Design and Evaluation of a Curve Matching-Based Spine X-ray Image Retrieval System

D.J. Lee [a] , Sameer Antani [b] , Xiaoqian Xu [a] , L. Rodney Long [b]

[a] Department of Electrical and Computer Engineering
Brigham Young University, Provo, UT 84602

[b] Communications Engineering Branch
Lister Hill National Center for Biomedical Communications
National Library of Medicine, Bethesda, MD 20894

ABSTRACT

A spine x-ray image retrieval system has been developed for retrieving images based on the pathology information such as the osteophyte. Osteophyte shows only in particular regions on the vertebra. This means the contour information on the vertebra regions that are not of interest hinder the image retrieval relevance precision. Curve matching or partial shape matching (PSM) methods based on dynamic programming for matching shapes with variable number of points and with different data point distribution have been developed to detect the osteophyte with similar shapes. Based on the shape property of spines, corner guided dynamic programming (DP) is introduced as the new enhanced searching strategy which dramatically increases the processing efficiency of the traditional DP. Shape representation method using multiple open triangles is presented in this paper. Performance evaluation of corner-guided DP on this shape representation based on human relevance judgment is presented. This paper also presents the implementation and performance of the retrieval system. The retrieval system consists of a user friendly graphical user interface (GUI) which has been developed for testing. All the shape matching methods that have been developed have been integrated into the system for the user to choose during a retrieval process. The retrieval results are ranked from the most similar to the least similar and can be all viewed by the user.

Keywords: content-based image retrieval, partial shape matching, dynamic programming, corner-guided DP.

1. INTRODUCTION

There has been growing interest in indexing images with biomedical content, especially in developing an automated or computer-aided interactive medical information retrieval system. A digital archive of 17,000 cervical and lumbar spine X-ray images is maintained by the Lister Hill National Center of Biomedical Communications. A lot of research has been done to index and retrieve these images so that the pathological features such as anterior osteophyte, disc space narrowing, could be extracted and used by both the expert and the potential patient users. Shape matching has been used and proven to be an efficient and effective method for spine X-ray image retrieval, since the images are gray scale with low qualities and doesn't provide much texture information to help with retrieval. Usually shape matching is processed in the sense of treating the shape as one single object, which can be referred as whole shape matching. Most of our previous work has focused on whole shape matching[1]. However, retrieval results using whole shape matching were found to have only about 56% relevance[2]. Partial shape matching (PSM) was motivated as our recent work and has been proven to be more relevance efficient in the process of X-ray image retrieval.

PSM enables querying on specific regions of the entire shape and searches for the best matching segment on the object shape. Anterior osteophytes appear and only affect a part of the whole boundary, which are the parts providing pathology information. Thus the users are often more interested in the particular pathological region of the shape boundary. Querying on specific regions is a necessary and important option for the users attempt to retrieve similar pathological parts from other shapes. Our recent work has focused on developing the appropriate shape representations

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and shape matching strategy for PSM [3, 4]. Procrustes Distance Matching was used on fixed point data and showed satisfactory results [3]. But variable point data and variable distributed point data require matching methods to eliminate the affect of the difference of point number and point distribution. Dynamic Programming (DP) is a searching strategy which meets this requirement. Merging point is allowed but with a well-defined cost during the matching process. DP finally ends up with the matching path which has the least cost. Line segments and multiple open triangles are two shape representation methods employed for PSM. DP was implemented for both representations and the retrieval results were very promising [3, 4].

Since DP allows possible merging of data points, a rather large amount of possible matching paths starting from the same starting point have to be tried until the one with least cost is found. Without knowing the starting matching point, every point on the object shape is a possible candidate and DP has to be performed for all of them. So the biggest drawback of DP is time-inefficiency [5, 6]. This becomes a severe issue when the database is large. Also, we have implemented a modular prototype system for content-based image retrieval for a subset of the spine x-rays and health survey text data associated with these x-rays. Both whole shape and partial shape matching have been integrated into the system to retrieve the image and the text data information. But as aiming to put such a system into real use for potential patient users with a large database support, the requirement of time-efficiency of DP algorithm is very critical. Based on the rectangular nature of spine shapes and the expert-marked 9 point model, corner-guided PSM using DP has been implemented to speed up the matching process. By limiting the possible searching regions to four corners, it dramatically increases DP searching speed. Traditional DP has been modified not trivially to perform matching starting from one corner, which is a point in the middle of the whole matching segment, instead of the first point of the matching segment. Multiple open triangles shape representation method has been chosen for corner-guided PSM for its better performance. The multiple open triangle shape representation method, algorithm for locating 9 data points for spine shape model, and modified corner-guided DP are discussed in Section 2. In Section 3, we show the performance of this shape retrieval method and our evaluation. Conclusions are discussed in Section 4.

2. PARTIAL SHAPE MATCHING USING CORNER-GUIDED DP

2.1. Shape representation: multiple open triangle

An open shape can be expressed as $M = M_1, M_2, M_3, ..., M_N$, where M_i is the i^{th} point on the shape with the coordinate (x_i, y_i). From the second point on, each point has at least one previous point and one subsequent point. An open triangle is formed by connecting the previous point to the current point and the current point to the subsequent point. For those points which have more than one previous point, another open triangle is formed by connecting M_{i-2} to M_i and M_i to M_{i+2}. In this manner, each data point can be represented by multiple open triangles [7] as a measure of its effect on the shape. In our application, we set $K = 3$ as the largest number of such open triangles associated with one point.

As shown in Fig. 1, point M_2 only has one open triangle; point M_6 could have up to 5 open triangles, but only the first three open triangles as shown in the figure are used to represent this point. The angle θ associated with an open triangle is also illustrated in Fig. 1. This angle is actually the supplementary angle of the relative orientation we calculated for the line segments. So for each point, there will be up to three angles as the features of this point. Besides the angles, the lengths of the two sides of an open triangle are also calculated as the features associated with this point since the points are not equally-spaced on x-ray shapes as in [7]. The similarity of the length S_l is calculated in the same way as for line segments [4]. The overall angle similarity for each data point is calculated as:

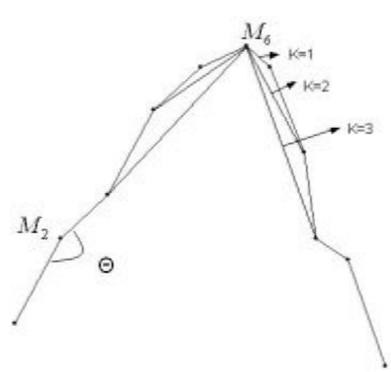

Fig. 1. Multiple Open Triangles and the angles

$$S_\theta = \frac{1}{n}\sum_{i=1}^{i=n}\cos(\theta_i - \theta_i^{'}) \tag{1}$$

, where n is the number of open triangles. For example, to use 3 open triangles to represent one data point, the overall angle similarity is the average of the three individual angle similarities (one for each open triangle).

2.2 Corner guided dynamic programming

2.2.1 Background

The vertebrae shapes are rectangular overall with four main corners. Anterior osteophytes (AO) show up on the anterior two corners (Points 8 and 9). When exist, the corners deform and extend to sticking out as shown in Fig. 2. So in terms of AO pathology, there are some critical points that the radiologist would look at rather than the whole shape. Fig. 2 shows nine morphometric landmark points model marked by a board certified expert radiologist. Points 8 and 9 indicate the existence of anterior osteophytes. Without AO, points 8 and 9 will coincide with points 3 and 6 respectively. As the 9-point model describes the AO pathology, it has been used as a ground truth in evaluating the retrieval relevance accuracy.

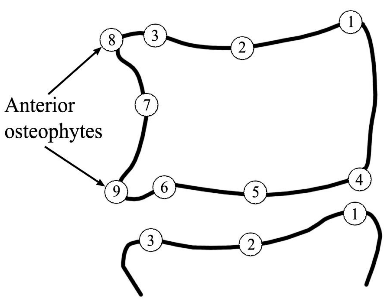

Fig. 2. Radiologist marked 9-point

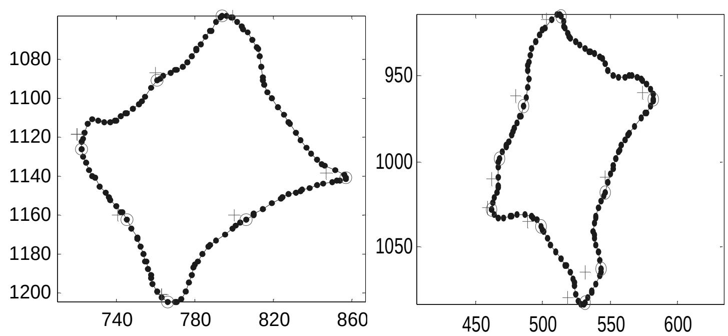

Fig. 3. Auto-localization of 9-point model

Our X-ray retrieval system allows querying on any part that the users want. But as we can tell, the retrieval results of a straight line query won't help determining the pathology. Thus, the users also intend to query on the pathologic part supposing they are seeking for medical information. A standard PSM query usually contains a corner of the whole shape, which is also a critical point in the 9-point model.

The above two facts prompt the thoughts of corner guided shape matching without losing the general accuracy but with dramatically increased searching speed, especially for DP strategy.

2.2.2 Auto-localization of 9 points

According to the semantic relevance of the 9 points, the algorithm for auto-localizing 9 points has been developed [8]. The radiologist marked a subset of 250 segmented spine boundaries from the 17,000 digitized x-rays. The auto-localization algorithm has been tested on these 250 spine shapes. In Fig. 3, it shows two samples of the 9-point localization performance with one 7-point (no anterior osteophytes) and the other 9-point (with anterior osteophytes). The crosses represent the points marked by the radiologist and the circles represent the selection made by the algorithm. Since the radiologist marked the 9 points on the original X-rays while our algorithm localized 9 points on the segmented shapes, there is minor inevitable discrepancy between these two sets of 9 points due to the difference between the X-ray image and the corresponding shapes. In spite of this difference, the algorithm performed very well in detecting the AOs and the corners.

Almost 5,000 cervical and lumbar shapes have been segmented from over 900 x-ray images. If the 9 points are pre-stored for corner guided use, the matching process will be further speeded up. So auto-localization of 9 points has been implemented and included in the GUI, which can save the 9 points in a file and retrieve for guiding DP secarches. We have pre-stored the 9 points for all 4,550 shapes in out database. This approach speeds up the corner guided DP process.

2.2.3 Corner guided DP:

Suppose there is a query shape A which is an open curve consisting of 5 points, and a candidate shape B which is a closed shape consisting of 7 points. In matching the open curve to the closed shape, the algorithm builds a typical DP table (Table 1). The rows of the table are indexed by i, which represents the query. The columns are indexed by j, which represents the object shape B [5]. Since B is closed and has 7 points, DP table has 14 columns, which is twice the number of points on B, so that every point on B could be a starting matching point of a complete match by having subsequent points. Starting from the cells at the bottom row which is called the "Initialization Area" and proceeding upwards and to the right, the table is filled with the previous matching node (so that we can trace back after finishing the matching process) and the total matching cost up to this point. After filling out the top row which is called 'Termination Area', all the possible matches on shape B with curve A have been picked and could be traced back starting from the termination area. The best match which has the minimum cost is finally picked as the most similar part on shape B to curve A.

i \ j	1	2	3	4	5	6	7	1	2	3	4	5	6	7	
5						T	T		T			T	T		Termination area
4					X			X		X		X			Computation area
3			X			X			X	X					
2		X		X			X		X						
1	S		S		S	S	S								Initialization area

Table 1. Typical DP Table

The regular DP needs to be modified when guided by the corners, which is not trivial. Since the corners are supposed to show up on both the PSM query and the matching parts from the object shapes, matching of the corners is the first step. So instead of having all the points on the object shape as a possible starting matching point, only the corners are considered to extend a partial shape matching path. Thus, for a whole spine shape with four main corners, four potential partial matching segments will be selected with each containing one corner. The one out of the four segments with least cost is finally selected as the most similar matching part on the current object shape.

Table 2 illustrates corner guided DP, which still has the same layout as the traditional DP table except for two termination areas. Suppose the query A has 7 points and the object shape B has 9 points. Instead of starting from Initialization area in Table 1, corner guided DP first matches the corners as indicated as 'C' in Table 2 on both the query and the object shapes, which is actually a point of Computation area in Table 1. Starting from 'C', DP search is performed in both two directions simultaneously and independently until hitting the termination area. At each cell, the total cost is computed as Equation 2 and compared with the previous highest similarity to determine which to keep:

$$S_{total} = Weight_1 \times S_l + Weight_2 \times S_\theta + Weight_3 \times S_{mer} \qquad (2)$$

, where S_{mer} is the merging similarity [4]. Fig. 4 shows the outline of the proposed corner guided DP algorithm. The outline of this corner-guided DP search is shown in Fig. 4.

The typical DP selects a best matching path for every point on the object shape while corner guided DP only selects four best matching paths for one individual object shape. Suppose an object shape has N points, the corner guided DP is supposed to be $N/4$ times faster than the typical DP. So the more points the object shape has, the more efficient the corner guided DP is compared to the typical DP. This will be a significant improvement when retrieving from a large database. The accuracy of corner guided DP obviously relies on the accuracy of the localization of the corners. But our 9 points localization algorithm has proved to be very accurate in localizing the four main corners with the test on over 1,000 shapes in the database. Corner guided DP is tested on almost 5,000 shapes for both retrieval accuracy and the time efficiency.

i \ j	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	
7											X								Termination area
6										X									
5								X											
4							X												
3					C														
2																			
1				X															Termination area

Table 2. Corner Guided DP Table

```
Input: Partial query shape A=A_1, A_2,…, A_M and the object shape (a whole shape)
B=B_1, B_2,…, B_N from the database
Output: "4×M" Cell Matrix, each cell containing the matching index and the cost

corner = localizecorner(A);  // find the corners on the query shape
9pt = textread('B.9pt');  //read in the pre-stored 9 points of B
for j=1: 4   //Four main corners on B is used to guide finding four matching
segments on B
      Index = 1;
      while  "4×M is not completed"
           if Index == 1
               search for three line segments on A and B (centered at the corner)
             with a minimum cost to match
           elseif Index <4
               search for two line segments on A and B simultaneously on both left
             half and right half (separated by the corner) with a minimum cost to
             match
           elseif Index >= 4
               search for one line segment on A and B on both halves with a
             minimum cost
           end
           Index = Index + 1;
      end
end
```

Fig. 4. Outline of the corner guided DP algorithm

3. Performance and Evaluation

Five queries each of cervical and lumbar shapes were picked and the best 15 shapes were retrieved for each query. Since we didn't have a reliable ground truth, we used human relevance judgments to evaluate the effectiveness of the method. For each retrieved shape, human judges determined whether it is a qualifying match or not. Corner-guided shape matching using Procrustes distance [3] was implemented to provide a comparison with corner-guided DP on multiple open triangles representation.

Fig. 5 is the retrieval results of corner-guided DP. Fig. 6 is the retrieval results for the same query as in Fig. 5 using corner-guided Procrustes. As we can see, corner-guided DP performed better in detecting the details in terms of the angle changes of the query. Since DP performs the matching based on multiple open triangles, DP marches line segment by line segment. Procrustes treats the partial query as a whole and performs global alignment to find the minimum distance. So theoretically, DP should perform better in detecting the details. Another advantage of DP is that it allows the merging of data points. Thus it doesn't require the same number of point to match two shapes. It also deals with noise by allowing data point merge. Procrustes requires the same number of points to match two shapes. It is less flexible and can not deal with noise and different point distribution. Also, the weights of merging cost, length distance and angle distance are adjustable during the retrieval process and thus it is possible to gain better results by adjusting the weights. The selection of weights also provides the potential for the user to be involved in the retrieval process known as relevance feedback.

Corner-guided DP also reduces the processing time by around 10 times compared to the traditional DP. It takes around 2 minutes for corner-guided DP to finish matching for a query on almost 5,000 shapes. But compared to Procrustes which only takes around 30 seconds, corner-guided DP is still relatively slow. Fig. 7 shows the retrieval results of corner-guided DP using another query.

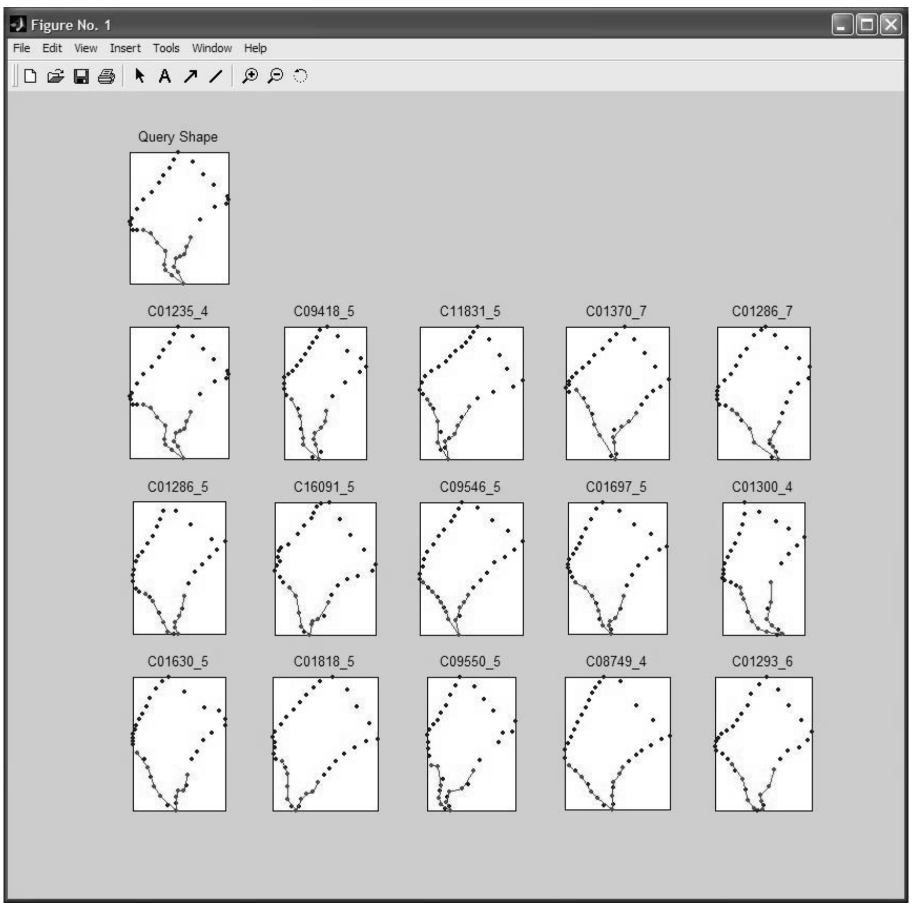

Fig. 5. Matching results of corner-guided DP

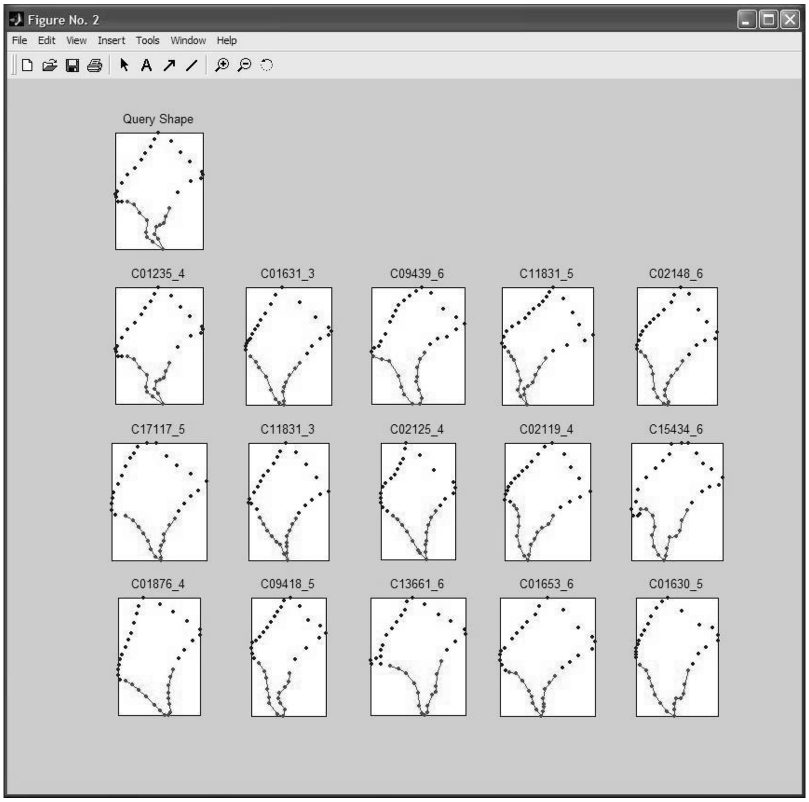

Fig. 6. Matching results of corner-guided Procrustes

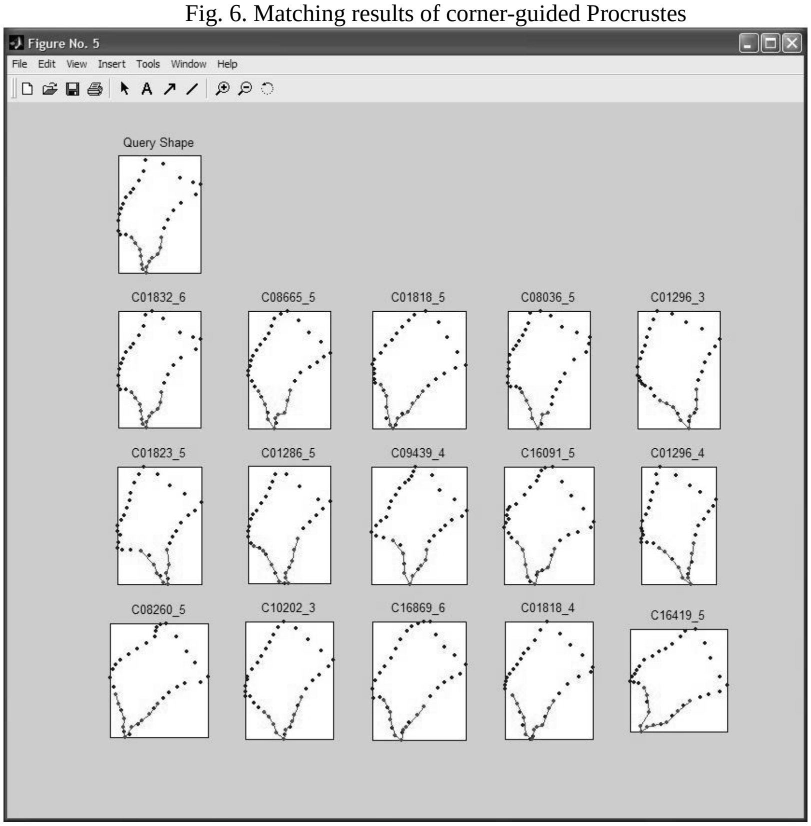

Fig. 7. Matching results of corner-guided DP

A simplified and common way of computing Precision and Recall is used to give a statistical evaluation of the corner-guided PSM method:

1. Precision is the percentage of qualifying shapes retrieved with respect to the total number of retrieved shapes.
2. Recall is the percentage of qualifying shapes retrieved with respect to the total number of similar shapes in the database.

Due to the large volume of the database, it is very difficult to find all the similar shapes in the database for a specific query manually. Similar matches for all the ten queries from half of the whole database were picked by human judges and the assumption that there is equal number of similar shapes to a specific query in both half of the database was made.

A precision-recall plot (Fig. 8) is presented for corner-guided DP matching. The horizontal axis corresponds to the measured recall while the vertical axis corresponds to precision. The plot contains 15 points, which corresponds to 15 best matches and each point in the plot is the average over 10 queries. The first point from the left of the plot corresponds to the precision/recall values for the best answer, while the last point from the left corresponds to the precision/recall values for all 15 best answers. Higher precision and higher recall correspond to a better retrieval performance. In Fig. 8, for the 10 queries we picked, the lowest precision for corner-guided DP was 89%, which is rather high.

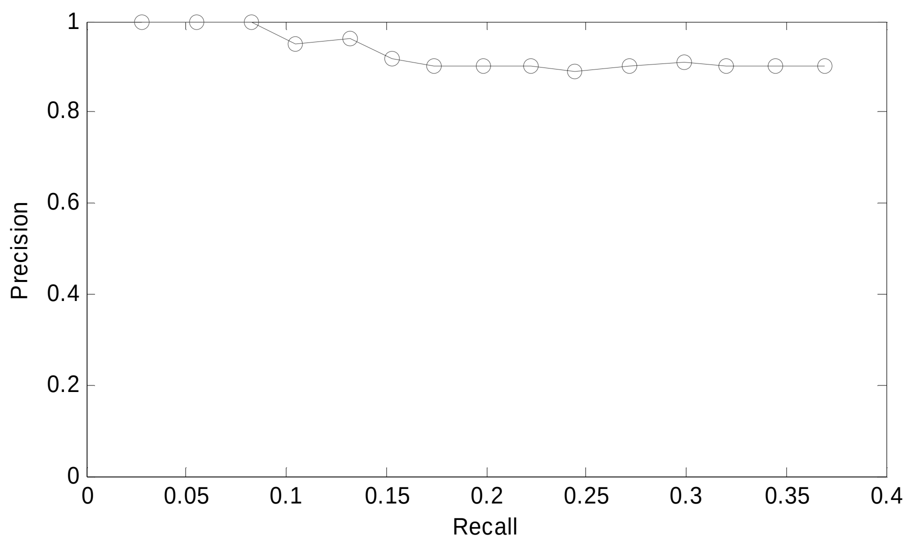

Fig. 8. Precision-Recall of Corner-guided DP

4. Conclusions

According to the 9-point model and the nature of spine shapes, we developed a corner-guided dynamic programming search method based on multiple open triangles for partial shape matching. Our approach treats noise and is adjustable according to the noise level. It is independent of translation, scale, rotation and starting point selection. Tested on 15 best answers of ten queries, the method has a rather impressive high precision. With higher time efficiency than traditional DP, corner guided DP for PSM is a very promising and practical method for spine shape retrieval. The processing speed can be further increased if implementing corner-guided DP with a more efficient programming language such as C/C++ instead of testing in Matlab. The weights of merging cost, length distance and angle distance are adjustable during the retrieval process and thus are also an issue for more testing to gain better results. At the mean time, the weights also provide the potential for the user to be involved in the retrieval process known as relevance feedback. Thus our future work includes building an interactive retrieval environment by allowing the users to be in the loop to regularly request their feedback as to refine the retrieval results.

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