Shape Based Retrieval in NHANES II

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ABSTRACT

NHANES II is a nationally significant medical image database of spine x-ray images located at the National Library of Medicine. A key feature of spine disease in these images is the presence of osteophytes which are bony processes that alter the shape of vertebrae. Shapes of vertebrae are conveniently described in shape spaces which are non-linear manifolds. Indexing in such non-linear manifolds is an open problem. In this paper, we describe a technique of embedding shape manifolds in Euclidean spaces in a way that allows the use of classical indexing techniques for indexing shape. Application of this to the NHANES II database is also described.

1. INTRODUCTION

The NHANES II national health survey is a database currently maintained at the National Library of Medicine and contains 17,000 spine x-ray images. Spine disease is often manifest in these images as *osteophytes*, which are bony prominences along the boundary of the vertebral body. An example image and a vertebra from NHANES II are shown in figure 1. The prominence at the bottom left corner of the vertebrae is an osteophyte (marked with a heavier line with dots). A small set of osteophytes in NHANES II have been graded by an expert neuro-radiologist for their severity.

The retrieval of images by osteophyte severity is an important query in NHANES II. Because manual grading of osteophytes is tedious and time consuming, it is difficult to create grades for all osteophytes in NHANES II. An alternative approach is to use the shape of the vertebra as a proxy for the grade of the osteophyte. Given a query image, we seek to retrieve all images with vertebrae that have a similar shape. We expect that the retrieved vertebrae will have grades that are similar to the query vertebra. Furthermore, independent of osteophyte grade, retrieval by shape is important in itself as a query mechanism.

This paper is intended to be a review paper summarizing our recent work on shape based retrieval.

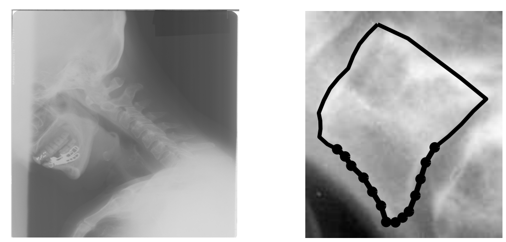

Figure 1: An example image and a vertebra from NHANES II

1.1 Shape, Similarity Retrieval, and Indexing

Vertebrae in NHANES II images are segmented interactively by a dynamic programming deformable template segmentation algorithm. The algorithm works by deforming a template along curves that are orthogonal to the template The deformation is obtained by dynamic programming, and is guaranteed to be optimal [2]. The result of segmentation is that the vertebral boundary is available as a set of a fixed number of boundary points. The boundary points inherit a numbering from the template so that points on all boundaries are consistently numbered.

The shape of a boundary or a set of points is commonly defined as that property of the set which is invariant to translation, rotation, and scale changes [3]. Shape space theory informs us that the shape of a set of points in 2-d naturally belongs to a shape space which is a complex projective space.

The shape of boundary points in the query vertebra forms a query shape q. Similarity retrieval asks to retrieve k images with boundary shapes most similar to q. This is the *k-nearest-neighbor shape query.* The (dis-)similarity of the shape features is measured by a *shape metric.*

Nearest-neighbor queries can be carried out by a linear search through the database. Indexing techniques can boost the performance by providing sub-linear complexity.

Classical indexing techniques such as kd-trees are designed

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to be used in Euclidean feature spaces with a Euclidean metric. They cannot be used to index shape because shapes naturally belong to shape spaces, which are significantly non-Euclidean curved manifolds.

The problem of indexing for shape similarity is thus a problem of creating indexing structures in non-Euclidean shape manifolds. The solution we propose is to embed the shape space back into a Euclidean space and to index the embedded shapes with standard techniques.

2. SHAPE- AND PRE-SHAPE SPACES

Suppose we are given m points in a plane. The *shape* of these points is taken to be that property which is independent of translation, rotation, and scaling. Two sets of points are considered equivalent if they can be mapped onto each other exactly by some element of the similarity group. This partitions the set of all m points into equivalence classes. Each equivalence class represents a shape – it is the shape of all of members of the class. The *shape space* is the quotient space of the set of all m points under the above equivalence relation. Kendall showed that for m points in the plane, the shape space is a familiar manifold – it is the complex projective space of complex dimensions $m-2$ [3, 7].

The quotient space under the similarity group can be constructed by first finding the quotient space under translation and scaling, followed by the quotienting of this space under rotations. Let the m 2-D points be represented as a complex position vector $z=[x_1+jy_1, x_2+jy_2, \ldots, x_m+jy_m]^T \in C^m$, where (x_i, y_i) is the coordinate for the i^{th} point, and C^m is the vector space of m complex variables. The quotient space of C^m with respect to translation and scaling can be easily shown to be a complex sphere in C^m. This space is called the *pre-shape space*. The *pre-shape* of z is $Z=(z-z^T 1_m)/\|z-z^T 1_m\|$, where $1_m=[1/m \cdots 1/m]^T$. We can further quotient out rotation in the pre-shape space to get the shape space.

Each vertebral boundary in the database (which is a set of m points) maps onto its shape in the shape space and similarity retrieval corresponds to retrieving the k closest shapes using a distance in the shape space.

3. INDEXING IN SHAPE SPACES

Since shape space is a non-Euclidean manifold, classical indexing techniques cannot be used with it.

We index the shape space by embedding it back in the pre-shape space as illustrated in figure. Suppose $z_1, z_2, \cdots, z_N$ are N different sets of points in the database with pre-shapes, $Z_1, Z_2, \cdots, Z_N$. The *average pre-shape* of this ensemble is given by the pre-shape $\hat{\mu}$, which is the eigenvector corresponding to the largest eigenvalue of the complex matrix $\sum_{i=1}^{N} Z_i Z_i^*$ ([7],page 44), where Z_i^* is the complex conjugate of Z_i.

Recall that the pre-shape space is a sphere in C^m. Given any point Z_i in the pre-shape space, rotation of the original points produces an orbit of Z_i in the pre-shape space. There is a unique point at which this orbit comes closest to the average pre-shape. This point is given by $Z_i^* \hat{\mu} Z_i/(Z_i^* Z_i)$ and we call it the *aligned pre-shape*. The mapping from the orbit of Z_i to $Z_i^* \hat{\mu} Z_i/(Z_i^* Z_i)$ is really a mapping from the shape of Z_i (since the orbit is the shape) to the pre-shape space. Under this map, each shape (i.e. orbit in pre-shape) is uniquely mapped to a single point in the pre-shape. We call it the *embedding map*.

Using the embedding map, all database shapes can be embedded back into pre-shape sphere. A summary of the procedure is as follows: (1) Convert each database point z_i to its pre-shape $Z_i=(z_i-z_i^T 1_m)/\|z_i-z_i^T 1_m\|$, (2) Calculate the mean pre-shape $\hat{\mu}$ as the eigenvector of the largest eigenvalue of $\sum_i Z_i Z_i^*$, where the sum is over all shapes in the database, (3) Align each pre-shape Z_i along its orbit to the aligned pre-shape, which is $Z_i^* \hat{\mu} Z_i/(Z_i^* Z_i)$.

4. SHAPE DISTANCE

The above procedure embeds shapes as aligned pre-shapes in the pre-shape space. Since the pre-shape space itself is embedded in C^m, we can represent each embedded shape as a vector from the average pre-shape to the aligned pre-shape. Thus, if $[z_i]$ is the vector representation of the shape of z_i, then

$$[z_i] = Z_i^* \hat{\mu} Z_i/(Z_i^* Z_i) - \hat{\mu}.$$

If z_i and z_j are any two sets of points, then the *Euclidean shape distance* $d_s(z_i, z_j)$ between them can be taken to be the Euclidean distance between $[z_i]$ and $[z_j]$:

$$d_s(z_i, z_j) = \sqrt{([z_i]-[z_j])^*([z_i]-[z_j])}.$$

The *weighted Euclidean shape distance* between z_i and z_j is

$$d_{ws}(z_i, z_j) = \sqrt{([z_i]-[z_j])^* W^* W([z_i]-[z_j])},$$

where W is matrix with positive entries. In particular, if we set W equal to the diagonal matrix with some entries equal to 1 and the rest equal to a small positive number (say 0.1), then the weighted shape distance will mostly compare the shapes those points that correspond to the weight of 1. This is a partial shape comparison.

5. INDEXING SHAPES

Because shapes are embedded in a Euclidean space and the relevant distance between them is a (possibly weighted) Euclidean distance, standard indexing techniques can be used to index shape. Specifically we use a kd-tree in C^m for indexing. The coordinates for the kd-tree are obtained from the data using Principal Component Analysis (PCA).

6. EXPERIMENTAL RESULTS

In this section, we report the results of applying our indexing technique to the vertebral images in NHANES II. At the moment, a total of 2812 boundaries are available. Each boundary is a set of 34 points. A subset of these points represents osteophyte location at the bottom left corner of the vertebra (recall figure 1).

A subset of 94 images have been graded by an expert with respect to osteophyte severity. The grading is from 0 to 5, where “0” represents normal vertebrae without osteophyte; “1” indicates sharp protuberance that is barely visible; “2” means a short osteophyte with length less than 1/2 disk spacing; “3” implies longer and thicker osteophyte with length greater than 1/2 disk spacing; “4” and “5” are rare cases of large osteophytes that can bridge or extend to the next vertebra but have osteophyte that are straight or bent respectively.

Our first experiment evaluates the utility of the two shape distance measures proposed in section 4 for this.

6.1 Shape Distance Rank and Osteophyte Grade

Five vertebrae of rank 0 and five vertebrae of rank 3 were chosen as queries. The rank 0 vertebrae simulate queries with normal vertebrae and rank 3 vertebrae simulate queries with osteophytes. For each query, the shape distances between the query and the 94 expert graded vertebrae were calculated and the 94 vertebrae ranked according to increasing distance from the query shape.

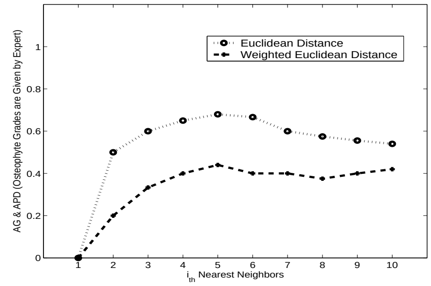
Suppose q is the query shape and $i = 1, \cdots, 94$ are the ranked vertebrae. Let $g(q)$ and $g(i)$ refer to the expert grading of the query and i^{th} ranked vertebrae. We expect $g(i)$ to be similar to $g(q)$ for low values of i. To measure this, we calculated the *average grade* (AG) up to rank i as $\frac{1}{i}\sum_{k=1}^{i} g(k)$. We expect this number to be close to the grade of the query $g(q)$. Of course, the grades of the ranked vertebrae are never exactly the same as the grade of query vertebra. To evaluate the difference, we calculated the *average positive difference* (APD) of the grades as$\frac{1}{i}\sum_{k=1}^{i}(g(k)-g(q))^{+}$, where $(g(k)-g(q))^{+} = (g(k)-g(q))$ if $(g(k) - g(q)) > 0$, else $(g(k) - g(q))^{+} = 0$. The average positive difference should tell us the number of more severe grades up to i. We also calculated the *average negative difference* (AND) of the grades as$\frac{1}{i}\sum_{k=1}^{i}(g(k)-g(q))^{-}$, where $(g(k) - g(q))^{-} = -(g(k) - g(q))$ if $(g(k) - g(q)) < 0$, else $(g(k) - g(q))^{-} = 0$. The average negative difference should tell us the number of less severe grades up to i.

Figure 2 shows the average AG, APD, and AND for the Euclidean and weighted Euclidean shape distances for grade 0 and 3 queries. The grade 0 results are somewhat special. Because there is no grade lower than 0, it does not have an AND. Futher, its AG and APD are identical. Thus we only plot the AG, which is shown in Figure 2(a) for grade 0. As the figure shows the AG of the weighted Euclidean distance is consistently closer to 0 than the AG of the Euclidean distance showing that the former matches more vertebrae with grade 0 to the query than the latter. Hence, the weighted Euclidean shape distance appears to perform better than the Euclidean shape distance. Figures 2(b) and (c) show the AG and the APD and AND for the grade 3 retrievals. From figure 2(b) it is clear the the AG for the weighted Euclidean distance is consistently closer to 3 than the AG for the Euclidean distance. The APD and ANG of figure 2(c) show that the weighted Euclidean distance retrieves marginally more higher grades, but significantly fewer lower grades than the Euclidean distance. Thus it appears that the weighted Euclidean distance is more useful as a proxy for retrieval by osteophyte grade.

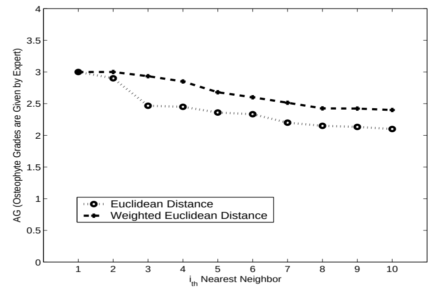
Figures 3-4 show typical queries and ranked vertebrae from these experiments.

6.2 Indexing Performance

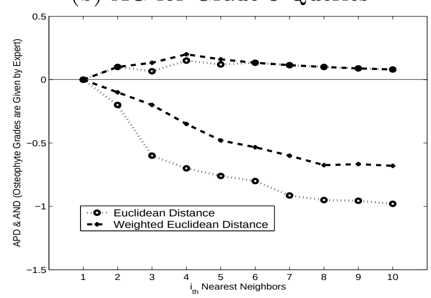
Having determined that the weighted Euclidean shape distance is more suitable for retrieval with respect to osteophyte grading, we evaluated the efficiency of the indexing scheme for this retrieval. The 2812 shapes were randomly sampled into sets of size 434, 1089, 1654 and 2812. Each set was indexed for shape with the algorithm described above. Every point in the database was used as a query image and k-nearest neighbor vertebral images were retrieved using the weighted Euclidean shape distance for $k = 10$ and 20 neighbors. The average number of node tests per query and the average number of surviving leaf nodes were recorded. Re-



(a) AG and APD for Grade 0 Queries



(b) AG for Grade 3 Queries



(c) APD and AND for Grade 3 Queries

Figure 2: Shape ranks using different shape distances vs. osteophyte grade

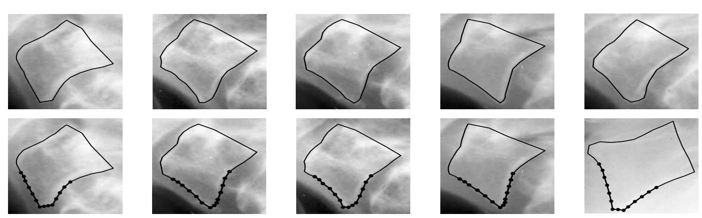


Figure 3: Query images plus first five ranked images for Grade 0. Each row shows the query on the left and ranked images to the right. Top row shows ranking by the Euclidean metric. Bottom row shows ranking by weighted Euclidean metric.

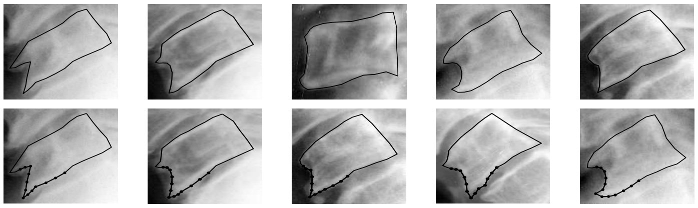


Figure 4: Query images plus first five ranked images for Grade 3. Each row shows the query on the left and ranked images to the right. Top row shows ranking by the Euclidean metric. Bottom row shows ranking by weighted Euclidean metric.

call that the first measures the computational burden of indexing while the second measures the disk access performance.

Figures 5 and 6 shows the performance measures as a function of the database size and k. The performance measures are expressed as percentages. The percentages should remain constant for an indexing scheme with linear complexity and should decrease with the size of the database for sub-linear complexity. The figures suggest that the indexing procedure is sub-linear in complexity. Thus, the procedure is effective in indexing shape.

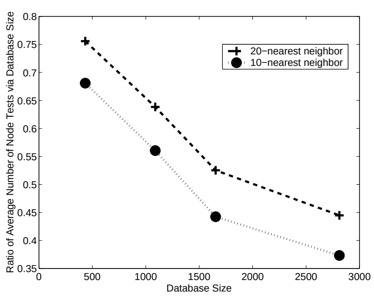


Figure 5: Average Computation

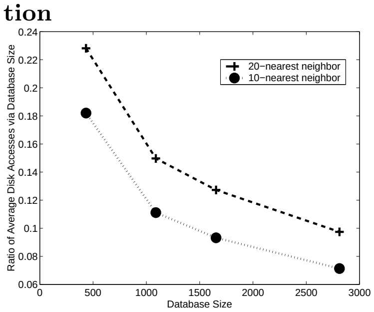
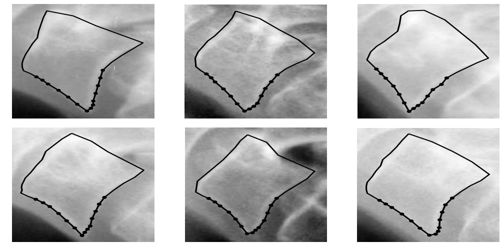


Figure 6: Average Surviving Leaves

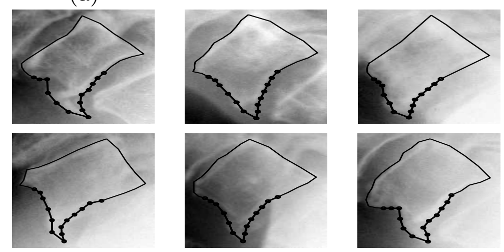
Figure 7 (a)-(b) shows two illustrative similarity queries. The top left images in 7 (a)-(b) are the query images. The retrieved images are displayed by rank in raster fashion after the query image.

7. CONCLUSIONS

We reported a procedure to index boundaries in medical image databases for complete and partial shape similarity retrieval. The technique embeds shape in pre-shape spaces in a canonical way. Standard indexing techniques can be used in the pre-shape space and we demonstrated that this combination has sub-linear complexity for shape similarity retrieval.



(a)



(b)

Figure 7: Two Sample Retrievals.

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