AN EFFECTIVE AND EFFICIENT TECHNIQUE FOR SEARCHING FOR SIMILAR BRAIN ACTIVATION PATTERNS

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ABSTRACT

In this paper, we introduce a new approach for content-based similarity search for brain images. Based on the keyblock representation, our framework employs the Principal Component Analysis to reduce the dimensionality and improve the computational efficiency. Moreover, the "similarity" between two images is measured using both the Histogram Model and the Summed Euclidean Distance. We performed experiments on different fMRI datasets, and compared the proposed framework with the keyblock approach. The results of the experiments demonstrated the improved effectiveness and efficiency of the proposed approach in similarity searches.

Index Terms — Biomedical imaging, Vector quantization, Information retrieval

1. INTRODUCTION

The Functional Magnetic Resonance Imaging (fMRI) is a powerful technology, which, over the past decade, has not only offered the promise of revolutionary new approaches to studying human cognitive processes, but also led to increasing interests in finding the appropriate data analysis methods in computer science community. The medical domain, as one of the principle application domains for content-based access technologies, calls for effective and efficient informatics tools for image querying, browsing and management.

In order to better assist and benefit neuroscience research, some fMRI repositories are provided to researchers from all disciplines. For instance, the Dartmouth College's fMRI Data Center [1], which is one of the widely known fMRI data repositories, provides access to a common dataset that everyone can use to develop and evaluate methods, confirm hypotheses, and perform meta-analyses. Certain datasets we have used for this type of analysis were contributed by the fMRI Data Center.

Early research in content-based image retrieval focused on using low-level features such as color, texture and shape extracted from images as characteristics to describe the image content [2]. Various content-based image retrieval systems, including QBIC (Query by Image Content) [3] and Photobook [4], have been built for general or specific image retrieval tasks. Recently, new approaches that solve more precise and general image retrieval tasks have been introduced, such as the keyblock approach [5] that has demonstrated its effectiveness in the image similarity search field. Another content-based image retrieval framework based on a two-step approach [6] that employs wavelets and a concentric sphere characterization approach, was proposed and applied in the brain imaging domain.

In this paper, along with introducing the application of the keyblock approach in the brain imaging domain, we propose an extension of the keyblock approach for improving content-based medical image retrieval. Although our approach employs keyblocks, we apply the widely used dimensionality reduction method, Principal Component Analysis (PCA), to reduce the dimensionality of the image segments and thus reduce the computational requirements of the original approach. In addition, we introduce two measures of similarity between images: the Histogram Model and the Summed Euclidean Distance [7] and provide a discussion on the experimental accuracy achieved using both distance measures. By performing comparative experiments we measure both the computational cost and retrieval accuracy, and evaluate the effectiveness and efficiency of the new method.

The rest of the paper is organized as follows: We first provide a brief introduction to the keyblock approach. Then we discuss the framework of the methodology and the similarity measures we propose. Finally, we present the experimental results and provide conclusions.

2. BACKGROUND

The keyblock approach decomposes each image into equi-size blocks and uses Vector Quantization (VQ) to represent each block with the closest codeword from a codebook. VQ is widely used in image compression and encoding; it is a lossy compression method based on the principal of block encoding.

First, given a fixed block size, each image is decomposed into a number of small blocks. Each block contains features of the sub area of the corresponding image. Based on such small blocks from different images, a codebook containing keyblocks is generated. To generate the codebook, the Generalized Lloyd Algorithm, which produces a "local optimal" codebook based on two conditions (the nearest neighbor condition and the centroid condition), is used.

Then, each image in the database is encoded using the codebook. Initially, each image is decomposed into blocks, and for each block, the closest entry in the codebook is located and the corresponding index is stored. In such a way, each image can be represented as a vector with each item linked to a keyblock in the codebook.

Finally, when a query image q is submitted, the similarity between the query q and each image t in the database is estimated according to a measure of similarity. The top k similar images retrieved by the system are those with the largest similarity value with the current query.

One drawback of the keyblock approach is that although it leads to high retrieval accuracy, it is usually computationally expensive when working with large images. Due to the fact that brain images, such as MRI or fMRI are often quite large (e.g., of size 79×95×68), the efficiency of the retrieval methods needs to be taken into consideration as a vital factor.

3. METHODOLOGY

In this paper we employ the keyblock approach for performing content-based similarity searches in brain images. We propose a new framework as an extension of the keyblock approach. The new framework achieves higher accuracy than the keyblock approach while at the same time reduces the computational requirements. Just like the keyblock approach, it decomposes an image into a certain number of blocks and encodes it based on a codebook. However, instead of performing GLA directly on the sub blocks of the sampled images, it reduces the dimensionality of the original data by performing Principal Components Analysis (PCA) and uses the reduced features for generating the codebook.

Namely, for a given set of N-dimensional (e.g., 2D) images, each image is decomposed into a number of small blocks, say, each of size 16×16. Then, the high dimensional data (16×16=256-D) is projected onto a much lower dimensional space (e.g., 4-D), using PCA. Since PCA preserves as much of the randomness in the original data as possible, the obtained low-dimensional vectors form a compact representation for each block.

The PCA projection matrices are computed separately for each spatial location in the image. More specifically, each block is represented by a vector and a PCA projection is computed on the matrix composed by blocks from the same spatial location in all images in the database. In other words, for a database that contains M images, in order to get reduced features to represent the j-th block (say, originally of 256 dimensions) in each image, PCA is performed on the M×256 matrix composed of all j-th blocks from the M images in the database. The fact that the same matrix is used for all co-located blocks makes possible to maximize the difference among blocks positioned at the same place of the images and thus provides a good chance to differentiate the texture of the images.

Figure 1 shows a flowchart of the proposed method. Figure 2 shows a sample 2D fMRI slice and the reconstructed image based on a codebook.

3.1 Similarity Measure

In our framework, we employ two similarity measures: the Histogram Model and the Summed Euclidean Distance.

3.1.1 Histogram Model

One widely used way to quantitatively measure the similarity between different images is the Histogram Model (HM). We use this model to measure similarity based on the codeword appearance frequency. More specifically, for a query Q, we compute the similarity Sim_{HM} between a query image Q and each image X in the database using the following formula:

$$Sim_{HM}(X,Q) = \frac{1}{1+dis(X,Q)}, where\ \ dis(X,Q) = \sum_{i=1}^{s} \frac{|f_{i,X} - f_{i,Q}|}{1 + f_{i,X} + f_{i,Q}}$$

In the above formula, $f_{i,X}$ and $f_{i,Q}$ refer to the appearance frequency of codeword C_i in images X and Q respectively, while s refers to the size of the codebook.

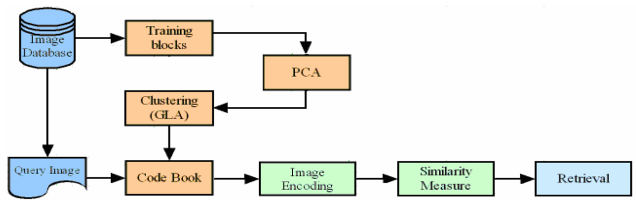
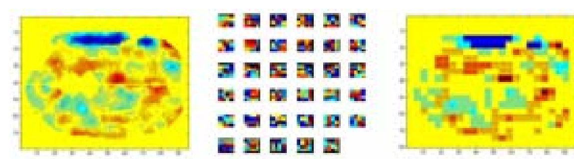


Figure 1 *Flowchart of the proposed content-based medical image retrieval framework*



(a) *(b)* *(c)*

Figure 2 *(a) An original 2D fMRI slice (79*95), (b) part of a codebook, (c) the reconstructed image*

3.1.2 Summed Euclidean Distance

An alternative way to compute the similarity between images is to use the summed Euclidean distance as a measure between each codeword pair. The advantage of the Summed Euclidean Model over HM is that it takes into consideration the order of appearance of codewords.

Using the codebook, an image can be represented as a vector $X = x_1, x_2, \ldots, x_k$, and correspondingly the query can be described by $Q = q_1, q_2, \ldots, q_k$. Each x_i and q_i ($1 \le i \le k$) is an index corresponding to a keyblock in the codebook. We sum up the distance (e.g., the Euclidean distance) between each pair of x_i and q_i to get a rough distance between the two images. Then the similarity Sim_{SED} between a query image Q and each image X in the database is computed as:

$$Sim_{SED}(X,Q) = \frac{1}{1+SED(X,Q)}, where\ \ SED(X,Q) = \sqrt{\sum_{i=1}^{k}(D(x_i,q_i)^2)}\ .$$

4. EXPERIMENTAL RESULTS

We experimentally studied both the original keyblock approach and the proposed extended keyblock approach with different image similarity measures. We performed experiments on both 2D and 3D brain image datasets, and evaluated both the efficiency and effectiveness of the extended approach. To obtain more stable results, we repeated each experiment 5 times and reported the average performance.

Each of the images in the dataset was taken as a query. For each query image, we computed its similarity to all other images in the database and retrieved the top K most similar matches.

Intuitively, the size of codebook, the size of keyblocks and the value of K, all influence the accuracy. In our experiments, the size of keyblock was set to 8×8 for the 2D case and to 8×8×8 for the 3D case, while the codebook size was set to 256. For each query, the top 10, 20, 30 or 50 matches were retrieved in each experiment.

4.1 2D experiments

The functional brain image (fMRI) dataset used in these experiments consisted of 18 3D images (each of size 79×95×68 voxels). The 3D images were fMRI contrast maps (when performing a task vs. rest) obtained from a study designed to explore neuroanatomical correlates of semantic processing in Alzheimer's disease [8]. Two groups of subjects were included in this study: 9 controls and 9 patients. Due to the small number of subjects involved in this dataset, we did not perform the retrieval on 3D volumes. Instead we considered the 2D slices as separate images. There were totally 18×68 = 1224 slices (images).

We used the GLA algorithm to generate the codebook from a randomly selected sample of 20 images. For keyblock dimensionality reduction, the original 8×8=64 dimensional features were projected by PCA onto a 3-dimensional space.

To quantify the retrieval results, we used two definitions for the accuracy. *Accu1* represents the percentage of retrieved images that are from the same subject as the query image and *Accu2* represents the percentage of retrieved images that are from the same group, in our case, controls or patients:

$$Accu1 = \frac{images\_from\_same\_volume}{K} * 100\% \qquad \text{Equation (1)}$$

$$Accu2 = \frac{images\_from\_same\_group}{K} * 100\% \qquad \text{Equation (2)}$$

Each of the 1224 slices was taken as a query; the average accuracy is reported in Table 1. Figure 3 illustrates the image retrieval results for a sample query image. The colors in these maps represent positive and negative changes in blood-oxygen level dependent (BOLD) signal intensity which is linked to blood flow and neural activity. The computation time for different processes is shown in Table 2.

4.2 3D experiments

We tested the proposed approach on a 3D fMRI dataset consisting of 179 images (each of size 53×63×46 voxels). These images are 3D fMRI contrast maps. Two groups of images corresponding to two different tasks were included in this study: (a) go/no-go (100 subjects) and (b) auditory oddball (79 subjects).

We generated the codebook from a randomly selected sample of 20 volumes. For keyblock dimensionality reduction, the original 8×8×8=512 dimensional feature vectors were projected onto a 10-dimensional space by PCA.

Table 1 *Average accuracy of the keyblock-based and the extended keyblock-based (with PCA) similarity search using the Histogram Model and the Summed Euclidean Distance as similarity measure*

		K= 10	K= 20	K= 30	K= 50
HM	*Accu1*	0.3273	0.2507	0.2132	0.1735
	Accu2	0.6613	0.6214	0.6018	0.5815
SED	*Accu1*	0.5626	0.3009	0.2115	0.1493
	Accu2	0.7789	0.6425	0.5932	0.5559
PCA +HM	*Accu1*	0.3435	0.2572	0.2168	0.1766
	Accu2	0.6592	0.6149	0.5930	0.5719
PCA +SED	*Accu1*	0.7726	0.4840	0.3442	0.2283
	Accu2	0.8883	0.7419	0.6654	0.6016

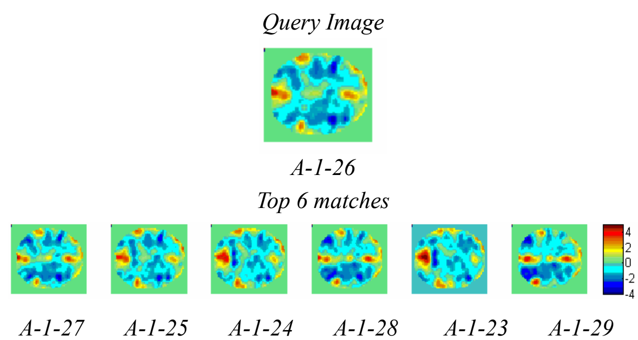


Figure 3 *The top 6 matches for a sample fMRI slice, measured by the Summed Euclidean Distance based on extended keyblock approach. The index of each image (slice) is of the form "G-V-S", corresponding to the Sth slice from the Vth subject in group G. For example, A-1-26 refers to the 26th slice of subject 1 in group A.*

Table 2 *Average computation time (in seconds), calculated using the cputime command, for image retrieval*

	Cdbk Generation	Image Encoding	Image Retrieval	
			HM	SED
Without PCA	1037.19	332.91	73.56	93.24
With PCA	209.79	281.62	74.52	90.58

To quantify the retrieval results, we computed the accuracy using the following formula. *Accu* represents the percentage of retrieved images that are from the same group, in our case, controls or patients, as the query image.

$$Accu = \frac{images\_from\_same\_group}{K} * 100\% \qquad \text{Equation (3)}$$

Each of the 179 images was taken as a query; the average accuracy is reported in Table 3. Figure 4 illustrates the retrieval result for a sample query. For easy visualization, 6 representing slices are displayed for each volume. The computation time for different processes is shown in Table 4.

Table 3 *Average accuracy of the keyblock-based and the extended keyblock-based (with PCA) similarity search using either Histogram Model or Summed Euclidean Distance as similarity measure*

	K= 10	K= 20	K= 30	K= 50
HM	0.5902	0.5700	0.5598	0.5531
SED	0.6693	0.6298	0.6069	0.5794
PCA+HM	0.6131	0.5877	0.5693	0.5509
PCA+SED	0.6841	0.6381	0.6208	0.5949

Query Image and top 6 matches

Slice No: 10 18 26 34 42

Query: A-26

Matches: A-50

A-15

A-62

A-77

A-44

A-73

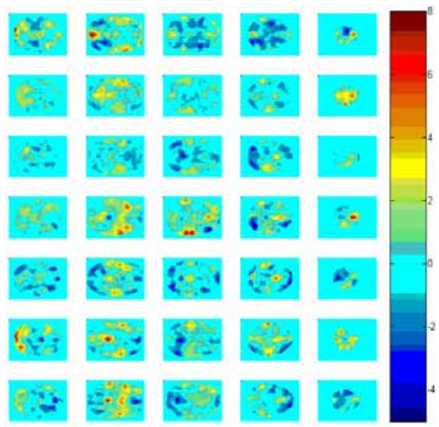


Figure 4 *The top 6 matches for a sample fMRI volume, measured by the Summed Euclidean Distance based on the extended keyblock approach. The similarity results were based on the analysis of the whole brain activity for each subject. The index of each image is of the form "G-V", denoting that it is the Vth subject in group G, (e.g., the query image A-26 refers to the 26th subject in group A).*

Table 4 *Average computation time (in seconds (calculated using the cputime command)) for image retrieval*

	Cdbk Generation	Image Encoding	Image Retrieval	
			HM	SED
Without PCA	1710.14	640.38	1.73	4.48
With PCA	201.89	133.11	1.75	3.70

5. DISCUSSION

In this paper, we introduced an extension of the keyblock approach that employs PCA to reduce the computational requirements and uses two measures of "similarity" between images: the Histogram Model (HM) and the Summed Euclidean Distance (SED). We used this extended keyblock approach to perform content-based similarity searches in brain images.

There is a trade-off between accuracy and efficiency: the SED measure leads to higher accuracy but requires more computation while HM is less computationally expensive but achieves worse retrieval results. All preliminary experimental results show comparable accuracy and improved efficiency of the proposed approach over the original keyblock approach in fMRI similarity searches.

Further speculation on the proposed techniques suggests that with prior knowledge, the texture analysis of the images can focus on certain regions of interest (ROI) and be less influenced by information in irrelevant areas. Therefore, the accuracy of the similarity search results might improve consequently.

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