Curve Matching for Spine X-ray Image Retrieval using Dynamic Programming

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ABSTRACT

Detection of medical information such as osteophyte on spine x-ray images is an important task for spine x-ray image retrieval. Curve matching can be used to match partial shapes for image retrieval. Using a curve segment that contains osteophyte information as the query for matching provides more accurate retrieval information than whole shape matching. This paper presents curve matching methods for matching curve segments that have different number of data points and different data point distribution. Dynamic programming (DP) is implemented to allow merging of the data points in the process of curve matching, which minimizes the impact of having different data point distribution. Two shape representation methods using line segments and multiple open triangles have been evaluated in conjunction with DP. This paper focuses on the improvement on the original DP to allow merging points on the query curve using a modified multiple open triangle shape representation method. It also includes matching result comparisons between two shape representation methods and between merging and non-merging query data points using multiple open triangles.

Keywords: Curve matching, image retrieval, dynamic programming, multiple open triangles, merging data points.

1. INTRODUCTION

There has been growing interest in indexing images with biomedical content. Shape matching has been adopted for x-ray image retrieval. Several different methods including Procrustes distance, Fourier descriptors, shape features, invariant moments, polygon approximation for tangent space matching, and token evaluation in multi-scale space [1, 2, 3] have been implemented for matching whole spine x-ray shapes. However, retrieval results using *whole* shape matching were found to have only about 56% relevance [4]. As the radiologists mark 9 morphometric landmark points on x-ray images to describe various pathologies, osteophyte only shows up at certain locations on the vertebra. This indicates that other locations on the vertebra shape that are not of interest may hinder the spine x-ray image retrieval relevance precision. It results in low relevance percent of *whole* shape matching and motivates our research in *partial shape matching (PSM)* or curve matching. This approach uses a curve segment that contains osteophyte information as the query to improve retrieval accuracy.

As an improvement on whole shape matching, partial shape matching has become a necessary step for accurate spine x-ray image retrieval. Partial shape matching provides a way to deal with occlusion and distortion when comparing two incomplete shapes [5-8]. In our application, PSM or curve matching enables querying on specific regions of the entire shape and searches for the best matching curve segment. By doing this, curve matching provides another view for image retrieval which can be more related to medical pathology. Different shape representation methods such as inflection point [8] have been used to extract shape features for matching. Inflection point is not a very suitable shape representation method for vertebral shapes since they all have a rectangular shape and do not have significant number of inflection points. Two shape representation methods, line segment and multiple open triangles, which are more suitable for spine x-ray image retrieval, are studied in this paper.

Shapes could be represented with different number of points and different data point distribution or data sample spacing. Merging data points is needed in order to determine the best match. Dynamic Programming allows merging of data points during the matching process to cope with the problem raised by different data point distribution. It can then search for all possible matching paths and select the most promising one with minimum distance. The minimum distance consists of differences between the corresponding shape features extracted from both the query curve and the candidate shape and the merging cost associated with the merging process. Since a shape matching algorithm must be based on the properties of its underlying representation, DP using line segments was implemented slightly different from the DP using multiple open triangles. This paper focuses on the implementation of DP that allows merging on the query curve using multiple open triangles as an improvement on our previous work [9].

The two shape representation methods and the similarity measurements are introduced in Section 2. Section 3 defines the merging cost and describes the implementation of the improved DP algorithm. Comparison between the original DP algorithm and the modified DP using multiple open triangles to allow merging on the query curve is also addressed. Results and evaluation are presented in Section 4. Future work and our conclusions are discussed in Section 5.

2. SHAPE REPRESENTATIONS

Two different shape descriptors are introduced in this section, with emphasis on the method using multiple open triangles. Different shape features can be extracted from the shape data points based on these two shape descriptors that are both eligible for Dynamic Programming implementation.

2.1 Line Segments

A line segment is formed by connecting two adjacent data points on the shape contour. Our line segment-based shape features include length, absolute orientation [7, 9], and relative orientation.

- Length: 2-norm of the line segment.
- Absolute Orientation: The angle between the abscissa axis and the line segment, which has the same length as the original line segment but starting from the original point.
- Relative Orientation: Bending angle between two adjacent line segments.

The similarity between two line segments is calculated based on these shape features [9-10].

2.2 Multiple Open Triangles

An open curve can be expressed as a sequence of data points $M = M_1, M_2, M_3, \ldots, M_N$, where M_i is the i[th] point on the curve with the coordinate (x_i, y_i). For an open curve, from the second point on and except for the last point, 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. Current point could have more than one open triangle if it has more than one previous point and more than one subsequent point. For instance, the second open triangle associated with M_i can be formed by connecting M_{i-2} to M_i and M_i to M_{i+2}. Each data point can be represented by multiple open triangles [11] as a measure of its effect on the curve. In our application, three open triangles were used for each point that has at least 3 previous points and 3 subsequent points. As shown in Fig. 1, point M_2 has only one open triangle, whereas point M_6 could have up to 5 open triangles. Only the first 3 open triangles as shown in the figure were used to represent this data point. The angle θ associated with an open triangle is also illustrated in Fig. 1. This angle is the supplementary angle of the relative orientation we calculated for each data point. It is a feature extracted from each open triangle that carries significant curve information. The lengths of the two sides of an open triangle are also calculated as the features associated with this point. Since data points are not equally-spaced on spine shapes as shown in [11], lengths of the two sides of an open triangle become important features for measuring curve similarity.

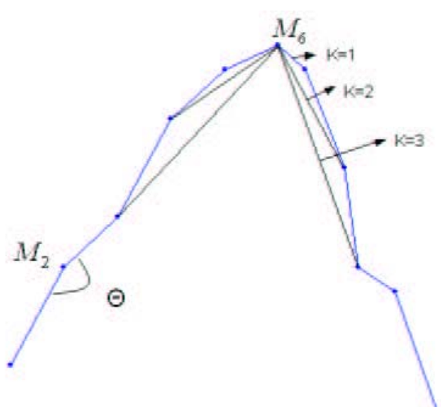

Fig. 1. Multiple Open Triangles

In order to obtain scale-invariant length similarity measurement, the global alignment, which is the overall average scale ratio between the query curve and the candidate curve, will be calculated and denoted as C_0. For each pair of matching line segments l and l', the length ratio c is calculated as $c = l / l'$. Length similarity can then be expressed as

$$S_l = \frac{4cc_0 + (c^2 - 1)(c_0^2 - 1)}{(c^2 + 1)(c_0^2 + 1)} \tag{1}$$

The overall angle similarity for each data point is calculated as:

$$S_\theta = \frac{1}{n} \sum_{i=1}^{i=n} \cos(\theta_i - \theta_i') \tag{2}$$

where $\boldsymbol{n}$ 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).

3. DYNAMIC PROGRAMMING

3.1 Fundamentals of DP

DP is a powerful tool for finding a desired path through all possible options. In partial shape matching, DP is employed to find a matching path with the minimum cost when multiple matching possibilities involved, especially when matching with shapes with occlusion. For the applications of matching shapes with different number of points and different point distribution, DP is also a useful tool because merging of data points is allowed to achieve better point-to-point matching. Because of different architectures of the two shape representation methods we used in this paper, we discuss the DP implementations separately in the following two sections.

3.2 DP Implementation for Line Segments

Suppose there is a query shape A that is an open curve consisting of 5 points, and a candidate shape B that is a closed shape consisting of 7 points. In matching the open curve to the closed shape, the algorithm builds a DP table (Fig. 2), where rows and columns correspond to the points of A and B, respectively [8]. 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.

In the process of filling the DP table, data merging happens if lower cost can be obtained. For example, if the cost of matching points 1 and 2 on curve A with points 4 and 6 on shape B, respectively is smaller than the cost of matching points 1 and 2 on curve A with points 4 and 5 on shape B, DP algorithm will choose to merge point 5 on shape B to achieve a smaller cost. When the shape is represented by line segments, DP table is filled one row each time since those shape features are based on only one line segment and the line segments are relatively independent to each other.

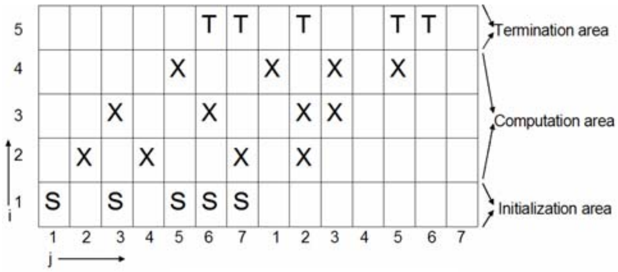

Fig. 2. A Typical DP Table

Merging process is associated with a cost since there should be a penalty for removing a point that is actually on the shape and should not be removed. When a point is removed, a new line segment is formed with new length. So, the merging cost consists of two parts. The first part is contributed by the change of length. The second part is the significance of the merged point in terms of the *cosine* value of its turn angle.

For two curves, a length scale factor is calculated based on the length of all the line segments on the curves, which is denoted as C_0 in equation 1. When a merging occurs, the new length changes the ratio, C which results in less similarity using equation 1 compared to updating C_0. A cost is automatically generated if the length scale factor is not updated. The other part of the merging cost reflects the significance of the point merged and is calculated as *cosine* of the sum of the bending angles of all the merged points:

$$S_{mer} = \cos(\theta_{rel1} + \theta_{rel2} + \theta_{rel3} + \ldots) \tag{3}$$

The bigger turn angle a point has, the more contribution it makes to the whole shape. As shown in Fig. 3, suppose there are four points and the matching path is from point 1 directly to point 4, which means point 2 and 3 are merged or can be removed. Then the merging similarity associated with this matching path is computed as $\cos(\theta_{rel2} + \theta_{rel3})$.

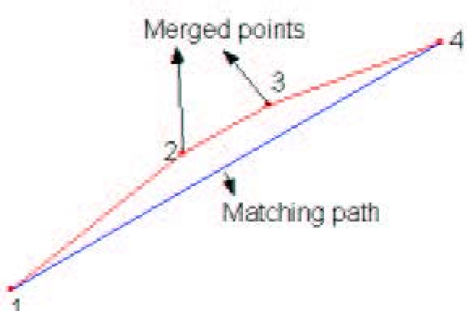

Fig. 3. Merging Process

Considering that DP is not a computationally efficient process and it is very unlikely that 10 points on the query shape match to only 2 points on the candidate shape, the number of consecutively points can be merged was limited to a small number to reduce the processing time for matching process. In our implementation, the limit on number of data points can be merged or removed was set to 5. In other words, the maximum number of points can be merged between any two possible matched curves is 5.

3.3 Modified DP for Multiple Open Triangles

Unlike line segment representation method, multiple open triangles could have up to 6 line segments involved when extracting the features. This posts a big challenge for DP algorithm implementation since merging one point could change the features of the current point as well as the features of its previous points. It requires the recalculation of shape features and the similarity measurements associated with the affected previous points. The implementation of updating the similarity measurements of all involved previous points is very complex. Also, considering the time-consuming nature of DP process, processing time required for updating similarity measurements seems to be a bigger concern than any other issues. In our previous work [9], DP was implemented without merging data points on the query curve. The matching results were good overall except that long segments tended to match with a short query open curve.

Merging on both query shape and candidate shape for multiple open triangle shape representation method allows a fair comparison between the two shape representation methods and is also a reasonable approach for getting good matching results. As an improvement of our previous work, merging on both query and candidate shapes was implemented in this paper.

According to the structure of multiple open triangles, DP was implemented for groups of data points. Each time DP determines a matching pair (which could be more than one line segment) and the determination of the subsequent matching pairs doesn't affect the current matching pair. DP table is first filled two rows each time since an open triangle has to have at least two line segments to start feature extraction and matching process. All the possible combinations of two line segments are searched on both query and candidate shapes. The matching pair with a minimum cost is picked as the first matching part. The algorithm continues to search for two line segments each time until it has 6 line segments matched. Then one line segment will be matched each time until the completion of matching the whole query curve. By doing this, only the features associated with the last point of the previous matching segments need to be extracted while the features of all the other points remain the same. The total cost of adding the new matching segment is just updated by adding the cost of matching the new segment, which overcomes the difficulties of possibly updating the cost

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Input: Query shape A=A1, A2,…, AM and candidate shape B=B1, B2,…, BN
Output: "2N×M" Cell Matrix, each cell containing the matching index and the cost

for j=1: N   //Every point on B is a possible starting matching point
    Index = 1;
    while  "2N×M is not completed"
        if Index < 4
            search for two line segments on A and B (starting point is Bj) with a minimum cost to match
        elseif Index >= 4
            search for one line segment on A and B with a minimum cost
        end
        Index = Index + 1;
    end
end
```

Fig. 4. Outline of the algorithm

associated with the previous matching segments. Fig. 4 shows an outline of the algorithm.

The merging occurs within each DP search. The merging cost is also calculated in *cosine,* but instead of the relative orientation, it is the *cosine* of the most significant angle among all angles associated with the open triangles. Again, the maximum number of points merged between any two points was set to 5. When searching two line segments at a time, the maximum number of points that could be merged on each side of the open triangle was 5.

4. MATCHING RESULTS

Fifteen shapes with different number of points and different point distributions were used to test the new DP algorithm. Comparison of the matching results using line segments and multiple open triangles without merging on the query shape has been discussed in [9]. DP implementation using multiple open triangles without merging data points on the query curve tended to match long segments with a short query open curve. Fig. 5 and Fig. 6 show matching results of the same query curve using multiple open triangles. Fig. 5 shows the result from DP implementation without merging data points on the query open curve. For this DP implementation, the number of points on the matching curve must be more than the number of points on the query curve. In some cases, the matching process went out of control and ended up matching the short query curve to a much longer curve. This can be seen in the fourth and fifth match in Fig. 5.

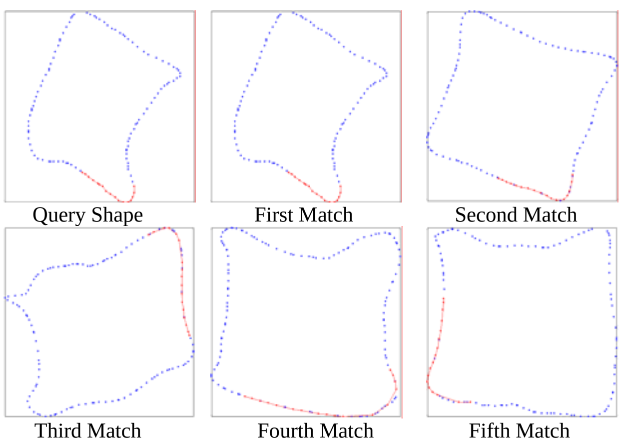

Fig. 5. Old DP approach using Multiple Open Triangles

Since the new DP implementation merges data points on both query and candidate shapes, it allows a fair comparison between the result of using line segment shape representation method and that of using multiple open triangles. Two sets of results are shown in Figs. 7 and 8. The results confirmed the expectation that multiple open triangle shape presentation method performs better than line segment method since intuitively multiple open triangles provide more information about the contribution and the importance of a point to the curve. The fact that there are only fifteen shapes in our database for this testing made it less likely to have many similar shapes. For the query curve (the osteophyte part on the whole shape) in Fig. 7 and 8, our ideal matching results should be the similar osteophyte parts on other candidate shapes. But among all the fifteen shapes we have, there were not enough similar osteophyte parts to be retrieved. But by human inspection and in terms of the shape similarity, DP algorithm did show very promising result in matching partial open curve, especially using multiple open triangles (Fig. 8 and Fig. 10).

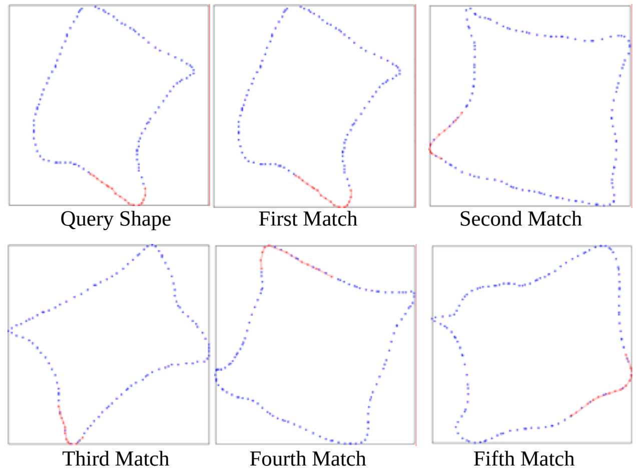

Fig. 6. New DP approach using Multiple Open Triangles

Fig. 7 and 8 use the same query shape and Fig. 9 and 10 share another query shape for the comparison purpose.

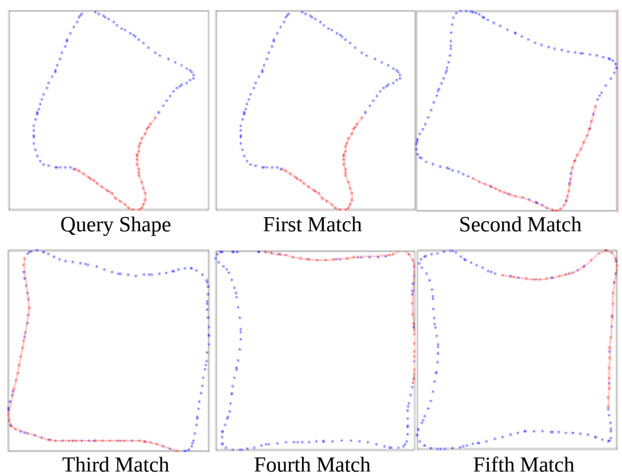

Fig. 7. DP approach using Line Segments

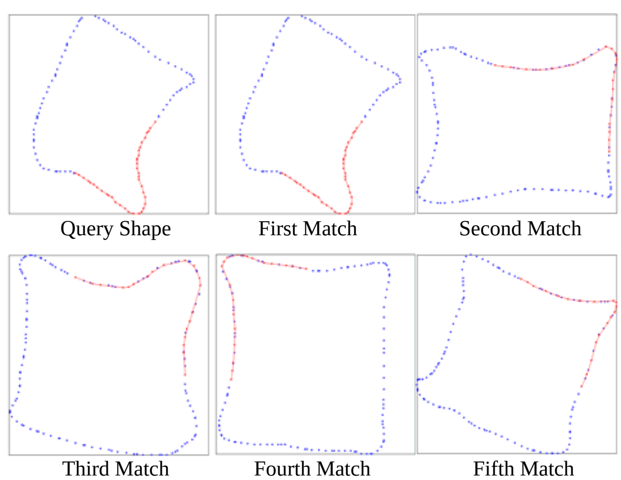

Fig. 8. New DP approach using Multiple Open Triangles

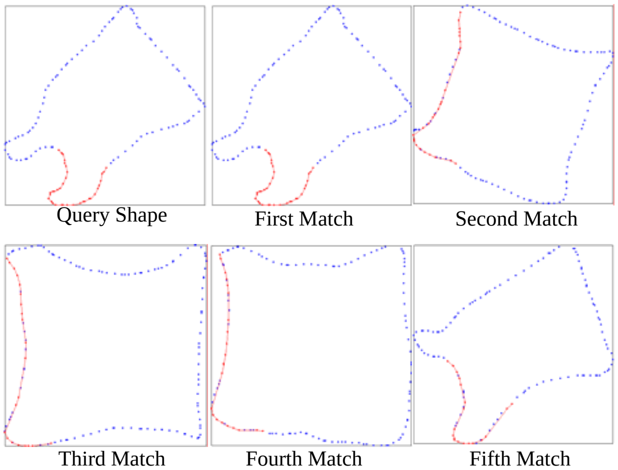

Fig. 9. DP approach using Line Segments

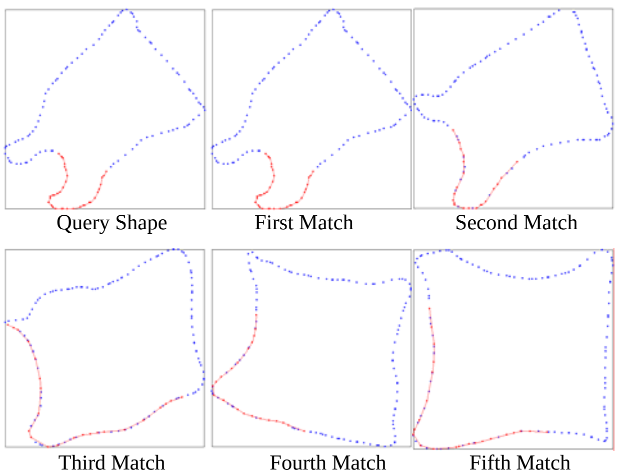

Fig. 10. New DP approach using Multiple Open Triangles

The lack of enough shapes in the database is shown more clearly in Fig. 9 and Fig. 10. The query shape is a very unique shape among all the fifteen shapes we have in the database. There was only one shape similar to the query curve, which was retrieved correctly as the second match in Fig. 10, but was only ranked as the 5th matches by using line segments as shown in Fig. 9. Overall, multiple open triangles performs better than line segments.

5. CONCLUSION AND FUTURE APPROACH

In partial shape matching, matching shapes with variable number of points and different point distribution is as important as matching shapes with fixed number of points [10]. DP was implemented for two shape representation methods: line segments and multiple open triangles. As an improvement from our previous work, DP was implemented to merge data points on both query and candidate shapes using both shape representation methods. Matching results show potential for solving matching problems for shape descriptions with different or uneven point distribution. But the comparison illustrates that multiple open triangles provides more accurate results in terms of matching the curve variation of the shape since it has up to 3 neighbor triangles to represent one point.

More shapes are needed for further testing. In order to reflect the detailed curve variation on a shape, more work can be done on balancing the weight of the length similarity and the angle similarity according to which one is more important to the application. An efficient evaluation against expert marked shapes is also a need to guide the improvement of DP method.

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