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Query System for Analysis of Medical Tomography Images

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의료 단층 영상의 분석을 위한 쿼리 시스템

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Abstract We designed and implemented a medical image query system, including a relational database and DBMS (database management system), which can visualize image data and can achieve spatial, attribute, and mixed queries. Image data used in querying can be visualized in slice, MPR(multi-planner reformat), volume rendering, and overlapping on the query system. To reduce spatial cost and processing time in the system, brain images are spatially clustered, by an *adaptive* Hilbert curve filling, encoded, and stored to its database without loss for spatial query. Because the query is often applied to small image regions of interest(ROI's), the technique provides higher compression rate and less processing time in the cases.

Key Words : adaptive space filling curve, medical image query system, medical tomography images, spatial query

1. Introduction

Morphometric and functional analysis of a human brain using medical tomography images such as MRI, CT, PET, SPECT, and fMRI needs a query on the image database, which should be able to store image data and to provide efficient and comprehensive query mechanism. The query[1], which might be as spatial query, an attribute query, a mixed query, and a data mining, can give relations between neuro-anatomic labels and the stereotaxic coordinate system. Reported query systems[1] for human brain mapping support visualization and query on the relational database containing image data accrued from various studies for structure and function of the brain.

For this purpose, the medical image query system should process the queries in real time on the image data in the searching space of the relational database, as well as store the image data with minimum size in the database. Lossless compression is needed to reduce the size of the image data stored to the database. A space filling curve[2], allowing data to be stored to the database to maintain high clustering, is a curve going all pixels in the image grids, in which pixel points are rearranged on a linear line with well defined order. To store image data to the database, a Hilbert curve[2] which can give highly spatial clustering with the small number of runs as a space filling curve was used[1][2]. Images for a medical image query frequently have small size of ROI's in many cases. To efficiently achieve queries for 3D spatial data sets, image data structure in the database should be well designed.

In this paper, we designed and implemented a medical image query system, as shown in Fig. 1, including a relational database and DBMS(database management system), which can visualize image data and can achieve spatial, attribute, and mixed queries. Image data used in querying can be visualized in slice, MPR(multi-planner reformat), volume rendering, and overlapping on the query system. To reduce processing time and spatial cost in the database, the system uses an adaptive space filling technique in which the *adaptive* means applying a space filling curve to the window defined as a region of minimum size containing a ROI, not to a whole image.

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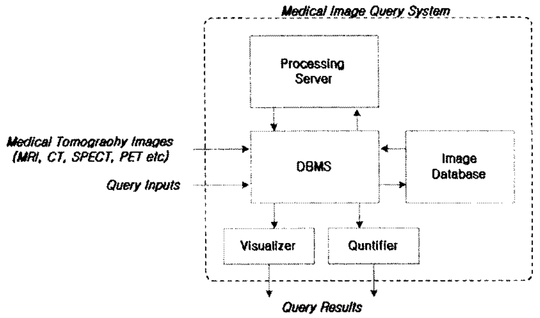


Fig. 1. The structure and query procedure of the medical image query system.

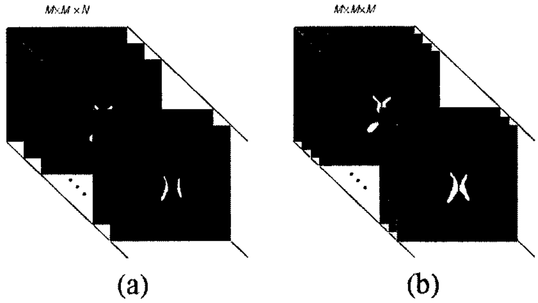


Fig. 3. A geometrical object represented as a (a) ROI and (b) VOI data type.

2. Medical Image Query System

A data type, spatial operation, database schema, and query should be considered in designing a medical image database and DBMS(database management system) for morphometric analysis of the brain.

The data types defined in our study are *IMAGE*, *ROI*, *VOLUME*, and *VOI* data types. *IMAGE* data type, which is DICOM format[3], consists of slices of *M M N* as shown in Fig. 2 (a) with pixel values of f(x, y, z)$\in$\{0, 1, 2, ⋯, 65535\}. *ROI* data has image slices of *M*×*M*×*N* with pixel values of f(x, y, z)$\in$\{0, 1\} as shown in Fig. 3 (a). *VOLUME* data has pixels values of f(x, y, z)$\in$\{0, 1, 2, ⋯, 255\} defined in 3D grids of *M*×*M*×*M* as shown in Fig. 2 (b). *VOI* data represents spatial objects like anatomical structures or ROI's, consisting of slices of *M*×*M* ×*M* with pixel values of f(x, y, z)$\in$\{0, 1\} defined in 3D grids as shown in Fig. 3 (b). *VOI* data are generated by interpolating between segmented slices with binary pixel values, and *VOLUME* data with 8 bits per pixel are generated by interpolating between original image slices.

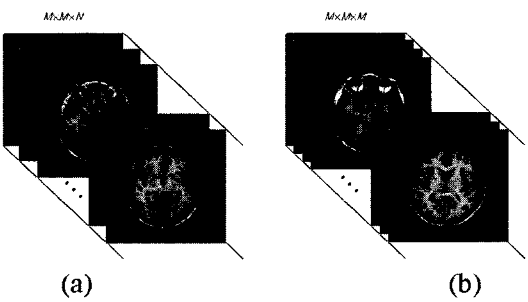


Fig. 2. A 3D scalar field represented as a (a) IMAGE and (b) VOLUME data type.

To achieve efficient queries for the image data represented as *VOI* or *VOLUME* data type needs to define spatial operators. Three operations[1] are as follows : *INTERSECTION*(*VOI* v1, *VOI* v2) returns *VOI* data resulting from spatial intersection between v1 and v2, *CONTAINS*(*VOI* v1, *VOI* v2) returns 0 or 1 whether v1 spatially belonging to v2 or not, *EXTRACT_DATA*(*VOLUME* vol, *VOI* v) returns *VOLUME* data of vol within v.

Data types to be stored for queries are *VOI* and *VOLUME*. Image data of *VOI* types, cubic volume types, with image size of *M*×*M*×*M* are generated by interpolating[4] between inter-slices with *ROI* data types as shown in Fig. 3. Image data of *VOLUME* types, cubic volume, with 8-bits per pixel and image size of *M*×*M*×*M* are generated by interpolating between inter-slices with *IMAGE* data types like MRI and PET as shown in Fig. 2. *VOI* and *VOLUME* data type have 1-bit and 8-byte per pixel, respectively. ROI's generated by manual drawing or automatic segmentation methods[5] are represented as *VOI* data type, and gray scale images like MR, PET, and Talairach brain atlas[6] as *VOLUME*.

To efficiently achieve queries for 3D spatial data sets, the data types, *VOI* and *VOLUME*, are rearranged by a space filling curve resulting in elevating data clustering and compressed with a lossless coding technique to be stored to the database. The structure of *VOI* data stored in the database consists of a *header* and start point, represented as *x* and *y*, and length, depicted as *run*, of a run. *VOLUME* data in the database additionally include a pixel value as shown in Fig. 5, in which the header has a data type, image size, image position, etc.

When a Hilbert curve and adaptive Hilbert curve are applied to a slice, of *VOI* type image volume, which has 4 pixels of 1's in the 16 pixels of the size of 44 as shown in Fig. 4 (a), the image data rearranged by the space filling curves to the slice is depicted in Fig. 4 (b). The adaptive Hilbert curve filling is applied to the window with the minimum size of 22 containing image pixels of 1's, in which the curve is smaller than the Hilbert curve in the number of runs as shown in Fig. 4 (b).

An example of the space filling curve applied to ventricle images is represented in Fig. 6. The curve is applied to one middle slice of the ventricle image

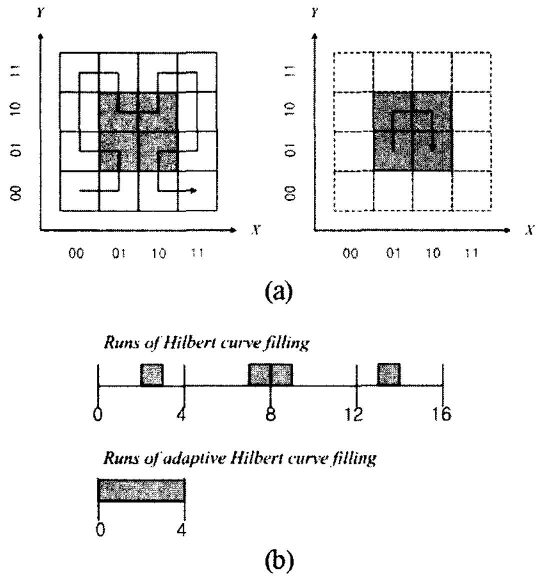


Fig. 4. An example of a space filling curve applied to the image of 44: (a) filling order of the Hilbert curve (left) and of the adaptive Hilbert curve (right), (b) 1D data rearranged by the Hilbert curve (top) and by the adaptive Hilbert curve (bottom).

header	*x*	*y*	*run*	•••

(a)

header	*x*	*y*	*pixel value*	*run*	•••

(b)

Fig. 5. Structure of (a) VOI and (b) VOLUME data type represented in the database.

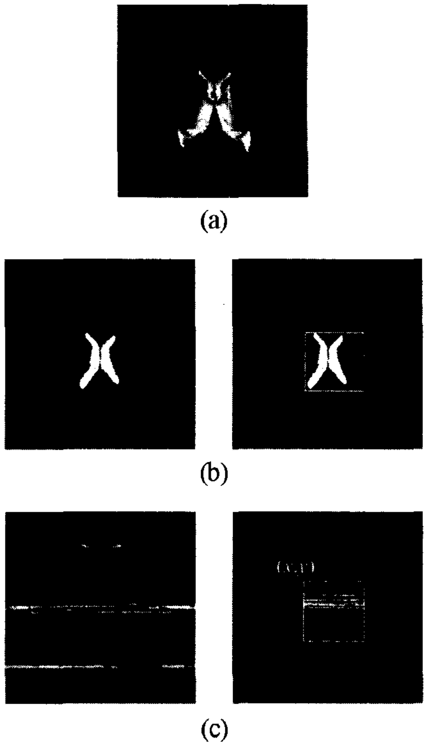


Fig. 6. Ventricle image applied by the space filling curves: (a) *VOI* image data visualized in volume rendering, (b) one slice of *VOI* data volume(left) and the slice depicted with the smallest window containing ROI(right), (c) data rearranged by the Hilbert curve(left) and by the adaptive Hilbert curve(right).

volume as shown in Fig. 6 (a), which is segmented and represented as *VOI* data type of 256×256×256 from MR images of a human head. Fig. 6 (a) is *VOI* data type of the ventricle in volume rendering, Fig. 6 (b) depicts one middle slice of the ventricle, and Fig. 6 (c) is image data rearranged by the Hilbert curve and the adaptive Hilbert curve, respectively. The adaptive curve is applied to the window of minimum size containing the ROI as shown in Fig. 6 (b), not to all pixels of the image. The start point and size of the region applied by the adaptive filling should be kept in the header of *VOI* and *VOLUME* data in storing.

Data compression techniques are categorized into a lossy compression method and a lossless one[7]. Lossy compression techniques, which cannot completely decode the compressed data to original data without loss, like transform coding and vector quantization, are not proper to analyze medical images not allowing data loss. There are prediction coding, entropy coding, etc in lossless compression techniques. In this paper, Elias code[8], which is a universal and entropy code, is used for lossless data compression. Unlike Huffman code[7], Elias code, consisting of a fixed set of codewords, does not require probability distribution of source messages, and needs only probabilistic ranking. *VOI* and *VOLUME* image data rearranged with the adaptive Hilbert curve are compressed by encoding a start point and length of run with Elias code, in which length of codeword is equal to one plus twice of the number of prefix 0.

3. Experimental Results

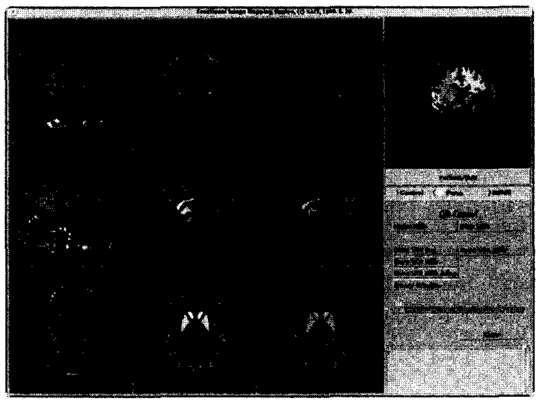
Our medical image query system was implemented using C language, Motif library, and IAP library(http://www.isgtec.com) under UNIX environment on SUN Ultra 2 workstation.

The appearance of our system is shown in Fig. 7. The query system can visualize studies and brain atlas in MPR, volume rendering, and overlapping as shown in Fig. 7 (a). Studies and brain atlas can be compared by overlapping both the images in MPR. The query window as shown in Fig. 7 (b) is to set query parameters for queries.

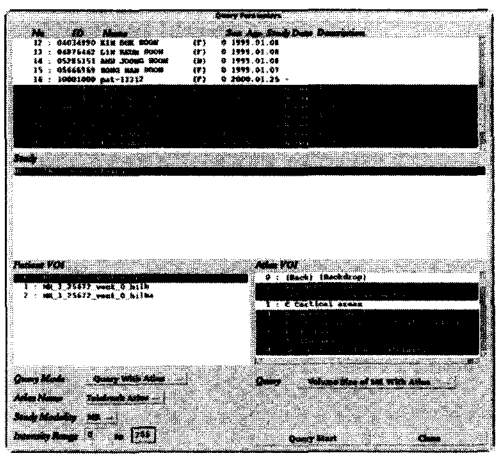
The window for queries has sub-windows to select a patient, a study, and ROI's of patients and the atlas. The window has control buttons to select query mode, atlas name, study modality, intensity range, and query. Query results are displayed on the windows for visualization and text out as shown in Fig. 7 (a).

Image data for the experiments are Talairach brain atlas[6], 10 sets of MR images, and 2 sets of PET images for normal cases. The Talairach brain atlas consists of 27 axial slices with the size of 256×256. MR SPGR(Spoiled Gradient) images of 124 slices with 256×256 pixels per slice, TE=5ms, and TR=24 ms were acquired on a 1.5 T GE Signa scanner. The PET FDG([18^{F}] fluorodeoxyglucose) images of 35 slices with 128×128 pixels per slice were acquired on a GE Advance PET scanner. *VOLUME* image data was generated by interpolating from original or warped images, and *VOI* data is generated using segmentation[5] and interpolation from the images.

Compressed data sizes for a set of ventricle images applied by the Hilbert and adaptive Hilbert curve filling were compared. The compressed data sizes for the images applied by the space filling curves are shown in Fig. 8. The mean values of the compressed data for the images applied by both techniques are 174 and 152 bytes, respectively. The processing times for the volume applied by the filling curves are 4191 and 2363 msec, respectively. The adaptive technique took 77.4% less time in processing the volume than the other. As the size of a ROI is smaller, the latter gives smaller compressed data size and significantly shorter processing time



(a)



(b)

Fig. 7. Our medical image query system with (a) visualization window, control window, and (b) window for setting query parameters.

Table 1. Compressed data size and processing time according to the size of a typical ROI in applying the Hilbert (H) and adaptive Hilbert curve filling (AH).

ROI size	compressed data size			processing time		
	H(byte)	AH(byte)	AH/H	H(msec)	AH(msec)	AH/H
32×32	43.7	29.7	0.68	3.742	0.157	0.04
64×64	123.6	95.8	0.78	3.742	0.424	0.11
128×128	202.9	180.9	0.89	3.742	1.319	0.35
256×256	1689.1	1682.0	1.00	3.742	3.742	1.00

Table 2. Query results for correlations between some structures of the brain atlas and the brain tumor with the size of 48291 voxels.

Brain Structure of Atlas	Volume Size of Atlas(VSA,Voxels)	Volume Size of Tumor Belong to Atlas(VSTBA,Voxels)	Ratio (VSTBA/Tumor)	Ratio (VSTBA/VSA)
3.Cortical areas	558837	715	1.48%	0.13%
5.Fasciculus longitudinals	5560	4351	9.01%	78.26%
9.Fasciculus occipito front	5999	1352	2.80%	22.54%
43.Gyrus precentrolis	11332	7413	15.35%	65.42%

than the former as shown in Table 1. The numbers of bytes to store brain's ventricle data rearranged with the Hilbert curve and the adaptive Hilbert curve are compared in Fig. 8.

A spatial query like "show correlations of volume size between the tumor and the atlas for the selected tumor case" was achieved as shown in Table 2, in which numbers, names, volume sizes of some structures of the brain atlas, and volume sizes and volume size rates of the atlas structures occupied by the tumor were extracted. The query was performed within one second per patient.

4. Conclusion

We designed and implemented a medical image query system which can visualize and achieve spatial, attribute, and mixed queries. A spatial query is achieved on data types of *VOLUME* and *VOI*, not requiring pre- or post-processing, which can be visualized in slice, MPR, volume rendering, and overlapping on the query system. After image data is spatially clustered using the adaptive Hilbert curve filling technique, it is encoded by Elias code and stored to the database without loss. In the experiments, the adaptive technique provided about 10% higher compression rate and about 77.4% less processing time than the Hilbert curve filling for the ROI of the ventricle in the brain MR images.

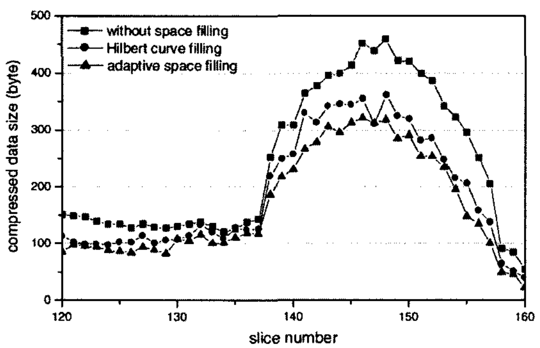


Fig. 8. Compressed data sizes for the ventricle images of Fig. 6 (a).

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