

Experimental results have been obtained for contour matching in benchmark data sets but also in datasets that have been compiled in the context of this study. The results demonstrate that the proposed approach outperforms existing methods and is capable of dealing with the shape matching problem in challenging situations.

1.2. Literature Review

Tomasz Adamek and Noel E presented a paper as a multi-scale representation method for non-rigid shapes with a single closed contour. In this paper, they proposed multi-scale representation of shape silhouettes that is matched with the use of dynamic programming. Initially, they apply different levels of smoothing on the shape contours[6]. In [4], Basri et al. propose amethod to estimate shape similarity based on both part articulation and local deformation cost. Backes et al. [3] use as descriptor the distribution of the distances between points on the

Boundary of the shape. Shape matching is a problem that has been the focus of a lot of research. Loncaric in [11] adopts three different classifications proposed by Pavlidis in [12]. A number of shape matching techniques are based on some kind of shape skeletonization. Torres and Falcäo [7, 8] compute image skeletons at multiple scales and use them to detect salient points on the contour of the shape. \\

Elastic matching algorithm is used to measure the similarity distance. It catches the similar shapes in an image database, successfully. It pays no attention to the initial points on the shape boundary. It is invariant to shape size and position. It is also stable under noise and shear transform [9].

D.C. Douglas Hung and I.R.Chen presented a technique for decomposing the overlapped or occluded shape into its components and recomposing the possible missing pieces back to their original form. The algorithm reduces the possible false matching and simplifies the problem of partial shape recognition. The current implementation has only applied to the tools with simple curved shapes [13].

Yoon-Sik Tak and Eenjun Hwang proposed a leaf image retrieval scheme based on the following two features: (i) first a series of Fourier Coefficients (FCs) was calculated from the distance curve to represent and compare the leaf shapes. Especially, in order to improve representation and matching accuracy, they proposed an algorithm PDTW for comparing two curves. (ii) In order to improve retrieval efficiency, 2-level filtering method was proposed, which firstly classifies images using the number of unit curves from images, and secondly, filters images using difference between FCs. They proposed a content-based leaf image retrieval scheme that is based on the shape (contour) feature of images.

The category of methods most relevant to the proposed one is those that represent and match shapes based on their contour points. The general strategy is to extract information concerning the points of the shape's silhouette and then match the extracted descriptions. Arica and Vural [13] propose a simple geometric transformation for the purpose of shape description. They compute the bearing angle of three consecutive contour points for variable offsets between these points. The values obtained for each point of the contour and for various offset sizes are considered as random variable measurements, the moments of which form the proposed descriptor.

A very interesting shape descriptor is the so called shape context, introduced by Belongie et al. in [5].

A method proposed by Cui et al. [6] efficiently match whole-to-part and part-to-part shapes. They choose the integral of absolute curvature as shape descriptor, and use the normalized cross correlation for matching parts of the occurring curves. The method is rotation, scale and translation invariant and tolerates moderate amounts of noise. Latecki et al. in [13] propose a method for shape matching based on dynamic programming. A particularly interesting aspect of this method is that it addresses the partial shape matching problem. More specifically, the method is able to establish the best match between an open silhouette and a part of a closed silhouette.

The method combines the strengths of Dynamic Time Warping [11] and the Longest Common Subsequence technique [12] in another dynamic programming based technique coined Minimum Variance Matching (MVM). Local tangents to silhouettes are used for the

Purpose of shape description. Like in the case of DTW, MVM reduces the problem of optimal alignment between two sequences to a shortest path problem in a Directed Acyclic Graph (DAG), which can be efficiently solved using Dynamic Programming. The key difference between MVM and DTW is the number of connections allowed in each

Node of the DAG, corresponding to different matching types in the original problem. More specifically.

2. Proposed approach

The proposed matching method employs only boundary points for shape description. A similarity measure between shapes is computed, together with shapes alignment. In the following sections, we describe the proposed shape representation and the shape comparison and matching processes.

2.1 Partial Shape Matching

Shape matching is an important ingredient in shape retrieval, recognition and classification, alignment and registration, and approximation and simplification. Partial shape matching is an essential process for image retrieval and computer vision. Its basic requirements are location-free, size-free, orientation-free, and noise-tolerance. We often treat image as shape. For example, image retrieval is a process searching similar shape from large amount of image data. Many shape matching methods have been proposed, but most of them can recognize only whole shape's similarity. For smarter search in image retrieval and recognizing occluded shape, partial similarity is quite important [2].

Our technique is also based on model of human visual information processing, in which shape matching consists of four phases: 1) image input, 2) shape description, 3) feature extraction, and 4) correspondence detection. Input image is black and white image and the shape is described as a set of discrete points. On our consideration, partial similarity means that two shapes are partly similar and relative location and direction of each similar part are most same in both shapes. In the following figure, there are two objects that (a) we consider partially similar and (b) those we do not.

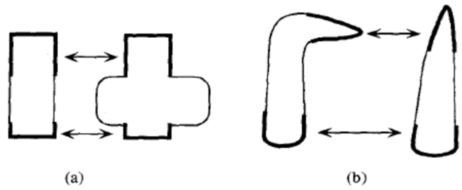


Figure 2.1: Partial similar images

Although it is impossible to detect precise partial similarity, such precise detection is not required for our aiming applications. Therefore, we treat partial similarity on feature level [2].

Shape matching is of central importance in a number of computer vision problems such as shape classification, retrieval, recognition, and simplification. Shape is an important cue as it captures a prominent element of an object. Shape matching amounts to developing computational methods for comparing shapes that agree as much as possible with the human notion of shape similarity. The aim of this problem is to compute the resemblance of shapes using some similarity measure. Shape matching also deals with transforming a shape, and measuring the resemblance with another one. The quality of the shape matching process depends on whether its final outcome agrees with human judgment [3]. Rough partial shape matching of images is shown in following figure.

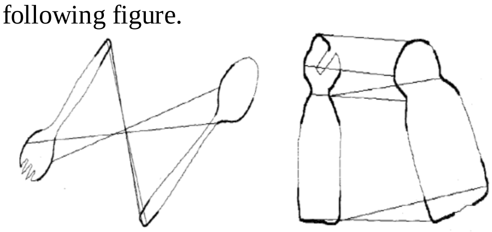


Figure 2.2: partial shape matching

The primary problem with matching is lack of knowledge on how to deal with geometric distortion i.e. noise. Almost all forms of shape representation are sensitive to geometrical distortions.

With the earlier investigation, the problem is two folds. There is a representation (coding) problem and matching (recognition) problem. The representation problem is largely geometrical in nature whereas matching is primarily an algorithm problem. However, the means of representation determines the complexity of the matching algorithm. Finally, the quality of the shape matching process depends on whether its final outcome agrees with human judgment. The Fig 1 shows some of the example of 2D shape matching and the process of shape matching is shown as Fig.2

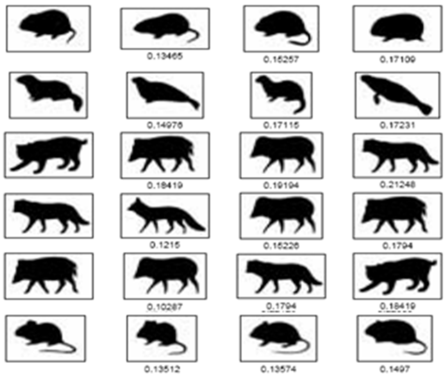


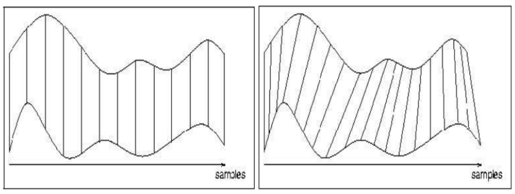
Figure 2.3: Mammal silhouette: column1: query image. Column2: matching images, sorted by similarity

Above figure shows the silhouette of mammals in which first column shows the query image and second shows the matching images. In this, minimum percent of matching is displayed rather our system shows the maximum percent of matching result.

3.Matching technique

The Dynamic Time Warping (DTW) is a well-known technique in many areas. It is used for measuring the similarity between given shapes. It is a technique for measuring similarity between two sequences which may vary in time or speed. DTW allows a computer to find an optimal match between two given sequences (e.g. time series) with certain restrictions.

DTW can compare characters in a way that is similar to the way humans compare characters, or at least generates the same results.



(a)one to one comparison (b) DTW comparison
Figure 3.1: Comparison of two curves using one to one comparison and Dynamic Time Warping

Efficiencies of DTW technique:

DTW is the efficient technique because unlike another shape matching techniques, it gets the right detection ratio even when the occlusion region is small, which causes due to the ambiguity between deformed boundary and small scale occlude boundary. And when the object to be detected is complex, this technique may obtain correct result. This is the reason we used DTW technique for matching shapes. As compared to other methods, it produces the matching result of more than two shapes in less time.

Dynamic Time Warping distance allows elastic deformations of objects' boundaries to be matched. The DTW distance has already proven to yield superior performance for the retrieval of time series and also the case for shape matching [16].

Shape Representation

The first step of our method is to represent the shapes by a sequence of points sampled from the contour. There are two different variants for point sampling: (a) sampling the same number of points from the contours or (b) equidistant sampling. Fixing the contour length between sampled points, the type of sampling significantly influences the invariance properties of our method. Based on equidistant sampling occlusions .By sampling the same number of points our method becomes invariant to similarity transformations, but strong occlusions cannot be handled anymore. All subsequent parts of the method are defined in a manner independent of the sampling type. Therefore, we can switch the sampling type without requiring any modifications of the method.

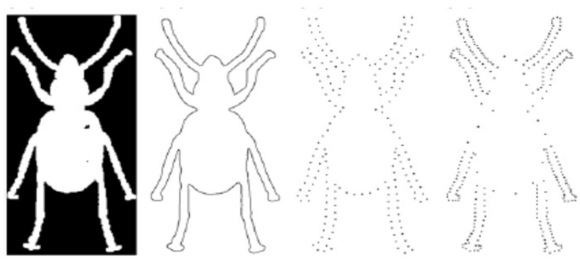
Comparing shape descriptors

Let d(sx)={lx1,lx2,…,lxk}, d(ty)={ly1,ly2,…,lyk} be two shape descriptors at points sx and ty, respectively. The goal is to establish a distance measure D (sx, ty) between the descriptors d (sx) and d (ty). D (sixty) is de.ned based on the pair wise comparison of the descriptors' coordinates, according to:

$$D(s_x, t_y) = \frac{1}{k}\sum_{i=1}^{k} \Delta(l_{xi}, l_{yi}),$$

Edge detection:

As we uses the boundary based representation, the outer boundary of the shape only is considered. This is done by describing the considered region using external characteristics i.e. edges of the image. For the extraction of the shape of the shape of the image, first we identify the object of the shape, second detecting edges and extracting the feature of the object, later applying the sampling.



(b) (c) (d)

Figure 3.2: Extracting feature the shape

An example of extracting feature of shape is shown in above figure, passing binary image is shown in (a) then detecting object and extracting the edges is shown in (b), (c) and after applying down sapling is shown in (d).

Shape matching:

Finally, shape of query image is compared with the shapes of answer images by using Dynamic time warping. Matching open contours against parts of closed contours i.e., the extracted edge of query image is then matched with that of the answer images. And the shape matching is carried out by applying DTW technique. Matching must be done in the presence of noise i.e. geometrical distortion. The goal of the matching step is to estimate the similarity of two given contours based on the descriptors already computed on them. This is achieved by establishing correspondences between contour points.

4. Experimental results

The proposed approach for 2D shape matching has been validated by several experiments. The experiments can be grouped into two categories, one that assesses the performance of the proposed method In matching open to closed contours and another one that concerns the matching of closed contours.

For performing a partial shape matching, first of all we have to insert a set of images. We have to calculate the shape descriptor of the each image. Along with shape descriptor, edges of all images are extracted by using filter. Then from the set of images, a query image is selected. Then the matching is carried out between query image and the answer images by using dynamic time warping technique. After matching is done, matching percentage is displayed.

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Finally, shape of query image is compared with the shapes of answer images by using Dynamic time warping.

5. Conclusions

As we know that Image processing field is explored in depth and pattern matching plays an important role in development of imaging software, however as compared with other similar matching methods, a model which we developed can be used for image recognition and matching in practice. This project provides a solution to the problem of partial shape matching. The key idea and main contributions of this project lie in the shape descriptor and scale dependent sampling. The shape descriptor is robust under significant deformation, efficient to compute and captures sufficient information to enable high performance.

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