Partial Shape Matching of Spine X-Ray Shapes Using Dynamic Programming

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Abstract

The osteophyte shows only on some particular locations on the vertebra. This indicates that other locations on the vertebra shape contain that are not of interest hinder the spine x-ray image retrieval relevance precision, which motivates our research in partial shape matching (PSM). This paper presents PSM methods for matching shapes with variable number of points and with different data point distributions. Dynamic Programming (DP) is proposed for matching partial shapes by allowing merging of the data points in the process of PSM. DP is implemented based on two shape representation methods: line segments and multiple open triangles. The performance evaluation, which is based on human relevance judgements of these two shape representations in PSM is also presented.

1. Introduction

There has been growing interest in indexing images with biomedical content, especially in developing an automated or computer-aided retrieval system. We developed query-by-sketch and query-by-example paradigms of shape-based image retrieval. Shape-based retrieval techniques based on the whole shape matching have been well studied and have shown great potentials in the x-ray image retrieval [1, 2, 3]. Several different methods have been implemented for the whole shape matching, including Procrustes distance, Fourier descriptors, shape features, invariant moments, Polygon Approximation for tangent space matching, and Token Approximation using multi-scale space. But in case of anterior osteophytes (AO), users of the image retrieval system are often interested in only a specific small region on the vertebra boundary that contains pathology information. And as a matter of fact, *whole* shape matching based retrieval results were found to have only about 56% semantic relevance [4]. The drawback of matching the whole shape is that the difference in local details tends to be washed out by the global shape difference.

As a necessary compensation for whole-to-whole shape matching, partial or incomplete shape matching has aroused great interest. Partial matching provides a way to deal with the occlusion and distortion when comparing two incomplete shapes [5, 6, 7, 8]. In our case, PSM enables querying only on some specific regions of the whole shape and searches for the best matching regions. By doing this, PSM provides another view of image retrieval which can be more related to medical pathology. Different shape representation methods such as inflection points [8] can be used for extracting shape features for matching. Inflection points are not suitable for spine shapes since it has a rectangular shape and doesn't have significant number of inflection points. Two shape representation methods that are suitable for spine x-ray image retrieval are studied in this paper.

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Shapes could have variable number of points with totally different data point distributions. Merging data points is needed in such cases in order to find the best match. Dynamic Programming (DP) searches for all possible matching paths and selects the most promising one with the minimum distance. The distance consists of the differences between the corresponding shape features extracted from both query shape and the candidate shape and the merging cost associated with a merging process. Since a shape matching algorithm must be based on the properties of its underlying representation, DP was implemented slightly different for these two shape representations.

The two shape representations and the similarity calculations are introduced in Section 2. Section 3 defines the merging cost and describes the implementation of DP algorithm. Results and evaluation are made in Section 4. We conclude with Section 5.

2. Shape Representations

Two different shape representations are introduced in this paper. They have different shape features but are both eligible for Dynamic Programming implementation.

2.1. Line Segments

Each line segment is formed by connecting two adjacent points on the shape. Suppose a shape has N points: if it's closed, it has N line segments; if it's open, it has $N-1$ line segments. Our line segment-based shape features include length, absolute orientation [7], 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.

Based on these shape features, we can define the similarity between two line segments a_k and $a_l^{'}$. We denote the attributes of a_k , $a_l^{'}$ -- absolute orientation and length -- by (θ, l) and $(\theta^{'}, l^{'})$, respectively. The ratio between the length attributes is denoted as relative scale $c = l / l^{'}$. The reference segments are calculated for each matching case: --$(\theta_0, l_0), (\theta_0^{'}, l_0^{'})$. Every point on the candidate shape is a possible starting matching point with the query shape. Before we search for the best matching path starting from the i^{th} point on the candidate shape, a partial shape is taken from the candidate shape which starts from the i^{th} point and has the same number of line segments as the query shape. Suppose the query shape has 6 line segments with the lengths $l_1, l_2, ..., l_6$ respectively. Then 6 consecutive line segments are taken from the candidate shape starting from the i^{th} point with the lengths $l_1^{'}, l_2^{'}, ..., l_6^{'}$. We calculate the ratio of the length as $c_i = l_i / l_i^{'}$. In order to be scale invariant, we take the mean of $c_1, c_2, ..., c_6$ as the scale factor between the query shape and the partial shape from the candidate shape that we are trying to match such that the difference in terms of length is scale invariant. If we denote the mean as $c_0 = l_0 / l_0^{'}$, then the length similarity can be expressed as

$$S_l(l, l^{'} \mid l_0, l_0^{'}) = \frac{4cc_0 + (c^2 - 1)(c_0^2 - 1)}{(c^2 + 1)(c_0^2 + 1)} \tag{1}$$

It calculates the differences between the overall scale factor c_0 and an individual scale factor c as the distance in terms of length. The absolute orientation similarity is:

$$S_\theta(\theta, \theta' \mid \theta_0, \theta_0') = \cos[(\theta - \theta') - (\theta_0 - \theta_0')] \quad (2)$$

The relative orientation similarity is:

$$S_{rel} = \cos(\theta_{rel} - \theta_{rel}') \quad (3)$$

The total similarity is defined as the sum:

$$S = S_l + S_\theta + S_{rel} \quad (4)$$

These similarity measurements are used for Dynamic Programming implementation for partial shape matching [9].

2.2. Multiple Open Triangles

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}. So each point can be represented by multiple open triangles [10]. In our case, 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 were used to represent this point. The angle θ associated with an open triangle is also illustrated in Fig. 1. Actually this angle is 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 [10]. The similarity of the angle is calculated in the same way as the relative orientation of the line segments since they are actually complementary angles; the similarity of the length is also calculated in the same way as line segments.

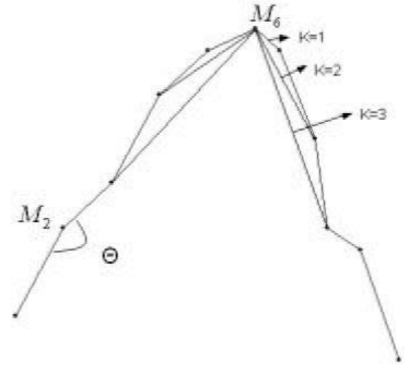


Fig. 1. Multiple Open Triangles and the angles

3. Dynamic Programming (DP)

DP tries to find a matching path with the minimum cost with both shape representations. But it is implemented slightly differently because of the different shape features being used. In matching two shapes A (query shape) and B (shape from the database), the algorithm builds a DP table (Fig. 2), where rows and columns correspond to the points of A and B, respectively [8]. Starting from the cells at the bottom row which is called 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 cost up to this point. After filling out the top row which is called termination area, all the possible matches on shape B with shape A have been picked and could be traced back starting from the termination

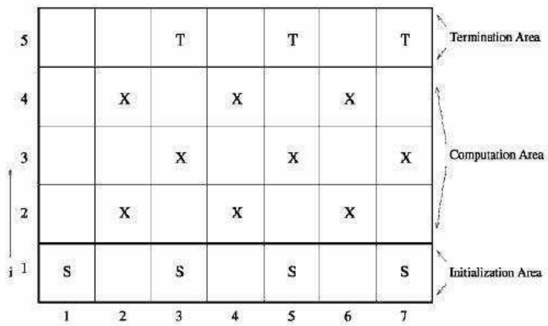


Fig. 2. DP Table

area. For our application, we want to find the best match on one shape with the query shape. So the matching which has the minimum cost will finally be picked as the most similar part on shape B to shape A .

In the process of filling the DP table, merging is allowed if lower cost can be obtained. For example, if the cost of matching points 1 and 2 on shape A with points 4 and 6 respectively on shape B is smaller than the cost of matching points 1 and 2 on shape A with points 4 and 5 respectively on shape B , the DP algorithm will choose to merge point 5 on shape B to achieve a smaller cost. When the shape is represented by line segments, the DP table is filled one row each time since those shape features are based on only one line segment. When the shape is represented by multiple open triangles, the DP table is filled two rows each time since an open triangle has to have two line segments to start with the process. All the possible combinations of two line segments are searched and the associated costs are calculated, then the one with the minimum cost is picked as the first match part. The next best matched two line segments are determined by a new searching of all the possible combinations of another two line segments starting from the endpoint of the previous two line segments. Although DP is implemented slightly differently for these two different shape representations, the matching result all ends up to be the matching path with the minimum cost based on each set of shape features.

Merging data points is allowed and actually is achieved by using DP. But a cost is associated with the merging process, since there should be a penalty to delete a point that is actually on the shape. The merging cost is split into two parts: a by-product of using the same reference as non-merging case and the significance of the merged point in terms of the cosine value of its turn angle. A reference is needed to calculate the similarity of the length and the absolute orientation. The reference is gained from the non-merging case which uses the same number of line segments as the query shape. There are taken from the candidate shape and to calculate the reference. If a merging occurs, the number of line segments (which were taken from the candidate shape and were used to calculate the reference) reduces. Additional line segments need to be extended from the candidate shape so that the matching part could still retain the same number of line segments as query shape. Thus the reference should be updated by using the new matching part. A cost is produced if the reference is unchanged.

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:

$$S_{mer} = \cos(\theta_{rel1} + \theta_{rel2} + \theta_{rel3} + ...) \qquad (5)$$

The bigger turn angle it 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. Then the merging similarity associated with this matching path is $\cos(\theta_{rel2} + \theta_{rel3})$.

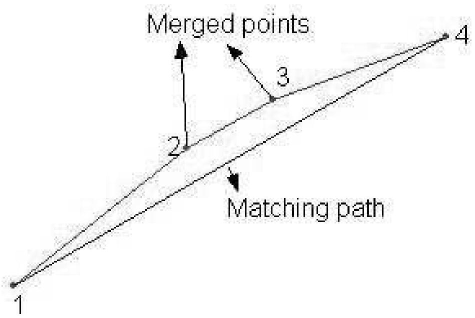


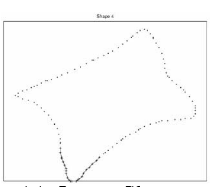
Fig. 3. Merging Process

Considering that DP is not a computationally efficient process, a limit is applied to the number of consecutively merged points to reduce the time of the matching process. This is a reasonable assumption since it is unlikely that all the points between the starting point and the last point of the shape would be all merged.

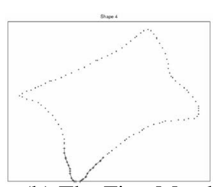
4. Results

Fifteen shapes have been used to test these two approaches. The largest number of consecutively merged points is set to be $K = 6$ for both shape representations. The matching results of these two methods are presented in Fig. 4 and Fig. 5, respectively.

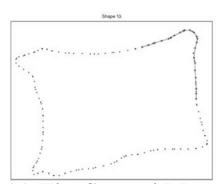
The results show that the methods not only meet the requirements of scale invariance, rotation invariance and translation invariance but also solve the problem of variable point description for each shape by allowing merging of data points.



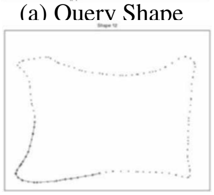
(a) Query Shape



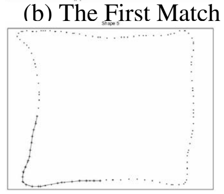
(b) The First Match



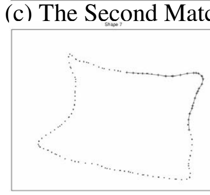
(c) The Second Match



(d) The Third Match

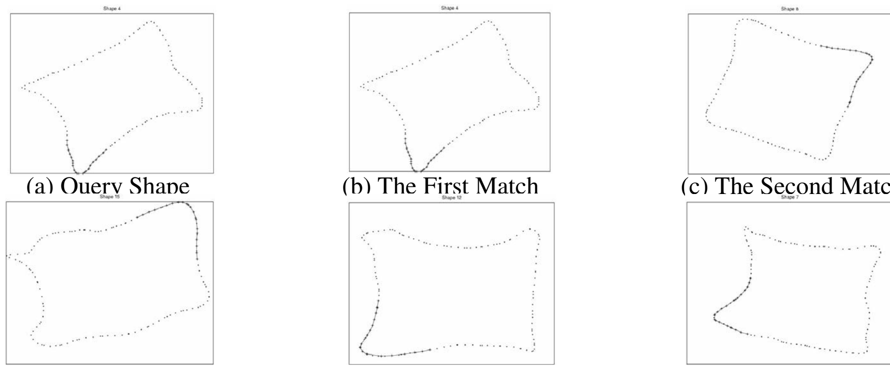


(e) The Fourth Match



(f) The Fifth Match

Fig. 4. DP Matching result of using line segments



(a) Query Shape (b) The First Match (c) The Second Match

(d) The Third Match (e) The Fourth Match (f) The Fifth Match

Fig. 5. DP Matching result of using multiple open triangles

5. Conclusion

In partial shape matching, matching for variable number of points is as important as matching for fixed number of points [9]. We have applied DP to two shape representations: line segments and multiple open triangles. The results show potential for solving problems with shape descriptions with difference point distributions. Future work includes more testing and thorough evaluation against expert marked.

6. References

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