Pre-Indexing for Fast Partial Shape Matching of Vertebrae Images

Xiaoqian Xu [a], D.J. Lee [a], S. Antani [b], and L.R. Long [b]
[a] *Dept. of ECEn, Brigham Young University, Provo, UT*
xiaoqian@et.byu.edu, djlee@ee.byu.edu
[b] *Communication Engineering Branch, National Library of Medicine, Bethesda, MD*
antani@nlm.nih.gov, long@nlm.nih.gov

Abstract

Fast retrieval of images from large databases especially from large medical image databases is of great interest to researchers. We have developed shape-based image retrieval system for spine X-ray images that applies Dynamic Programming (DP) in Partial Shape Matching (PSM) techniques to vertebral boundary data. As we enable Internet access to this system with an aim to enable CBIR access to the entire NHANES II spine X-ray image collection, retrieval efficiency has become critical. In this paper, we present enhancements to our existing sequential retrieval model to provide faster partial-shape-based vertebrae retrieval. Based on the characteristics of vertebral osteophyte pathology, anterior superior and anterior inferior parts are the areas with the most interest to the users and are indexed for each shape. Pair-wise distances between indexed parts are pre-calculated and used by agglomerative clustering algorithm to index the whole database. To increase the retrieval speed, PSM with DP is therefore conducted only on a small selected set of shapes by the pre-indexing retrieval.

1. Introduction

Fast retrieval of images has become a critical issue nowadays with interest in establishment of large medical image databases. A digital archive of 17,000 cervical and lumbar spine X-ray images from the second National Health and Nutrition Examination Survey (NHANES II) is maintained at the US National Library of Medicine (NLM). Associated with each of these images is text information including symptoms, survey participant health data, physicians' diagnosis, etc. A fast web-based retrieval system for these X-ray images can greatly benefit researchers, educators and other interested parties.

Despite the challenges, Content-Based Image Retrieval (CBIR) is still considered as the most effective way to gain access to large image databases. Figure 1 shows a spine X-ray image with the segmented boundary represented as a shape contour. For these spine X-ray images, shape contour is the only effective feature in characterizing various reliably detectable pathologies [1-4] and has laid the basis for shape representation and matching algorithms for retrieval [4-6].

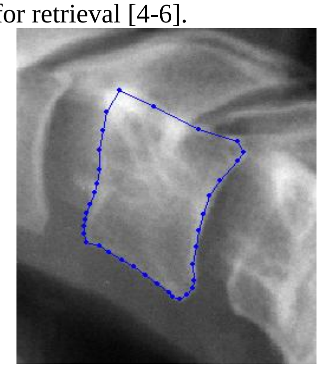

Figure 1. Spine X-ray image with the superimposed shape contour.

We have studied and developed methods for both Whole Shape Matching (WSM) and PSM for spine X-ray image retrieval [4-6, 8]. PSM has been proved to provide more relevant retrieval results compared to WSM. A brief introduction of PSM method is included in Section 2. Our PSM method uses Dynamic Programming (DP) for searching the best match. Due to the time inefficiency of DP and the increasing number of segmented shapes from the NHANES II image collection, indexing becomes an essential factor for efficient retrieval.

Spatial access (coordinate-based) methods and metric-based (distance-based) indexing methods comprise the majority of indexing approaches [9-12]. For specific shape-based image retrieval, spatial access methods are applicable to cases where each shape is represented by a set of features whose distance is defined in the Euclidean space. Typical

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tree structures including KD-tree, R-tree, Quadtree, etc can be adopted for this task. There is a major limitation called *curse of dimensionality* to the performance of spatial access methods. In practice, this limitation takes effect when the dimension of the feature vector exceeds twenty.

The basis for metric-based indexing methods is a matrix of pair-wise distances between each shape in the database. These approaches essentially employ different clustering algorithms to group shapes with closer distances into clusters. The biggest merit of a metric-based indexing method over a spatial access method is that it can be applied to a large group of shape representations or shape matching algorithms which were possibly developed for specific image applications. For instance, metric-based methods can cooperate with shape representations, which are not a merely simple feature vector, and shape matching algorithms, which employ non-Euclidean distance measurements. However, because of the well-explored tree structures, spatial access methods are usually expected to have higher indexing efficiency than metric-based indexing methods. For our specific shape-based image retrieval application, we employ agglomerative clustering algorithm to hierarchically cluster shapes for indexing.

This paper is organized as follows. In Section 2, we briefly discuss our past work on partial shape-based spine image retrieval. The challenges of indexing partial shapes and our approach are introduced in Section 3. Experimental results and analysis are presented in Section 4. We draw some conclusions in Section 5.

2. Partial Shape Matching

Both WSM and PSM methods are explored and tested on spine X-ray shapes. WSM takes a closed shape contour as the query and searches for similar whole shapes in the database, while PSM allows the user to query on some specific intervals along the vertebral boundary shape and searches for the best matching intervals on other whole shapes. As shown in Figure 2, the osteophyte pathology often exhibits in partial areas of the whole boundary contour. Therefore, PSM is more useful by allowing the user to query on specific pathological intervals regardless of the whole shape and to retrieval similar pathological information.

Two PSM methods including Procrustes distance and Multiple Open Triangle representation with DP searching strategy are employed for retrieval in this paper. The Procrustes method performs a linear transformation (translation, rotation, and scaling) on one shape to find the best match between two shapes. Suppose (x, y) and (x', y') are n boundary point coordinates of shapes of A and B, respectively. The

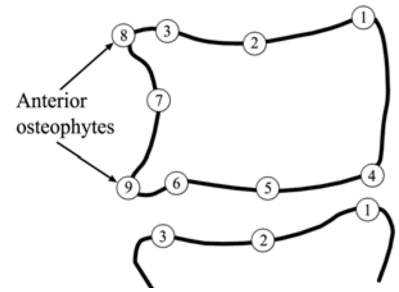


Figure 2. Radiologist marked 9-point model for vertebrae shape description. Points 8 and 9, if not coincide with Points 3 and 6, respectively, indicate the existence of osteophytes.

Procrustes distance is then represented by Equation (1), where shape A is translated by (T_x, T_y), scaled by S, and rotated by α:

$$P = \sum_{i=1}^{n} \left| \begin{bmatrix} S\cdot\cos\alpha & -\sin\alpha & T_x \\ \sin\alpha & S\cdot\cos\alpha & T_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}_A - \begin{bmatrix} x_i' \\ y_i' \\ 1 \end{bmatrix}_B \right|^2 \quad (1)$$

The drawback of Procrustes distance is that it requires the same number of points on the two partial/whole shapes.

Multiple Open Triangles were developed by us as an efficient shape representation for PSM [6]. A partial/whole 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. 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. A second open triangle can be formed by connecting M_{i-2} to M_i and M_i to M_{i+2} if both M_{i-2} and M_{i+2} exist. In our application, we set $K = 3$ as the largest number of such open triangles associated with one point. As shown in Figure 3, 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.

For each open triangle, length ratio (of the two sides of an open triangle) and angle (θ as shown in Figure 3) are calculated as features. Suppose there are n open triangles associated with two current points under consideration for matching. Their features are represented as (l, θ) and (l', θ'), respectively. The dissimilarity of length ratio is calculated as:

$$D_l = 1 - \frac{1}{n}\sum_{i=1}^{n} \frac{4c_i c_0 + (c_i^2 - 1)(c_0^2 - 1)}{(c_i^2 + 1)(c_0^2 + 1)} \qquad (2)$$

, where $c_i = l_i / l_i'$ and c_0 is the reference ratio. The dissimilarity of angle is computed according to the following equation:

$$D_\theta = 1 - \frac{1}{n}\sum_{i=1}^{n} \cos(\theta_i - \theta_i') \qquad (3)$$

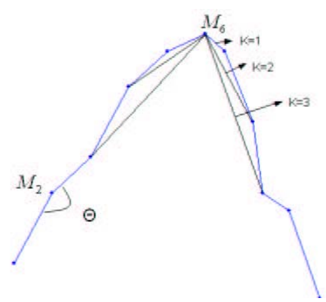


Figure 3. Multiple Open Triangles

DP is employed as the searching strategy, which allows point merging. A distance D_{mer} is calculated as the penalty for merging process. Multiple Open Triangle with DP method does not require the same number of points on two shapes for matching. The overall dissimilarity is a weighted summation:

$$D_{MOT} = W_1 D_l + W_2 D_\theta + W_3 D_{mer} \qquad (4)$$

3. Partial Shape Indexing

3.1. Challenges of indexing partial shapes

Our experimental results showed that Multiple Open Triangle with DP provides more accurate results than Procrustes distance. However, DP is known to be time-consuming, which can become impractical when database grows. A fast retrieval is also preferred to enable Internet access to large image sets. A fast indexing approach is one possible solution.

In the literature, such effort has been made and contributed to image retrieval research work [9-12]. However, DP cannot be pre-calculated and has to be performed on the fly for each individual query. Moreover, besides general difficulties, indexing for partial shapes becomes more complicated. For our specific application, we provide users the flexibility to select a partial query. This flexibility suggests an unmanageably large number of partial queries that could be specified by the user. This is illustrated in Figure 4, which shows 4 random partial queries possibly selected from the same whole shape.

It is intractable to index for every possible partial query no matter using spatial access methods or metric-based indexing methods. However, a feasible alternate indexing approach may be possible for individual image application. We propose our solution in the following subsections.

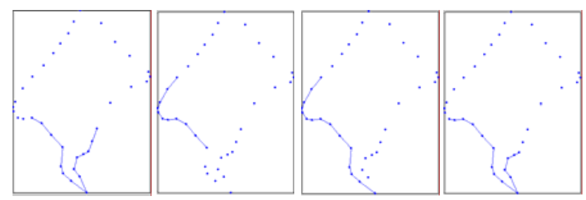


Figure 4. Various partial queries from the same whole shape.

3.2. Solution for indexing partial spine shapes

Spine shapes are overall rectangular with some protrusion/distortion exhibiting osteophyte pathology. Since the focus has been on anterior osteophytes, the radiologist-marked 9-point landmark model has been introduced in Section 2 (shown in Figure 2). Prompted by the 9-point model, a solution is proposed as follows to pre-index partial shapes around anterior corners.

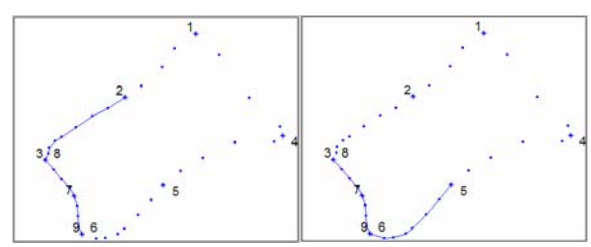


Figure 5. Two partial queries selected from each shape for indexing.

The 9-point model for each shape in the database was pre-calculated by our automatic localization algorithm [13]. By employing the 9-point model, two partial shapes are selected from each shape and indexed for retrieval. As demonstrated in Figure 5, one partial shape (superior corner) is the interval between Points 2 and 6, while the other (inferior corner) is the interval between Points 3 and 5. We call these two partial shapes – "indexed shapes" and they are indexed independently. Thus, the retrieval will be conducted on the corresponding indexing results depending on which corner the query includes.

For instance, in order to index "superior corner", Procrustes distance is calculated between each pair of the selected "superior corner" indexed shapes. A *distance* matrix is then created to include all the pair-wise distances and provides the basis for metric-based indexing.

3.3. Agglomerative clustering algorithm

To construct a metric tree is essentially to hierarchically cluster the whole database based on pair-wise distances. We employ agglomerative clustering algorithm [14] to hierarchically cluster shapes in a bottom-up manner. The following diagram outlines this algorithm:

Agglomerative clustering algorithm

1. Initially, put each indexed shape in its own cluster.
2. Among all current clusters, pick the two clusters with the smallest distance.
3. Replace these two clusters with a new cluster.
4. Repeat Step 2 and 3 until there is only one remaining cluster.

This algorithm indicates a technical detail which is the method to measure distance between clusters containing multiple indexed shapes. In general, there are three common approaches: single linkage, complete linkage, and comparison of centroids [14]. The single linkage method defines the distance between two clusters as the distance between their *closest* members, while the complete linkage method defines the opposite. Our approach is similar to "comparison of centroids" method. An indexed shape is selected from each cluster as its representative shape. The distance between two clusters is then defined as the distance between their representative indexed shapes.

There are two approaches for selecting the representative shape for the new cluster depending on the circumstances. When two clusters to be merged are two individual indexed shapes, the one has the maximum overall distance from the rest of clusters is selected as the representative shape for the new cluster; when otherwise, the indexed shape which has the minimum overall distance from the rest of the shapes in the new cluster is selected as the representative shape. Each cluster is considered as a sphere, whose radius is the biggest distance between the representative shape and any other shapes in the cluster.

3.4. Retrieval process

Since the user is allowed to specify any partial query which may not be like the indexed shape, the retrieval process consists of two phases: pre-retrieval and final retrieval. In the pre-retrieval phase, regardless of the actual partial query specified, its corresponding indexed shape is taken as the query and the retrieval is performed based on the metric tree constructed in the previous subsection. Depending on how many matches the user intends to retrieve and also the data distribution across the database, the pre-retrieval returns roughly a number of times of the desired amount. For instance, in our case, suppose the user wants to retrieve top 20 matches, the pre-retrieval can select roughly the top 100 matches to the query's corresponding indexed shape.

A range search is the same as a *k-nearest-neighbor* search when the range is equal to the distance between the *k*-th nearest neighbor and the query. Therefore, a threshold T is selected for a range search so that it roughly equals to 100-nearest-neighbor search in our case. The retrieval performs in a typical tree search manner. It starts from the biggest cluster and proceeds to the smallest one. Suppose in the metric tree, each cluster can be treated as a node. Then each node has a representative shape and a radius R. The search can be achieved by two node tests: one compares the distance d between the query and the representative shape against the threshold T while the other compares d against the summation of T and R. For the first test, if $d \le R$, the representative shape will be included in the pre-retrieval results; otherwise, it will be excluded from the results. For the second test, if $d < T + R$, all the child nodes will be accepted for further search; otherwise, all the child nodes will be rejected for further search.

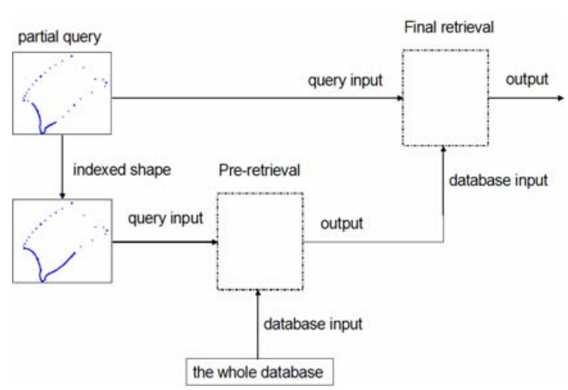


Figure 6. Retrieval Process

The final retrieval is then performed only on the selected matches from the pre-retrieval process. The final retrieval uses our retrieval model: Multiple Open Triangle with DP. It conducts real-time search and calculation to find matches to the actual query. Since DP is performed only on the selected shapes (around 100 in our case) from the pre-retrieval process as opposed to the whole database, a large amount of time can be saved in real time. The whole retrieval process is shown in Figure 6.

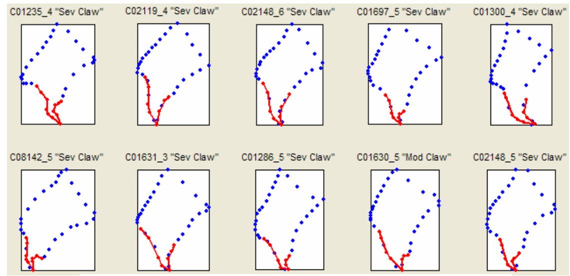
4. Experimental Results

A testing data set was generated from a total of 207 spinal X-ray images (107 cervical and 100 lumbar films) selected from the NHNAES II collection. Thus, this testing data set consists of a total of 888 shapes with 431 cervical and 457 lumbar shapes, respectively. Each shape contour is composed of 36 points. The new retrieval model with pre-indexing is evaluated in terms of both time efficiency and retrieval accuracy comparing with our original approach without pre-indexing. Based on the Procrustes distance distribution for indexed shapes, the threshold is set to be $T = 0.08$ in our experiments.

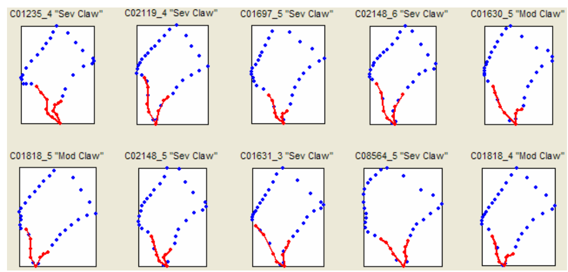
Two classification schemes: Macnab types (*claw* and *traction*) and severity levels (*slight*, *moderate*, *and severe*) were adopted and combined to classify each shape as the ground truth. Detailed information about the classification schemes can be found in [15]. A set of 24 queries, one for each unique combination of the severity levels, Macnab types, locations of the osteophytes (superior and inferior) and image types (cervical and lumbar), was selected. Considering the low representation of certain queries in the database and the difficulty to select a fair query, only 15 of the selected 24 queries were used for evaluation. Each query was tested using both methods: with and without pre-indexing. Top 20 matches were returned using each method for comparison and evaluation.

Figure 7 shows the top 10 matches (ranked from left to right) to the same partial query selected from the shape "C01235_4" using both methods. The query itself was retrieved and ranked the first by both methods as shown in both (a) and (b). With pre-indexing retrieval, it took only 22 seconds while the old method took 56 seconds. Among top 10 matches, the two methods shared 7 in common.

The time efficiency is evaluated by average processing time per query. The average time was 20 seconds for the new approach with pre-indexing, while it was 58 seconds for the old method. Among the 20 seconds, the pre-retrieval process occupied the first 6 seconds. DP process hence required an average 14 seconds per query, which is roughly 1/4 of the 58 seconds for the original method without pre-indexing. This verifies our assumption that the selected threshold T made the range search roughly equal to *100-nearest-neighbor* search. Obviously, the time efficiency of pre-indexing can be further enlarged when database grows.



(a) Without pre-indexing



(b) With pre-indexing

Figure 7. Top 10 matches to a partial query selected from "C01235_4" as shown in the first grid.

Two sets (*Severity* and *Type*) of testing were conducted for evaluation and comparison. In *Severity*, a shape is considered as a good match if it has the same severity level as the query according to the ground truth. Therefore, in *Severity*, the recall is calculated as the percentage of the shapes with the same severity level as the query among top 20 matches. Similarly, in *Type*, the recall is defined as the percentage of the shapes with the same Macnab type as the query. Besides the average recall over all queries, in *Severity*, the average recall percentages are also calculated for all the *severe*, *moderate*, and *slight* queries, respectively. Similarly, in *Type*, the recall results are calculated for all the *claw* and *traction* queries as well.

Table 1 compares the recall results of both approaches. The new method with pre-retrieval process presents a lower recall percentage in most categories, except for a higher recall percentage for *Traction* in *Type* and an equal percentage for *All queries* also in *Type*. The reason for lower recall percentage is that the pre-retrieval process excluded some potential good-match-shapes from reaching the final retrieval phase. However, the recall percentages of the new method are very comparable to the results using the old approach without pre-indexing. It is a fair tradeoff for a faster retrieval.

Table 1. Recall results using both approaches

	Severity				*Type*		
	Severe	Moderate	Slight	All queries	Claw	Traction	All queries
With Pre-indexing	55%	61%	81%	69%	80%	86%	84%
Without Pre-indexing	60%	65%	85%	73%	94%	79%	84%

5. Conclusions

This paper presents a pre-indexing approach for fast retrieval of spine X-ray images. This approach was proposed based on the characteristics of spine shapes. It made it possible for indexing partial shapes by employing the 9-point model for vertebral shapes. It also solved the problem that metric-based indexing usually requires the same distance metric in both retrieval and tree construction processes. In other words, our method does not need to construct a different tree when the user chooses different partial parts from a shape.

The pre-retrieval process retrieves a smaller set of shapes using the pre-indexing tree. Our Multiple Open Triangle with DP method then runs on this pre-selected set of shapes instead of the whole database. While maintaining comparable retrieval accuracy, this approach takes advantage of indexing and helps to overcome the intractable time-inefficiency of DP method when database grows. Combining indexing with real-time searching is a feasible scheme to an online medical image retrieval system which employs both pre-calculable image features and special features that have to be calculated on the fly.

Further discussions and testing on how the time efficiency and retrieval accuracy evolve with the growth of database will be conducted in the future.

6. References

[1] Mlsna, P.A., and Sirakov, N.M., "Intelligent Shape Feature Extraction and Indexing for Efficient Content-Based Medical Image Retrieval", *The 6th IEEE Southwest Symposium on Image Analysis and Interpretation,* March 2004, pp. 172-176.

[2] Wei Zhang, S. Dickinson, S. Sclaroff, J. Feldman, and S. Dunn, "Shape-Based Indexing in a Medical Image Database", *The IEEE Workshop on Biomedical Image Analysis*, June 1998, pp. 221-230.

[3] D. Comaniciu, D. Foran, and P. Meer, "Shape-Based Image Indexing and Retrieval for Diagnostic Pathology", *The 14th IEEE International Conference on Pattern Recognition,* Aug. 1998, pp. 902-904.

[4] S. Antani, L.R. Long, G.R. Thoma, and D.J. Lee, "Evaluation of Shape Indexing Methods for Content-Based Retrieval of X-Ray Images", *Proc. of IS&T/SPIE 15th Annual Symposium on Electronic Imaging, Storage and Retrieval for Media Databases,* vol. 5021, Jan. 2003, pp. 405-416.

[5] S. Antani, D.J. Lee, L.R. Long, and G.R. Thoma, "Evaluation of Shape Similarity Measurement Methods for Spine X-ray Images", *Journal of Visual Communication and Image Representation,* vol. 15, no. 3, 2004, pp. 285-302.

[6] Xiaoqian Xu, D.J. Lee, S. Antani, and L.R. Long, "Partial Shape Matching of Spine X-ray Shapes Using Dynamic Programming", *Proc. of the 17th IEEE Symposium on Computer-Based Medical Systems,* June 2004, pp. 97-102.

[7] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis and Machine Vision,* Brooks/Cole, 1999.

[8] Xiaoqian Xu, D.J. Lee, S. Antani, and L.R. Long, "A Spine X-ray Image Retrieval System Using Partial Shape Matching", *IEEE Transactions on Information Technology in Biomedicine*, in revision.

[9] Sebastian, T.B. and Kimia, B.B., "Metric-Based Shape Retrieval in Large Databases", *Proc. of the 16th International Conference on Pattern Recognition,* vol. 3, Aug. 2002, pp. 291 – 296.

[10] Beis, J.S. and Lowe, D.G., "Indexing Without Invariants in 3D Object Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, Issue 10, Oct. 1999, pp. 1000 – 1015.

[11] Xiaoning Qian, H.D. Tagare, and R.K. Fulbright, "Re-embedding vs. Clustering as Shape Indexing Strategies for Medical Image Databases", *Proc. SPIE Medical Imaging: PACS and Imaging Informatics,* vol. 5748, April 2005, pp. 144-151.

[12] Zheng, Z.J. and Leung, C.H.C., "Automatic image indexing for rapid content-based retrieval", *Proc. of International Workshop on Multimedia Database Management Systems*, Aug. 1996, pp. 38 – 45.

[13] Xiaoqian Xu, D. J. Lee, S. Antani and L. R. Long, "Localizing Contour Points for Indexing an X-ray Image Retrieval System", in Proc. 16th IEEE Symposium on Computer-Based Medical Systems, New York, June 26-27, 2003, pp. 169 – 174.

[14] J.H. Ward, "Hierarchical Groupings to Optimize an Objective Function", *Journal of American Statistical Association,* vol. 58, 1963, pp. 234 – 244.

[15] Xiaoqian Xu, D.J. Lee, S. Antani, and L.R. Long, "A Hybrid Approach for Online Spine X-ray Image Retrieval Based on CBIR and Relevance Feedback", *IEEE Transactions on Information Technology in Biomedicine*, submitted in Dec. 2005.