A Method for 3D Image Retrieval

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Abstract: *The usefulness of 3D image retrieval paradigm is evaluated in the context of neurological research using 265 high resolution MRI-T_1 brain datasets of healthy controls. The method is based on multi-sort co-occurrence descriptors. It is shown that the approach can be used for localization of specific brain regions (mean deviation of 2.4 mm for searching anterior/posterior commissures), retrieval subjects from different age groups (more than 90% correct in top-10 for retrieval of young and aged subjects), and distinguishing very weak differences associated with gender (62% correct in top-10 query results on 210 young healthy subjects).*

Keywords**:** Image retrieval, 3D MRI, Co-occurrence.

1. INTRODUCTION

The content-based image retrieval (CBIR) is aimed for searching images in large image archives by their content. Once emerged, CBIR remains the research field that is under intensive development for the last 10-15 years [1]. It is known that the main body of work done in CBIR is devoted to the color image retrieval from image databases containing digital photographs or color images of similar kind. They often categorized to something like «holiday pictures» and «magazine image» classes [1-3]. However, as CBIR methods, algorithms and software become more and more sophisticated and the whole research area entries to its mature age, the more and more specific domains and practical applications getting involved into CBIR technology. In particular, one of the very promising application areas is biomedical imaging where the CBIR may play a very important role being incorporated into the existing tools of searching similar cases in medical image archives for computer-aided support of the existing diagnosis and treatment processes [4, 5, 1].

Recently, the neurological research, diagnosis and treatment involve large amounts of 3D image data of different modalities. It is obvious that the problem of searching «similar» brain images is different from the general image retrieval problems studied in computer vision (e.g., [1, 6, 7]). Also, even in the medical imaging domain [4], the problem of retrieving the whole 3D image volumes instead of slice-wise searching in medical databases is rarely addressed and remains to be explored.

Thus, the purpose of this work is to evaluate the feasibility and potential usefulness of the brain image retrieval paradigm on 3D MRI-T_1 brain datasets.

The approach presented in this paper is a query-by-example approach and it is based on multi-sort, multi-dimensional co-occurrence matrices proposed in [8-10]. These 3D image descriptors are sensitive to tenuous differences in brain image patterns and reflection/rotation invariant. In context of brain image analysis with the characteristic «reflected» intensity distribution in the left and right hemispheres and unpredictable sulcal variability, this is a highly desirable property. Being normalized to the sum of elements, they are also insensitive to individual differences in brain volume.

In this study we are evaluating the fitness of the approach on the following non-trivial tasks:

(a) searching for specific brain regions such as anterior and posterior commissures;

(b) retrieval of MRI brain datasets of healthy subjects from different age groups;

(c) testing the ability of the image descriptors to capture almost inconsiderable differences associated with gender.

Query results are represented as top-*N* images most similar to the given example. The query unit is always a 3D volume of interests (VOI). Depending on specific retrieval task, the VOI may contain the whole brain, certain brain region, or even a single 2D image slice. In most of cases, image descriptors can be pre-computed and stored in a database so that searching can be performed in real time. The evaluation procedure used for quantitative analysis of image retrieval quality is similar to the testing technique described in [2].

This pilot study was performed by author using MRI scanning facilities and 3D brain image data of Max-Planck Institute of Cognitive Neuroscience, Leipzig. Dr. F.Kruggel and Prof. von Cramon have provided all the necessary consultations on neurological aspects the research.

2. SUBJECTS

The Max-Planck Institute of Cognitive Neuroscience maintains a database of subjects enrolled for functional MRI experiments. Before admission, a high resolution T_1-weighted MRI scan of the head is acquired. Subjects are included in this database if they comply with the informed consent for conducting general fMRI experiments, pass the examination, and do not exhibit pathological or abnormal features (such as ventricular enlargements, subarachnoidal cysts) in their MR tomograms. All scans used in this study stem from this database.

For the first and the second experiments, the age- and gender-matched group of 210 young healthy subjects was selected (103 males and 107 females, mean age 24.8, SD 3.97 years). For the third experiment on retrieval of brain images with respect to age we used 55 image datasets that have been conditionally sub-divided into the «young» subgroup, AG-Y (33 subjects aged 16-25 years, 17 males and 16 females) and "aged" subgroup, AG-A (22 subjects, 50-70 years, 11 males and 11 females).

3. MRI DATA

MR acquisition was performed on a Bruker 3T Medspec 100 system equipped with a bird cage quadrature coil using a T_1-weighted 3D MDEFT protocol [11]: FOV 220×220×192 mm, matrix 256×256, 128 sagittal slices, voxel size 0.9×0.9 mm, 1.5 mm slice thickness, scanning time 15 min. Scan data were interpolated to an isotropic voxel size of 1.0 mm by a fourth-order *b*-spline method [12] and aligned with the stereotactical co-ordinate system [13] while removing the outer hulls of the brain. Datasets were finally cropped into a minimum box enclosing the brain of 160×200×160 mm extent. Fig. 1 shows an example of 3D brain image prepared for the analysis.

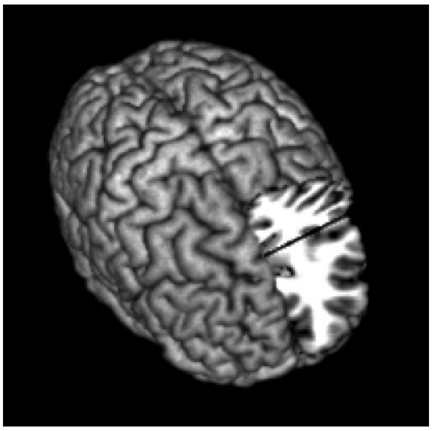

Fig.1 – Example of segmented 3D MRI brain image.

4. THE METHOD

Image comparisons were performed by calculating *L2* distance between their descriptors. We have employed multidimensional co-occurrence matrices suggested in [8] as VOI descriptors.

For a formal definition of the corresponding co-occurrence matrix, let us consider an arbitrary voxel pair (i,k) defined on discrete voxel lattice by voxel indices, $i=(x_i,y_i,z_i)$, $k=(x_k,y_k,z_k)$ and with the Euclidean distance $d(i,k)$. Let us denote intensities of these voxels by $I(i)$ and $I(k)$, local gradient magnitudes by $G(i)$, $G(k)$ and the angle between their 3D gradient vectors by $a(i,k)$. Then the general, six-dimensional co-occurrence matrix can be defined as:

$$W = \| w(I(i), I(k), G(i), G(k), a(i,k), d(i,k)) \|.$$

Gradient magnitudes $G(i)$, $G(k)$, and the angle between gradient vectors $a(i,k)$ can be calculated as:

$$G(i)=\sqrt{G_x^2(i)+G_y^2(i)+G_z^2(i)}\ ,$$

$$a(i,k)=\cos^{-1}(g(i)\bullet g(k))\ ,$$

where $g(i)\bullet g(k)$ is the dot vector product and $g(i)$, $g(k)$ correspond to the normalized gradient vectors. Gradient vector components G_x, G_y and G_z can be calculated by any suitable 3D operator. Since we are mostly dealing with high frequency textures with 1 mm spatial resolution, we use a filter with a small 3×3×3 window proposed by Zucker and Hummel [14].

Denoting integer intensity bins $I(i)$, $I(k)$ by indices $b_I=1,\dots,B_I$, gradient magnitude bins $G(i)$, $G(k)$ by $b_G=1,\dots,B_G$, relative gradient angle bins $a(i,k)$ by $b_a=1,\dots,B_a$, and distance bins $d(i,k)$ by $b_d=1,\dots,D$, the matrix element $w(I(i), I(k), G(i), G(k), a(i,k), d(i,k))$ can be formally defined as:

$$w(b_{Ii}, b_{Ik}, b_{Gi}, b_{Gk}, b_a, b_d) = \mathrm{card}\{(i,k)\in R^3 \mid i\neq k,$$
$$b_{Ii}=I(i),\ b_{Ik}=I(k),\ b_{Gi}=G(i),\ b_{Gk}=G(k),$$
$$b_a=a(i,k),\ b_d=round(d(i,k)),$$
$$x_k=(x_i+\Delta x),\ y_k=(y_i+\Delta y),\ z_k=(z_i+\Delta z),\ -D\le\Delta x\le D,$$
$$-D\le\Delta y\le D,\ 0\le\Delta z\le D,\ \Delta zS^2+\Delta yS+\Delta x>0,\ S=2D+1\},$$

where Δx, Δy, and Δz are offsets on X, Y and Z axes measured in image raster units. The last two lines of the definition formalize the requirement of selection of all possible voxel pairs with no repetition. When calculating the matrices, we always follow the original image raster and round Euclidean distances *d(i,k)* to integer matrix bins in order to avoid incorporation of non-existing intensity values caused by interpolation. Therefore the *round* operator is defined in the common sense, i.e., as rounding to the nearest integer value. These descriptors are rotation/reflection invariant because they take into account the relative orientations only.

The image analysis methods were implemented in the C programming language for recent PC workstations. Key implementation details are given in [8, 9].

5. RESULTS OF SEARCHING FOR SPECIFIC BRAIN REGIONS

The anterior/posterior commissures (AC/PC for brevity) have been chosen for this experiment because they represent the brain region, which can only be defined reliably in any brain image. A schematic representation of location of commissures and example of axial MRI image slice containing both commissures are given in Fig. 2.

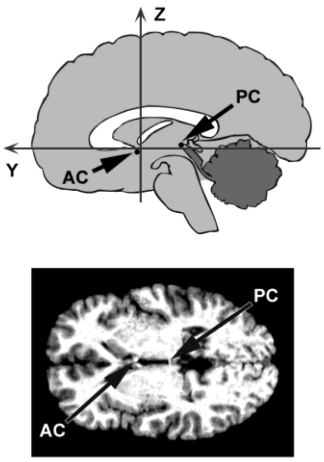

Fig.2 – Location of anterior (AC) and posterior (PC) commissures in the human brain.

Co-occurrence matrices were calculated with 8 bins for both intensity and gradient magnitude and inter-voxel distances ranged from 1 to 4 mm. The angle axis was omitted because in this experiment we are not interested in the anisotropy properties of brain images. The basic step of the experiment is as follows (Fig. 3): we take a 160×200×3 mm image VOI containing AC/PC plane in the middle slice as a query example, scan another dataset, choose the best match, and calculate its deviation from the true AC/PC location. Fig. 4 shows typical query examples and corresponding searching results.

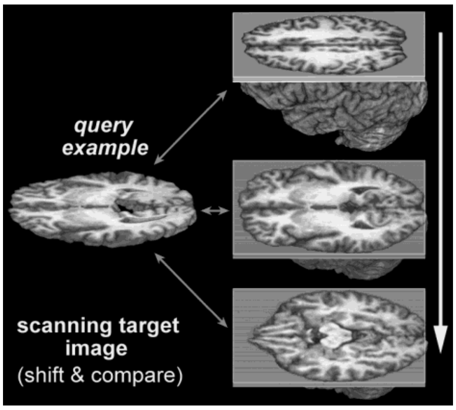

Fig.3 – Scanning by query example volume for locating brain commissures.

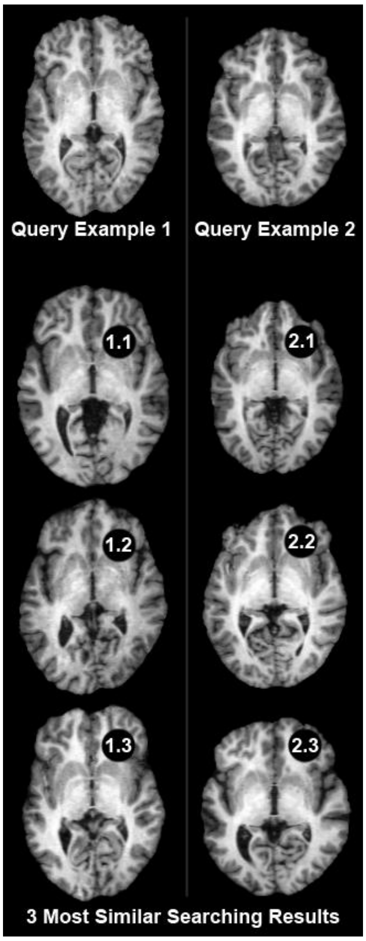

Fig.4 – Example of searching for brain commissures (only central axial slices of 3D brain volumes are shown).

In order to avoid the influence of random factors, in each run we used the mean VOI descriptor computed over the 10 different subjects as a query example for the rest 200 subjects. Thus, our statistical results are based on 21×200=4200 queries. Fig. 5 presents histogram of deviation of detected commissural plane from its real position (mean deviation *m*=2.4 mm with the standard deviation value *SD*=2.5 mm). Investigation of gross errors (about 5% of cases, see the left shoulder of the histogram depicted in gray) has revealed that they were caused either by «atypical» brain anatomy or certain miss-alignments of original datasets made by image processing engineers. Therefore the actual error of detecting commissural plane by the method is significantly lower.

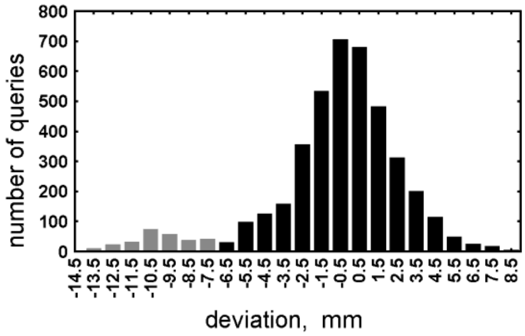

Fig.5 – Deviation of commissural plane from its real position.

6. RETRIEVAL BY GENDER

It is commonly known that the anatomical brain differences associated with gender are very weak, often on the border of statistical significance. Therefore this experiment was performed to test the sensitivity of the approach rather than examine the utility of the retrieval task itself. Again, each 3D brain image of 210 subjects was subsequently used as a query example. The correctness of retrieval results was judged according to the gender of the query image and gender of subjects whose brain images were retrieved as a result. Corresponding statistical data are summarized in the first row of Table 1.

Table 1. Percent of correct cases in top *N* searching results

% correct in top *N*	*N*=20	*N*=15	*N*=10	*N*=5	*N*=1
Male vs. Female	67.6	65.1	61.9	61.1	60.5
Young vs. Aged	96.4	93.8	90.6	86.3	82.2

7. RETRIEVAL BY AGE

This experiment is closely related to the neurological problem of quantification of brain atrophy due to the normal aging. The whole brain is considered as a VOI in the case. Descriptors were calculated with the same parameters except the number of angle bins set to 6. Each image from both AG-Y and AG-A subgroups was subsequently submitted as a query example. Searching results were considered as correct if they belong to the same age group as given query. Typical searching results are shown in Fig. 6 (all are correct). Statistical data are provided in the second row of Table 1.

8. CONCLUSION

Results of the first experiment suggest that retrieval of 3D brain sub-regions by their visual similarity may provide certain assistance in pre-processing and the analysis of 3D MRI datasets. However, the usefulness of this technique is limited. This is mostly because of complex spatial structure of anatomical brain images and high inter-subject variability. In contrast, the last experiment on retrieval of subjects from different age groups based on the whole brain images, has demonstrated very promising results. The reason for such high rate of correctly retrieved datasets (>90% in the top 10) is perhaps the ability of multi-sort co-occurrence descriptors to capture various features of brain atrophy (e.g., change of gray/white matter ratio, ventricle enlargements, decline of white matter anisotropy). Note that these measurements are poorly defined or may not be available from 2D image slices at all. The rate of 60-65% of correct gender retrieval in the second experiment is another evidence of high sensitivity and specificity of 3D image descriptors we employed (for n=210 it corresponds to the statistical z-scores of 5.0-6.0 with $p<10^5$).

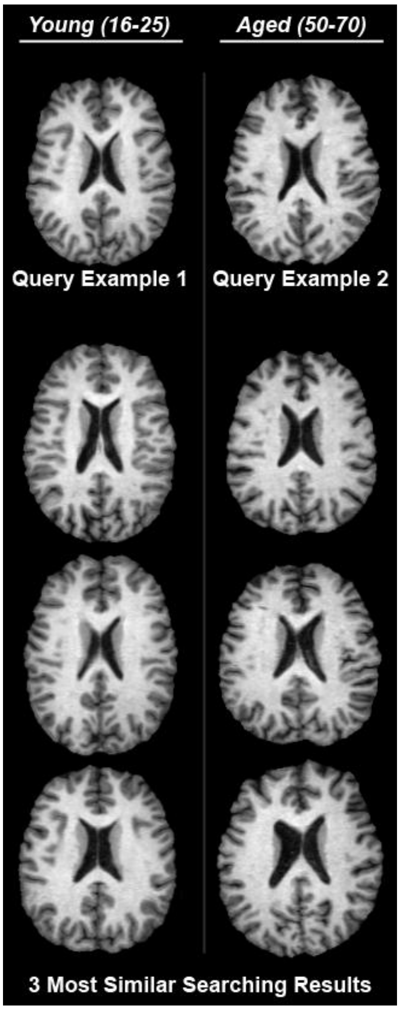

Fig. 6 – Example of retrieving 3D images of young and aged subjects (only axial slices of 3D brain volumes are shown).

In conclusion, this feasibility study has demonstrated the usefulness of 3D MRI image retrieval paradigm in neurological research. The utility of slice-based approaches remains doubtful. To our best knowledge, this is one of the first studies on 3D medical image retrieval.

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