MEDICAL IMAGE SEARCH AND RETRIEVAL USING LOCAL BINARY PATTERNS AND KLT FEATURE POINTS

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ABSTRACT

In the medical domain, experts usually look at specific anatomical structures to identify the cause of a pathology, and therefore they can largely benefit from automated tools that retrieve relevant slice(s) from a patient's image volume in diagnosis. Accordingly, this paper introduces a novel search and retrieval work for finding relevant slices in brain MR (magnetic resonance) volumes. As intensity is non-standard in MR we explore performance of two complementary intensity invariant features, local binary patterns and Kanade-Lucas-Tomasi feature points, their extended versions with spatial context, and a simple edge descriptor with spatial context. Experiments on real and simulated data showed that the local binary patterns with spatial context is fast, highly accurate, and robust to geometric deformations and intensity variations.

Index Terms— search and retrieval, brain MR, local binary patterns, Kanade-Lucas-Tomasi feature points, spatial context

1. INTRODUCTION

Progress in imaging technology has multiplied the number of digital images in the medical domain. Thus, automated search and retrieval of medical images has evolved into a popular and essential research topic.

In diagnosing diseases with high prevalence and unknown cause or progress, medical experts can largely benefit from patient-to-patient search methods that compare multiple patient data and retrieve relevant cases. Moreover, to identify the cause of a pathology medical experts generally focus on a region-of-interest (single slice) or a volume-of-interest (several contiguous slices). Accordingly, retrieving the relevant slice given a query, which is a specific case of patient-to-patient search, can be of further help to the expert in diagnosis of anatomical structure specific diseases, such as hypocampus or basal ganglia disorders of the brain.

To the best of our knowledge, Bucci et al. [1] introduced the only work focusing on retrieval of relevant slices. Their method used Karhunen-Loéve transform and performed retrieval of the relevant slice in the eigenimage domain, but required a computationally expensive registration and intensity normalization step beforehand.

In this study we propose four retrieval methods based on two intensity invariant features with/without spatial context, as well as a simple edge descriptor with spatial context for comparison. The proposed methods are not only fast, but also do not require computationally intensive registration, intensity normalization and bias field correction of the data. The paper is organized as follows: Section 2 introduces the challenges in processing brain MR images, Section 3 details the materials and methods, Section 4 presents the experimental results, and finally Section 5 concludes this paper.

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2. CHALLENGES IN BRAIN MR IMAGES

The retrieval problem tackled in this paper is to find the target slice from a brain MR volume that is the most similar to a query. The challenges for this problem include:

- Intensity variations from one patient's volume to another due to possible differences in MR settings. This limits the use of intensity information in comparing different MR volumes.
- Intensity variations within the same MR volume (bias field) due to imperfect, inhomogeneous magnetic field. This requires the use of computational bias field correction algorithms.
- High similarity between relevant and irrelevant segments in brain MR volumes, such as brain tissue vs. non-brain structures in the same slice and relevant slice vs. neighboring slices in the same volume, makes their search and retrieval more challenging.
- Inter and intra-patient misalignment of the images, because of which anatomical structures are observed at different spatial positions, orientations and scales in the images. Although registration could solve this problem, it is computationally very expensive.

3. MATERIALS AND METHODS

3.1. Image Data

The database is composed of 15 T_1-weighted brain MR volumes with 50 axial slices acquired using a 1.5T Philips Intera whole body scanner with spin echo weighted sequence (TR/TE: 25,6/12 ms, FLIP: 45), 250mm FOV, 3mm slice thickness, no slice gap and 256x256 matrix.

As changes in cerebral ventricles and the surrounding structures are often associated with central nervous system disorders, from each MR volume we manually selected four landmark slices corresponding to the ventricles (Figure 1).

3.2. Pre-Processing

The pre-processing step consists of brain tissue extraction [2] and mid-sagittal plane detection [3], where the former discards background and non-brain structures while the latter indicates orienta-

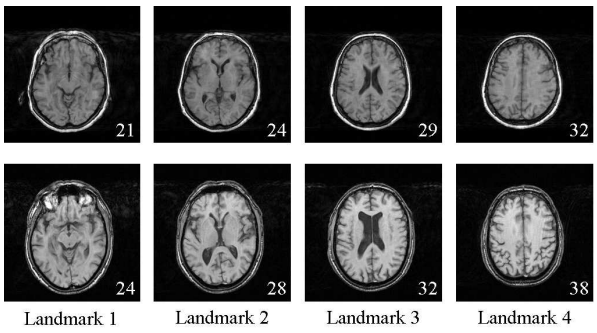

Fig. 1. Landmark slices of two MR volumes displayed in each column with the corresponding slice numbers.

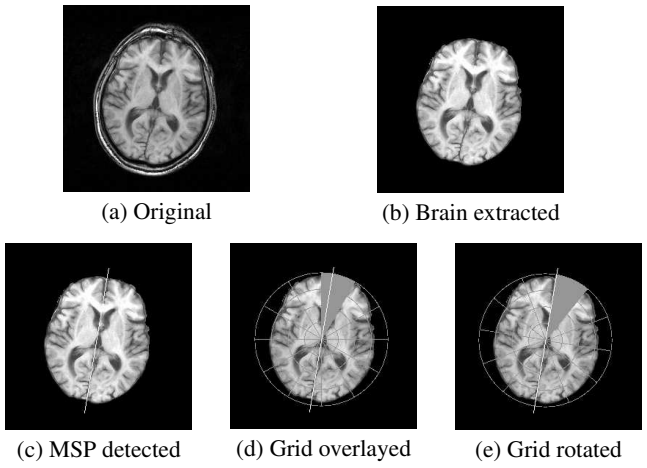

Fig. 2. Example of brain tissue extraction, mid-sagittal plane (MSP) detection and rotation of the grid relative to MSP.

tion to compensate for rotation in spatial description of the features, which will be explained afterwards (Figure 2).

3.3. Feature Extraction

3.3.1. Local Binary Patterns

Local Binary Pattern (LBP) [4] is an intensity invariant texture descriptor with low computational complexity. Recently, we have shown LBP to be robust to some common MR artifacts [5].

The original LBP operator describes the texture in the image by thresholding a neighborhood with the gray value of its center pixel and representing the result as a binary code.

3.3.2. KLT Feature Points

LBP computes texture features in all local regions of the image. However, one may argue that not all parts of an image contain valuable information. Consequently, we propose to find interesting regions of an image using the Kanade-Lucas-Tomasi (KLT) feature point tracker [6], [7].

Feature point selection in KLT is performed by searching the whole image through a window, and selecting the regions that have adequate intensity variation in vertical and horizontal directions, i.e. corner points.

3.4. Feature Description

In this section we propose four methods based on either LBP or KLT features, and a baseline method for comparison. These five methods are organized depending on whether their features are spatially indexed (Sp) or not (nSp).

3.4.1. Non-Spatial Feature Description

nSp-LBP As LBP features correspond to all local regions of an image, we describe them by their statistical distribution. Therefore, in nSp-LBP we use the histogram of the extracted LBP image.

nSp-KLT The essence of nSp-KLT method lies in the idea that salient feature points extracted from an image will be successfully matched on another if the two images are similar. Hence, this method extracts feature points from the query and attempts in matching them on the target (Figure 3). The number of matched feature points are then used as attributes in retrieval.

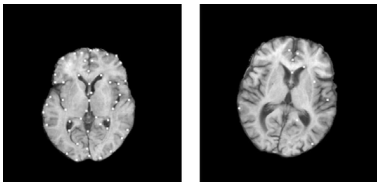

Fig. 3. Feature point matching. Among 50 feature points (in white) extracted from the query (left), 10 are matched on the target.

3.4.2. Spatial Feature Description

As anatomical structures in the brain are spatially related to eachother, we argue that incorporating this information in the features will enhance their descriptive ability. Therefore, spatial description of features in the following methods is achieved using a grid with 4 annular and 12 angular partitions. Moreover, the grid is fitted on the largest brain area observed in an MR volume providing a single reference for all the corresponding slices.

Sp-LBP This method exploits spatial indexing [8] of the LBP image histogram, where the entries of each bin are spatially indexed over the grid.

Sp-KLT This method skips the matching step in nSp-KLT and compares spatial distributions of feature points extracted from the query and the target simultaneously over the grid (Fig. 4).

Sp-Sobel As baseline method, we use a histogram constructed from the spatial distribution of Sobel edge points over the grid.

3.5. Retrieval

Fig. 5 illustrates the retrieval scheme used for all five methods. The measure of similarity is defined in two ways:

1. $$D_1\left(p_q, p_t\right) = 1 - \sqrt{\sum_{\forall i} \left(p_q(i) - p_t(i)\right)^2}$$

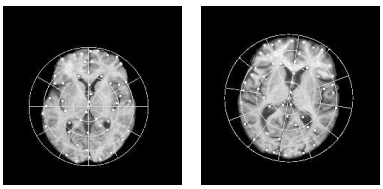

Fig. 4. Spatial distribution of 50 feature points (in white) extracted from a query (left) and a target slice.

where p_q and p_t are the normalized histograms (features) of query and target, respectively. This measure is used with nSp-LBP, Sp-LBP, Sp-KLT, and Sp-Sobel methods.

2. $$D_2 = \frac{\text{number of matched feature points}}{\text{number of feature points}}$$
which is used with nSp-KLT method.

Both measures provide a *similarity score* in the range of [0-1], with scores closer to 1 indicating high-level of similarity between slices. Consequently, for a retrieval task the target slice with the highest score is assigned as the most similar one to the query and retrieved at rank=1.

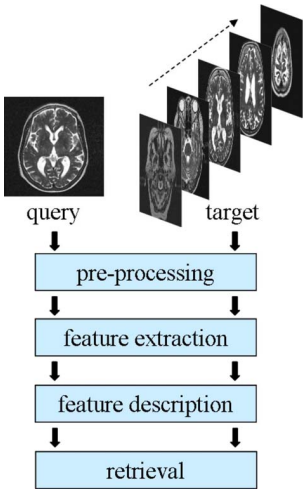

Fig. 5. Illustration of the retrieval scheme.

3.6. Performance Evaluation

We measure the error of a retrieval task as the sum of actual distances of returns ranked higher than the relevant slice:

$$error = \sum_{i=1}^{N-1} (S_i - S_N) \times d$$

where N is the rank of the relevant slice, S_i the slice number at rank=i, and d the slice thickness. As our database consists of 15 MR volumes with 4 landmark slices per volume, there are 15×4 query landmarks. Excluding the retrieval tasks where query and target originate from the same volume, there are $15 \times 4 \times 14 = 840$ unique retrieval tasks in total. Accordingly, performance of retrieval in the following results is measured as the average error of all unique retrieval tasks.

4. EXPERIMENTAL RESULTS

4.1. Performance of Retrieval

Comprehensive tests with different parameter settings for the methods have been performed, and Table 1 presents the best retrieval performances achieved by all five methods. We observe that addition of spatial context largely improves the accuracy of the LBP-based method (Sp-LBP vs. nSp-LBP), whereas with the KLT features this is not the case due to the feature point matching step ignored in Sp-KLT. Sp-LBP is the best method, followed by nSp-KLT and the baseline method (Sp-Sobel). Moreover, we observe that the errors for the outermost landmarks (L1 and L4) are greater, probably because similarity in brain tissue between these landmarks and their neighboring slices is higher. This observation unveils the issue of semantic gap between our high-level interpretation of the ground truth (selection of the landmarks) and the low-level pixel data we process.

Table 1. Retrieval error of the methods in mm.

	landmark				
method	L1	L2	L3	L4	all
nSp-LBP	157,4	189,1	179,7	228,3	188,6
Sp-LBP	27,9	12,0	19,5	73,0	33,0
nSp-KLT	68,7	14,7	29,7	78,6	47,9
Sp-KLT	124,8	54,5	54,2	94,1	81,9
Sp-Sobel	89,2	18,5	32,2	75,4	53,8

Figure 6 displays an examplary retrieval performed using the Sp-LBP method. The relevant slices for L1, L2, and L3 are retrieved at the top rank, while the one for L4 is retrieved at rank 3, which is consistent with the above observation.

Additionally, we tested retrieval performance of the methods relative to intensity variation (bias field), and geometric deformations (rotation and scaling).

Bias Field: The database is degraded by three simulated bias fields from the BrainWeb MR Simulator [9]. We observed that addition of bias field, even at 40% intensity variations, had negligible effect on the accuracy of the methods.

Rotation: The database is rotated in the axial plane by ± 15 degrees and retrieval is repeated using the original images as query and rotated versions as target. Results showed that Sp-LBP and nSp-KLT are robust to rotation, while performance of other methods considerably decreased.

Scaling: The database is linearly scaled in the axial plane by a factor of $\{0.9, 0.8, 0.7, 0.6, 0.5\}$. We observed that Sp-LBP and nSp-KLT are robust at scales above 0.7, while the other methods coped worse with scaling.

4.2. Computational Complexity

Implementation of the algorithms are done in C/C++ and the average processing time per slice (excluding the pre-processing step) on an Intel Pentium processor (2.8 GHz) with 1G memory is measured as 103ms for Sp-KLT, 201ms for nSp-KLT, and around 50ms for the other methods.

5. CONCLUSIONS

This paper presented a novel and fast search and retrieval work for brain MR images where the task is to search for a key-slice from an image volume. As intensity is non-standard in MR, we tested

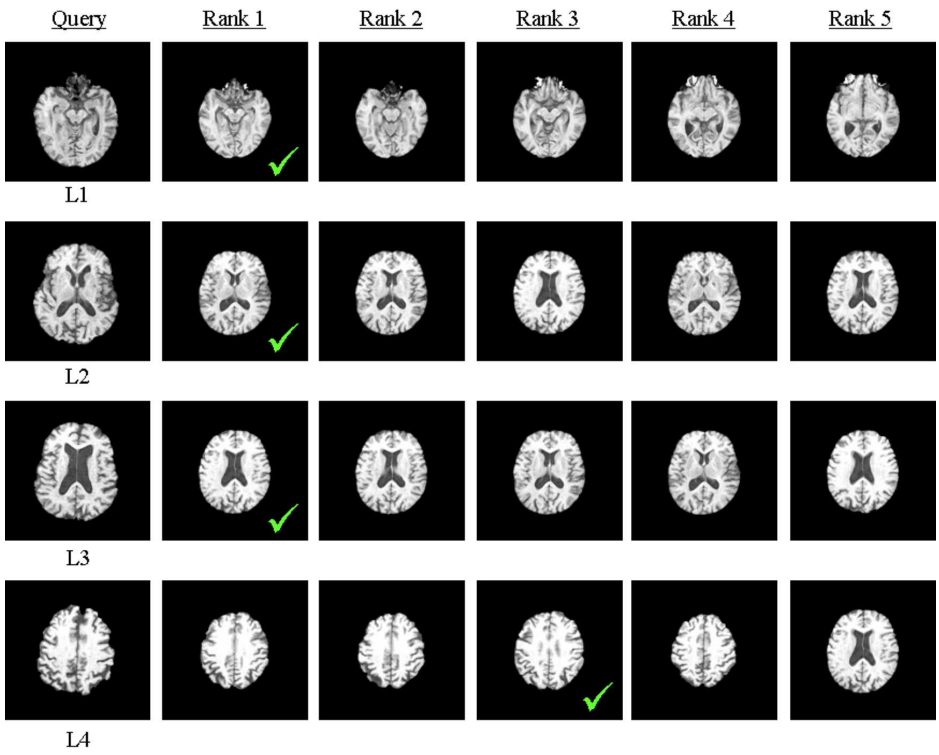

Fig. 6. Example of a retrieval performed by Sp-LBP. Each row refers to a retrieval task, where the query and the corresponding top 5 returns are displayed. The return with the checkmark refers to the relevant slice searched for.

two complementary intensity invariant features, local binary patterns and Kanade-Lucas-Tomasi feature points, and compared them with a baseline method. Experiments on real and simulated data showed that incorporating spatial information in the local binary patterns substantially improved accuracy, whereas avoiding matching of Kanade-Lucas-Tomasi feature points considerably degraded performance. Local binary patterns with spatial context consistently surpassed its rivals in retrieval accuracy. Furthermore we observed that nSp-KLT, the second best method, was computationally expensive and does not permit database indexing due to the feature point matching step. Accordingly, we recommend the use of Sp-LBP for search and retrieval of a key-slice from an MR volume, because it is accurate, fast, robust to bias field and geometric deformations, and does not require registration, intensity normalization or bias field correction.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] G. Bucci, S Cagnoni, and R De Domenicis, "Integrating content-based retrieval in a medical image reference database," *Computerized Medical Imaging and Graphics*, vol. 20, no. 4, pp. 231–241, 1996.

[2] S. M. Smith, "Fast robust automated brain extraction," *Human Brain Mapping*, vol. 17, no. 3, pp. 143–155, Nov. 2002.

[3] A. Ekin, "Feature-based brain mid-sagittal plane detection by RANSAC," in *Proceedings of 14th European Signal Processing Conference*, Florence, Italy, 2006.

[4] T. Ojala, M. Piettikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, July 2002.

[5] D. Unay, A. Ekin, M. Cetin, R. Jasinschi, and A. Ercil, "Robustness of local binary patterns in brain MR image analysis," in *29th Annual International Conference of the IEEE-EMBS*, Lyon, France, 2007, pp. 2098–2101.

[6] C. Tomasi and T. Kanade, "Detection and tracking of point features," Tech.Rep. CMU-CS-91-132, Carnegie Mellon Univ., Pittsburgh, PA, apr 1991.

[7] J. Shi and C. Tomasi, "Good features to track," in *Proceedings of IEEE Computer Vision and Pattern Recognition Conference*, Seattle, USA, 1994, pp. 593–600.

[8] A. Rao, R. K. Srihari, and Z. Zhang, "Spatial color histograms for content-based image retrieval," in *Proceedings of IEEE International Conference on Tools with Artificial Intelligence*, Chicago, USA, 1999, pp. 183–186.

[9] [online], "http://www.bic.mni.mcgill.ca/brainweb/," .