INTENSITY VERSUS TEXTURE FOR MEDICAL IMAGE SEARCH AND RETRIVAL

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ABSTRACT

The ever-increasing number of digital images in the medical domain, has amplified the need for automated search and retrieval tools. Furthermore, medical experts generally focus on specific anatomical structures to identify the cause of a pathology. For such cases, automated tools that can retrieve relevant slice(s) from a patient's image volume can assist the expert in diagnosis. Accordingly, in this paper we introduce a new search and retrieval work for finding relevant slices in brain MR (magnetic resonance) volumes. The features explored in this framework are based on intensity, texture, and their extended versions complemented with spatial context. Experiments on real data revealed that texture information outperformed its intensity counterpart, incorporating spatial context in the features substantially improved the accuracy, and finally texture features with spatial context provided fast and highly accurate retrieval of relevant slices.

Index Terms— search and retrieval, brain MR, local binary patterns, spatial context

1. INTRODUCTION

Advances in imaging technology have increased the number of digital images in the medical domain. Accordingly, automated search and retrieval of images from medical databases has become a popular research topic.

Patient-to-patient search, which can compare multiple patients and retrieve relevant cases among them, should especially help the expert in diagnosis of diseases whose causes and progress have not yet been completely unraveled, and diseases that affect large number of patients. Furthermore, in the medical domain experts generally focus on a region-of-interest (single slice) or a volume-of-interest (several contiguous slices) in order to identify the cause of a pathology. In such cases, patient-to-patient search problem can further be simplified as retrieving the relevant slice given a query, which can be used in diagnosis of structure specific diseases in the brain (e.g. hypocampus or basal ganglia disorders).

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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 to produce eigenimage base from reference images, represented slices as a combination of eigenimages, and performed similarity comparison in the eigenimage domain. However, the accuracy of their method depends largely on the selection of reference images, which is application specific.

Accordingly, in this study we propose four retrieval methods based on intensity and texture features, and their extended versions with spatial context. The proposed methods are not only fast, but also do not require a reference database. The rest of the paper is organized as follows: Section 2 details the materials and methods, Section 3 presents the experimental results achieved, and finally Section 4 concludes this paper.

2. MATERIALS AND METHODS

2.1. Image Data

The database is composed of 31 T2-weighted axial brain MR volumes acquired from subjects with memory-related problems at Leiden University Medical Center 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.

Changes in cerebral ventricles and the surrounding structures are often associated with central nervous system disorders. Accordingly, from each MRI volume we manually selected four landmark slices that are related to the cerebral ventricles (Figure 1).

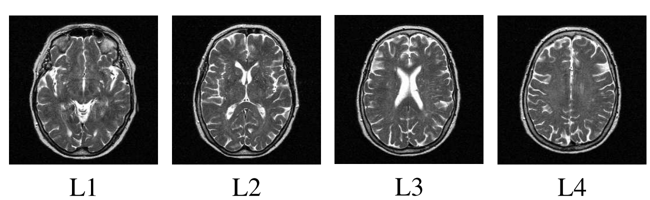


Fig. 1. Landmark slices manually selected from the database.

2.2. Pre-Processing

In order to eliminate possible problems caused by misalignment of images, the database is spatially aligned using the publicly available FMRIB FSL toolkit [2]. Furthermore, the intensity values in MR images do not have a standard scale, which degrades the performance of intensity-based retrieval methods. Therefore, we used an in-house built method that performs intensity normalization by optimizing local and global image constraints. Finally, a typical MR image of the head consists of brain tissue as well as background and non-brain structures, like skull and skin in which we are not interested. Hence, we perform the extraction of the brain tissue (mask in Fig. 2-b) by using the Brain Extraction Tool [3].

2.3. Feature Extraction

2.3.1. Intensity-based features

Intensity is one of the widely used visual features in medical image retrieval systems [4]. Accordingly, the first feature used for search and retrieval of brain MR slices in this work is the intensity histogram (Fig. 2-d) that has 256 bins.

2.3.2. Texture-based features

Local Binary Pattern (LBP) [5], which is an intensity invariant local texture descriptor with low computational complexity, was shown to be robust to some common MR artifacts in a recent study [6].

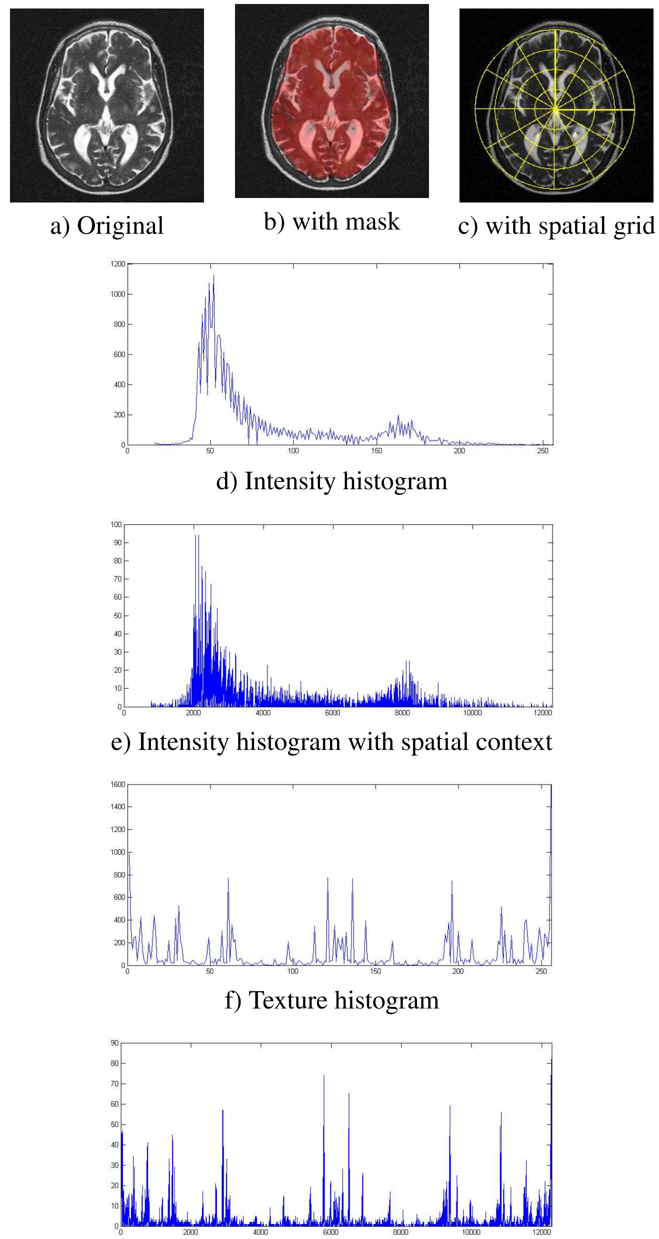
The original LBP operator describes the local texture in the image by thresholding a neighborhood with the gray value of its center pixel and represents the result as a binary code (Fig. 3). Once an image is processed pixel-by-pixel with the operator, a corresponding texture image is produced. The histogram of the resulting image (texture histogram in Fig. 2-f), which has 256 bins, is then used for retrieval.

2.3.3. Spatial Context

Histogram is a global representation of intensity distributions in an image. Incorporating spatial context into the histogram will provide a more powerful descriptor. Consequently, we exploit a spatial histogram [7], where the entries of each bin of an intensity or texture histogram are spatially indexed using a grid (Fig. 2-c) that partitions the brain area into 4 annular and 12 angular regions. The grid is fitted on the largest brain area observed in the database providing a single reference for all slices. The resulting histograms with spatial context (Fig. 2-e and g) have a total of $256 \times 12 \times 4 = 12288$ bins.

2.4. Retrieval

Based on the feature extraction performed, we propose four retrieval methods as listed in Table 1.



a) Original b) with mask c) with spatial grid

d) Intensity histogram

e) Intensity histogram with spatial context

f) Texture histogram

g) Texture histogram with spatial context

Fig. 2. Intensity and texture information extracted from one slice.

The retrieval problem tackled in this work is to find the target slice from an MR volume that is the most similar to a query. Fig. 4 illustrates the retrieval scheme used for all four methods. The measure of similarity between query and target brain slices is defined as

$$D\left(p_1, p_2\right) = \sqrt{\sum_{\forall i} \left(p_1(i) - p_2(i)\right)^2}$$

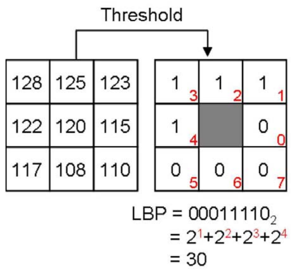


Fig. 3. Computation of the original LBP code on a 3x3 neighborhood (left).

Table 1. The proposed retrieval methods

method	feature used
M1	intensity histogram
M2	intensity histogram with spatial context
M3	texture histogram
M4	texture histogram with spatial context

where p_1 and p_2 are the corresponding histograms (features).

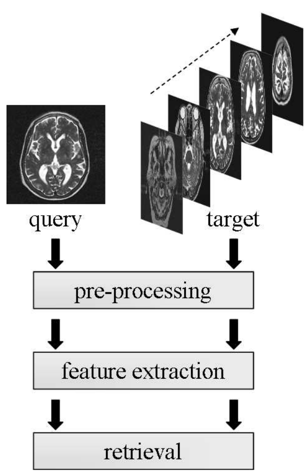


Fig. 4. Illustration of the retrieval scheme.

2.5. Performance Evaluation

We measure the error of a retrieval task as the sum actual distances of returns ranked higher than the relevant slice (Fig. 5). As our database consists of 31 MRI scans with 4 landmark slices per scan, there are 31×4 query landmarks. Excluding the retrieval tasks where query and target originate from the same image data, there are $31 \times 4 \times 30 = 3720$ unique retrieval tasks in total. Accordingly, performance of retrieval in the following results is measured as the average error of all unique retrieval tasks.

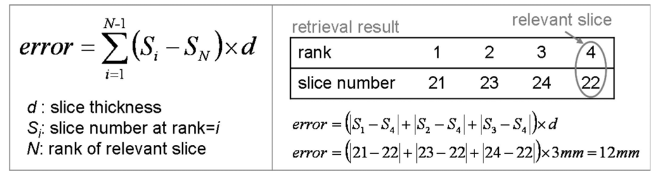


Fig. 5. Performance measure and an examplary computation.

3. EXPERIMENTAL RESULTS

3.1. Performance of Retrieval

Table 2 presents retrieval performances achieved by all four methods. We observe that incorporation of spatial information largely improves the accuracy of both methods (M1vs.M2 and M3vs.M4). Furthermore, texture with spatial context (M4) outperforms its intensity-based counterpart (M2), most probably because intensity is more affected from abnormalities in the brain (e.g. lesions or atrophy). Note that, texture with spatial context (M4) is highly accurate in terms of overall retrieval error when the 3mm slice thickness of the database is taken into account. Additional experiments with varying parameters (bin size and spatial grid) produced results consistent with the above observations.

Table 2. Retrieval error of the methods in mm.

	intensity		texture	
landmark	M1	M2	M3	M4
L1	293,0	67,5	143,1	5,9
L2	131,3	29,1	180,7	3,1
L3	329,2	153,2	300,6	5,6
L4	420,1	153,2	440,6	4,4
overall	293,4	100,7	266,2	4,7

Figure 6 displays an examplary retrieval performed using the M4 method. The relevant slice for the landmark L2, which depicted the lowest retrieval error in Table 2, is retrieved at the top rank, while the ones for the other landmarks are retrieved at rank 3 at most. Furthermore, we observe that the slices retrieved at top ranks have very similar content (e.g. returns of L4), which unveals the issue of semantic gap between our high-level interpretation of the ground truth (selection of the relevant slices or landmarks) and the low-level pixel data we process.

3.2. Computational Complexity

Implementation of the algorithms are done in C/C++ and the average retrieval time per slice on an Intel Pentium processor (2.8 GHz) with 1G memory for methods M1, M2, M3, and M4 is measured respectively as 6, 31, 55, and 79ms. Note that the computation time can be further reduced using optimized software and dedicated hardware.

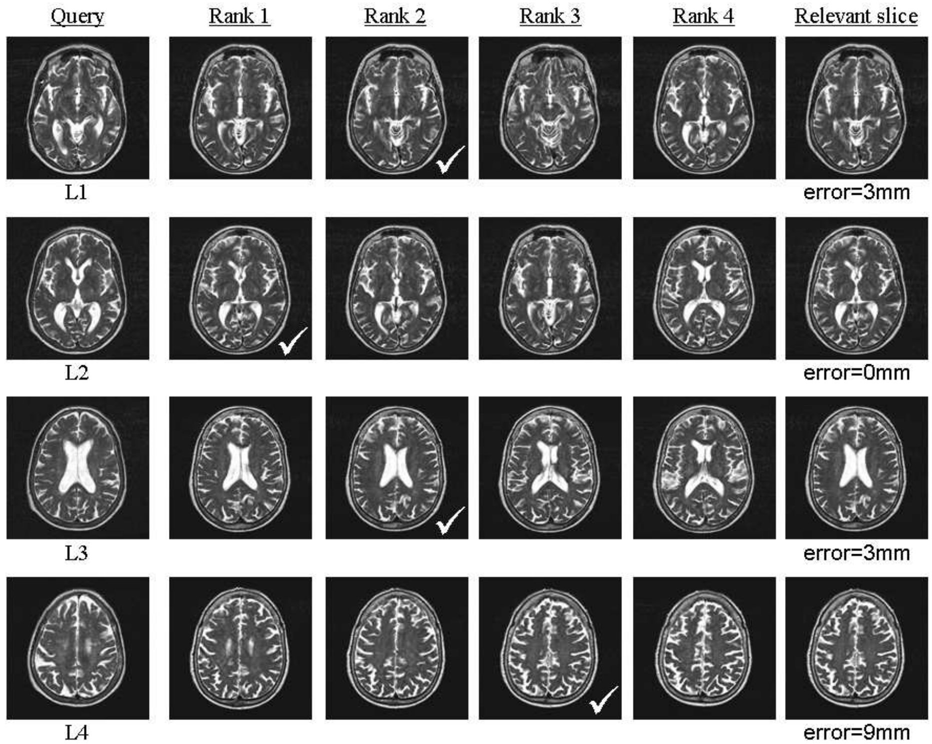


Fig. 6. Example of a retrieval performed by the M4 method. Each row refers to a retrieval task, where the query, the corresponding top 4 returns and the searched relevant slice (with its retrieval error) are displayed. The return with the checkmark refers to the relevant slice searched for.

4. CONCLUSION AND FUTURE WORK

In this paper, we presented a novel search and retrieval work for brain MR images where the task is to search for a key-slice from an image volume. We compared the accuracy of intensity and texture features in the aforementioned retrieval problem, and showed that incorporating spatial context in the features substantially improved the accuracy. Furthermore, we observed that texture information with spatial context outperformed its intensity-based counterpart. Experiments on real data revealed that the method using texture features with spatial context achieved high accuracy and speed. Please note that, this method can be easily extended for unregistered data by midsagittal plane detection and orientation of the spatial grid accordingly.

5. REFERENCES

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