Optimized Pathological and Visual Content-based Neuroimaging Retrieval

Sidong Liu[a], Weidong Cai[a], Lingfeng Wen[a,b], Stefan Eberl[a,b], Michael J Fulham[a,b,c], Dagan Feng[a,d]

[a] Biomedical and Multimedia Information Technology (BMIT) Research Group,
School of Information Technologies, University of Sydney, Australia
[b] Department of PET and Nuclear Medicine, Royal Prince Alfred Hospital, Sydney, Australia
[c] Sydney Medical School, University of Sydney, Australia
[d] Centre for Multimedia Signal Processing (CMSP), Dept. of Electronic & Information Engineering,
Hong Kong Polytechnic University, Hong Kong

ABSTRACT

Neuroimaging provides important insights for understanding neurobiology and is essential for accurate neurological and neurosurgical diagnosis and patient care. The volume and complexity of the neuroimaging datasets have greatly increased due to advances in scanning instrumentation. These large datasets now pose challenges for images retrieval / management and more effective approaches are needed. Content-based image retrieval (CBIR) takes advantage of the rich visual/physiological information in the images and can provide the opportunity for more efficient and reliable image retrieval. Although a number of investigators have used CBIR systems in neuroimaging, few of these approaches have explored all the potential features in these images. We suggest that such image retrieval could be optimized by using pathological and domain-specific visual features rather than texture features alone. We used the cerebral metabolic rate of glucose (CMRGlc) as the physiological parameter from static brain $[^{18}F]$ *2-fluorodeoxy-glucose* (FDG) positron emission tomography (PET) images and a customized disorder-oriented mask (DOM) specific for a particular neurodegenerative disorder, with the regions of interest (ROIs) specific for each disease sub-type. We designed 8 Gabor filter banks with different parameter settings and identified the optimum Gabor function parameter setting for the visual feature extraction. Our experimental data indicate that optimization of the Gabor filter parameters, targeted to disease specific regions enhances retrieval precision.

Keywords: Neurological image, image retrieval, positron emission tomography, dementia

1. INTRODUCTION

Functional neuroimaging techniques, such as positron emission tomography (PET), are essential for the diagnosis and management of neurological disorders. As a result of the introduction of the hybrid imaging devices, such as PET-CT and PET-MR, the functional neuroimaging datasets have also increased explosively. Traditional text based retrieval methods are not suitable for these large datasets, because it is hard to describe the visual and physiological features by text. Therefore, content-based image retrieval was developed to offer fast and reliable image management.

A number of investigators have reported different CBIR systems for efficient and reliable retrieval and management of large medical image repositories [1-3]. Recently, Batty *et al.* designed a system for semantic retrieval [4]. They identified a set of ROIs in the images and extracted the Gabor function based texture features, which had been used by Ma and Manjanuth [5]. Batty *et al*. also combined the features with a mean index ratio, which was an important attempt to combine the localized visual feature with a coefficient that reflected a physiological property.

We believe that such an image retrieval approach could be further enhanced by the addition of pathological disorder-oriented masks (DOM) and by optimizing the Gabor function parameters. Therefore, in this study, we proposed a localized pathological and visual content-based retrieval approach with the optimized Gabor function parameters to enhance the neuroimaging data retrieval.

2. METHOD

Our optimized pathological and visual CBIR approach contains three components: the neuroimaging data pre-processing, the pathological ROI selection and the Gabor-function based texture feature extraction. Fig. 1 demonstrates the overall dataflow of our proposed framework.

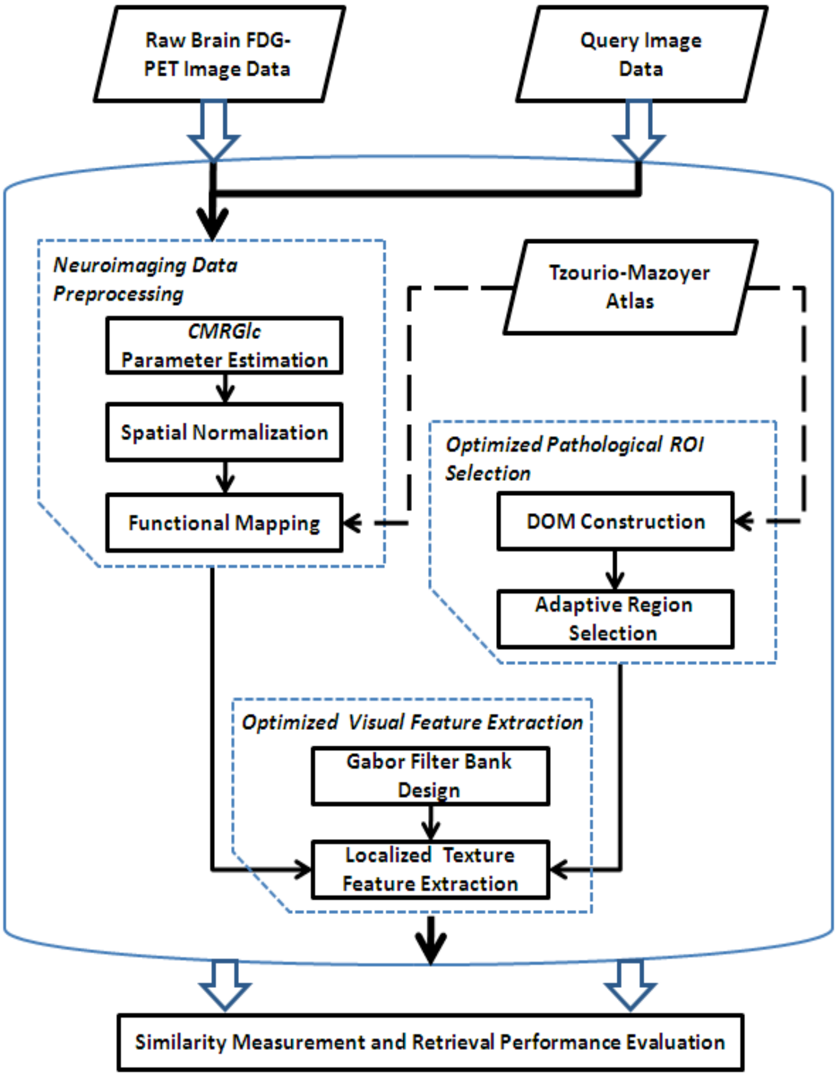

Fig. 1 The framework of our proposed optimized pathological and visual CBIR approach.

2.1 Neuroimaging Data Pre-processing

Parametric images of CMRGlc were derived from raw brain PET neurological images using the autoradiographic (ARG) algorithm [6] and then spatially normalized with SPM2 [7] to eliminate inconsistencies between individuals in size and scan orientations. The spatially normalized CMRGlc images were further labeled based on the Tzourio-Mazoyer atlas [8].

2.2 Optimized Pathological ROI Selection

Different types of dementia have different patterns of reduced cerebral glucose metabolism. Initially, we used the Tzourio-Mazoyer atlas and constructed a set of DOMs, each of which corresponded to one type of dementia, based on clinical expertise. The initial DOMs were further refined by *t-map* [9], which translated the voxel values of the CMRGlc images into values in a normal distribution that was calibrated by the mean and standard deviation of the age-matched normal cases. The resulting t-maps were then thresholded (p-value << 0.05) to extract the lesion areas which were subsequently added to the initial DOMs.

2.3 Optimized Visual Feature Extraction

A complex Gabor filter covers certain frequencies in the spectrum. To eliminate the frequency overlap between different Gabor filters and preserve the spectrum, four parameters were used to describe one Gabor filter bank: the number of frequency scales, the number of orientations, the bandwidth and the filter size. For a given image, the Gabor filter transform coefficients for each pixel are the complex conjugate result of the image itself and the Gabor filter in specified scale m and orientation n. Then the mean μ_{mn} and standard deviation σ_{mn} of the transform coefficients can be used to represent the region for retrieval purpose. To make the optimum use of the Gabor filters, we designed 8 banks with different parameter settings. The experimentation was performed in three steps on the whole brain based features. In the first step, we selected a Gabor bank with 4 scales and 6 orientations and bandwidth of 1, which has been claimed to best model human visual system [10] and tested 4 different filter sizes to identify the optimum filter size. In the second step, we used the optimized filter size found in the first step to evaluated four different combinations of filter scales and orientations. Finally, we investigated two bandwidths with fixed scales, orientations and filter size that determined in last two steps. The findings in these three steps could suggest the optimized Gabor function parameter setting.

2.4 Similarity Measurement and Performance Evaluation

We tested our approach on a dataset that comprised 142 neurological FDG-PET studies undertaken at Royal Prince Alfred Hospital, Sydney. The DOMs for Alzheimer's disease (AD) and frontal-temporal dementia (FTD) were tested on 38 AD cases and 37 FTD cases together with 18 normal cases and 37 cases of other disorders. The retrieval was conducted by the leave-one-out strategy on the whole dataset using query by example paradigm. The similarity was calculated by Euclidean distance and the performance was evaluated by the average precisions versus the number of images retrieved curves.

3. RESULTS

In Fig. 2, we show the overall performance of Gabor banks with different filter sizes on the 142 cases. These curves demonstrate that the filter size of 25 x 25 (in pixel) offered the highest average precision.

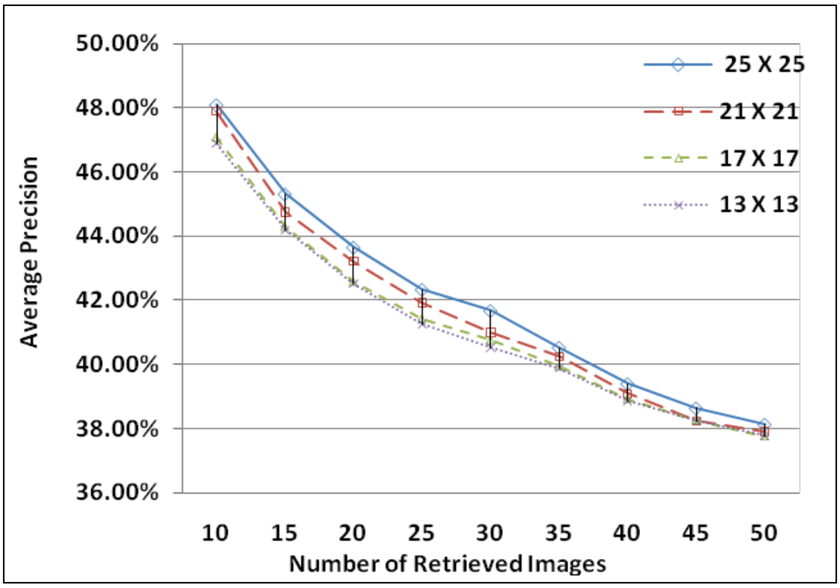

Fig. 2 Effects of different filter sizes.

Fig. 3 shows the effects of different filter orientations and scales on the entire dataset when using fixed 25 x 25 filter size and bandwidth ($b = 1$), and we found that the Gabor bank with 3 scales and 8 orientations achieved the best results.

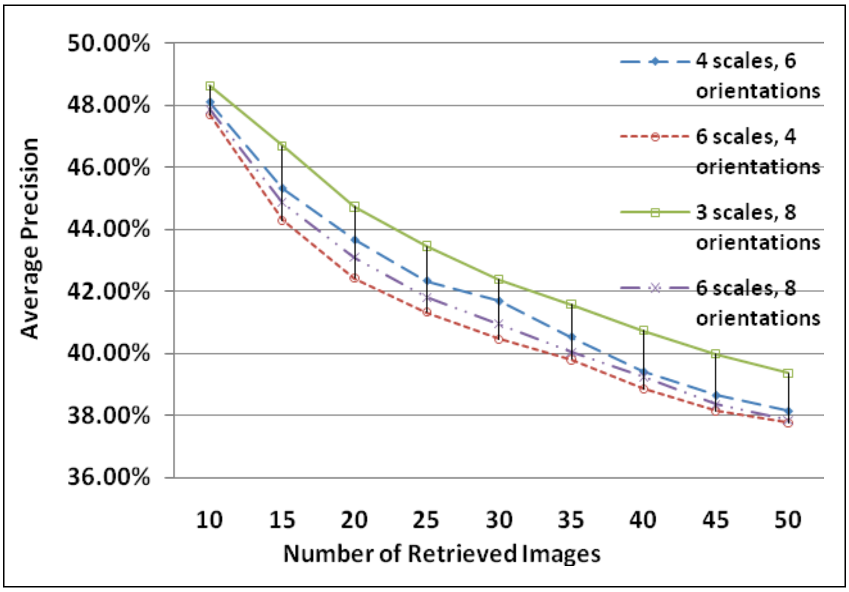

Fig. 3 Effects of different orientations and scales.

In Fig. 4, we show the results of using two bandwidths with fixed 3-scale, 8-orientation, and 25 x 25 of the filter size. A better result was achieved when bandwidth was equal to 1.

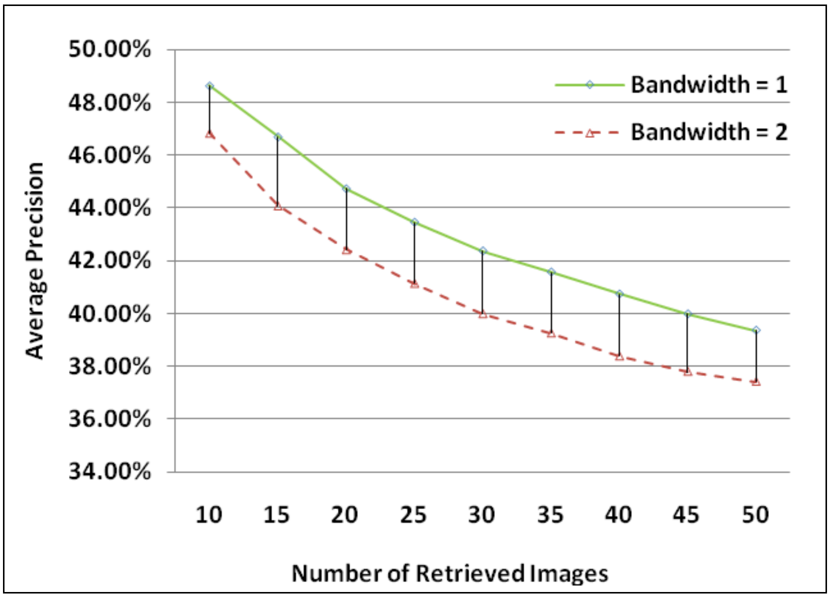

Fig. 4 Effects of different bandwidth.

Fig. 5 shows retrieval performances of whole brain (WB) based features and DOM-based features on AD and FTD cases when using the optimized Gabor function parameters. The comparison results show that the DOMs can further improve the retrieval performance.

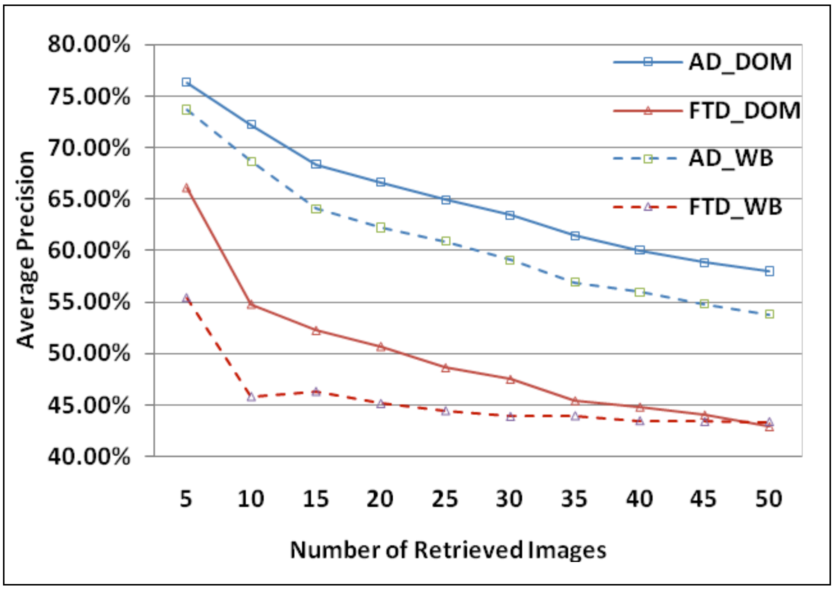

Fig. 5 DOM-based features versus Global features.

4. DISCUSSION

In this study, we developed an optimized pathological and visual content-based retrieval approach for neurological images. Firstly, we investigated the effects of different Gabor function parameters in neuroimaging retrieval and identified the optimum Gabor function parameter for this application. In addition, we designed a set of DOMs for different types of dementia which further enhanced the neuroimaging data retrieval precision. While for this evaluation, the diagnosis of the query image was specified a priori to select the appropriate DOM, this framework can be extended by constructing the full range of DOMs to achieve CBIR without pre-knowledge of the query image's diagnosis.

5. CONCLUSION

In this study, we developed a CBIR approach for neuroimaging retrieval that was based on pathological and visual features. Our preliminary data suggest that the DOM-based features achieve better results than global features, the optimum Gabor parameter setting identified was 3 scales, 8 orientations, bandwidth of 1 and 25 x 25 of the filter size, and our approach potentially enhances neuroimaging retrieval.

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