# A New Method of Medical Image Retrieval for Computer-Aided Diagnosis

Hui Liu
Dept. of Computer Science & Technology, Shandong University of Finance and Economics, Jinan, China
Digital Media Technology Key Lab of Shandong Province, Jinan, China
Email: liuh_lh@126.com

Guochao Sun
Central Hospital of Binzhou, Binzhou, China
Email: sunguochaobz@163.com

*Abstract*—**In the field of computer-aided diagnosis the topics of image retrieval is an important approach. According to the difference of retrieval technology, modeling spatial context (e.g., autocorrelation) is a key challenge in image classification and retrieval problems that arise in image regions. This work proposes a new approach to the retrieval of medical images from traditional Markov Random Field model. Contrasting with previous work, this method relies on coping with the ambiguity of spatial relative position concepts: a new definition of the geometric relationship between two objects in a fuzzy set framework is proposed. Furthermore, Fuzzy Attributed Relational Graphs (FARGs) are used in this framework, where each node represents an image object and each edge represents the relationship between two objects. The generalization performance of this approach is then compared with alternative models over the IRMA dataset. These experiments show that our method outperforms the traditional models, such as MRF, FGM, SVM e.g., in terms of several standard measures.**

*Index Terms*—**spatial context, spatial relative position, fuzzy set, Fuzzy Attributed Relational Graphs(FARGs).**

## I. Introduction

As we all known, an enormous mass of digital image data is stored in big archives, e.g. at medicine radiographs, publishing companies, news agencies and also on our home desktop computers[1]. For example, in the medical image research domain, considering an electronic multimedia patient record, this may help to find similar cases. Especially when using original medical DICOM (Digital Imaging and Communication in Medicine)[2] files for processing this can aid in diagnosis and treatment.

So, all kinds of retrieval systems are necessary in order to find useful data again [3], in a previous study it was shown that people who describe images often use position descriptions like “On the left side” or “Below object x” [4]. This is due to the fact that what is depicted in an image is highly subjective. Spatial information, however, is mainly objective.

There are two major notions for incorporating spatial geometric dependency into classification/prediction models: Markov random field (MRF) models [5,6] and spatial context, which refers to spatial autocorrelation and the image processing community. Over the last decade, several researchers [7, 8] have exploited spatial context in classification using MRF to obtain higher accuracies over their counterparts (i.e., noncontextual classifiers). However, it should be noted that those relative position concepts are rather ambiguous, they defy precise definitions, but human beings have a rather intuitive and common way of understanding and interpreting them [9], it is clear that any “all-or-nothing” definition leads to unsatisfactory results in several situations, even of moderate complexity. Therefore, relative position concepts may find a better understanding in the framework of fuzzy set, as fuzzy relationships. The earlier methods represented a fuzzy set depending on an angle $\theta$, on the objects, the angle $\theta(a,b)$ is measured between the segment joining two points a and b and the x-axis of the coordinate frame [10]. Other methods use projections of regions on the coordinate axes and try to reason about spatial relations either using dominance relations [11] or fuzzy logic [12]. More recent methods have included approaches based on neural networks [13], mathematical morphology [9], and gravitational force models [14].

In this paper, a new fuzzy set framework for medical image retrieval is proposed. In addition to the position and the scale of the object in spatial geometric relationships, we also consider the orientation, which can help future image retrieval systems to evaluate the relative position and orientation of objects in an image better. Furthermore, we carried out a great deal of experiments by using of medical images, which illustrating the excellent impacts of this method

## II. Fuzzy Approach for Spatial Context

Several previous studies [6, 7] have shown that modeling of spatial geometric dependency (often called context) during the image process can improve overall classification accuracy. Spatial geometric context can be defined by the relationships between spatially adjacent object in a small neighborhood.


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A set of random variables, the spatial geometric interdependency relationship of which is represented by an undirected graph (i.e., a contiguity matrix), are called a Markov Random Field (MRF) [5]. The Markov property specifies that a variable depends only on its neighbors and is independent of all other variables.

The essential idea is to specify the pairs of locations that influence each other along with the relative intensity of interaction. The sites in S (where S denotes the spatial framework) are related to one another via a neighborhood system. A neighborhood system for S is defined as:

$$N = \{N_i \mid \forall i \in S\}.$$

where $N_i$ is the set of sites neighboring i. The neighboring relationship has the following properties:

(1) a site is not neighboring to itself: $i \notin N_i$ ;

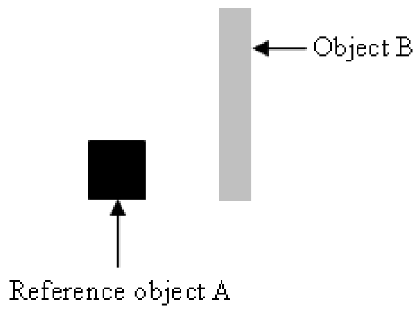
(2) the neighboring relationship is mutual:

$$i \in N_j \Leftrightarrow j \in N_i.$$

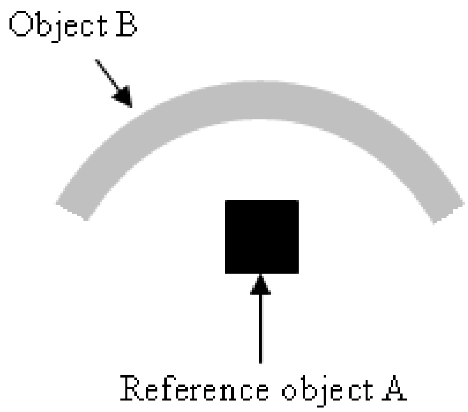
For a regular lattice S, the neighboring set of i is defined as the set of nearby sites within a radius of r:

$$N_i = \{ j \in S \mid [\text{dist}(\text{object}_j, \text{object}_i)]^2 \le r,\ j \ne i\}.$$

where $\text{dist}(A, B)$ denotes the Euclidean distance between A and B. Note that sites at or near the boundaries have fewer neighbors.




(a)




(b)

Figure 1. Examples where the relative position of objects with respect to the reference object is difficult to define in an "all-or-nothing" manner: (a) Object B is to the right of A, but it can also be considered to be to some extent above A; (b) Object B is strongly above A, also to the left and right of A partly

The applications that are anticipated from this work are related to structural pattern recognition, where we are not just interested in the dominating relationships between objects: an object may satisfy several relationships with respect to the other components of the image (see e.g., Figure.1 and it is clear that the shape of the considered objects has to play an important role in assessing its relative position, any "all-or-nothing" definition is difficult to accord with actual image spatial context, even of moderate complexity.

So, based on neighborhood system S described in MRF, a direction can be defined by angle $\alpha = (\alpha_1, \alpha_2)$ in the 3DEuclidean space, where:

$$\alpha_1 \in [0, 2\pi] \quad \text{and} \quad \alpha_2 = \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$$

Then the direction in which the relative position of an object with respect to another one is evaluated as Eq.(1):

$$\vec{u}_{\alpha_1,\alpha_2} = (\cos\alpha_2 \cos\alpha_1, \cos\alpha_2 \sin\alpha_1, \sin\alpha_2)^t \tag{1}$$

Now, between the objects A(reference object) and B, we can define the degree to which A is in direction $\vec{u}_{\alpha_1,\alpha_2}$ with respect to A. And membership function $\mu_\alpha(\text{A})$ denotes the fuzzy set defined in the image in such a way that points of areas which satisfy to a high degree the relation "to be in the direction $\vec{u}_{\alpha_1,\alpha_2}$ with respect to reference object A" have high membership value. We denote by P that looks precisely at the domains of space that are visible from a reference object point in the direction $\vec{u}_{\alpha_1,\alpha_2}$ , and by Q any point in A, then $\beta(P,Q)$ (e.g., see Eq.(2))expresses the angle between the vector $\overrightarrow{QP}$ and the direction $\vec{u}_{\alpha_1,\alpha_2}$ computed in $[0, \pi]$

$$\beta(P,Q) = \arccos\left[\frac{\overrightarrow{QP} \cdot \vec{u}_{\alpha_1,\alpha_2}}{\left\|\overrightarrow{QP}\right\|}\right] \tag{2}$$

We then determine for each point P the point Q of A leading to the smallest angle $\beta$ , denoted by $\beta_{\min}$. In the crisp case, this point Q is the reference object point from which P is visible in the direction the closest to $\vec{u}_{\alpha_1,\alpha_2}$ $\beta_{\min}(P) = \min_{Q\in \text{A}} \beta(P,Q)$ :The fuzzy landscape $\mu_\alpha(\text{A})$ at point P is then defined as: $\mu_\alpha(\text{A})(P) = f(\beta_{\min}(P))$ , where f is a decreasing function of $[0, \pi]$ into $[0,1]$ .

So, the evaluation of relative position of B with respect to A is given by a function of $\mu_\alpha(\text{A})(x)$ and $\mu_\text{A}(x)$ for all x in object B. An appropriate tool for defining this function is the fuzzy pattern-matching approach [14]. Following this approach, the evaluation of the matching between two possibility distributions consists of two numbers, a necessity degree N (a pessimistic evaluation) and a possibility degree $\Pi$ (an optimistic evaluation), as often used in the fuzzy set community(e.g., see Eq.(3)):

$$\prod_{\alpha_1,\alpha_2}^{A}(\mathrm{B}) = \sup_{x\in \mathrm{B}} \; t[\mu_\alpha(\mathrm{A})(x), \mu_\mathrm{B}(x)] \tag{3}$$

The possibility corresponds to a degree of intersection between the fuzzy sets B and $\mu_\alpha(\mathrm{A})$, while the necessity corresponds to a degree of inclusion of B in $\mu_\alpha(\mathrm{A})$. They can also be interpreted in terms of fuzzy mathematical morphology, since the possibility $\prod_{\alpha_1,\alpha_2}^{A}(\mathrm{B})$ is equal to the dilation of $\mu_B$ by $\mu_\alpha(\mathrm{A})$ at the origin.

Several other functions combining $\mu_\alpha(\mathrm{A})$ and $\mu_\mathrm{A}(x)$ can be constructed. An average measure can also be useful from a practical point of view, and is defined as Eq.(4):

$$N_{\alpha_1,\alpha_2}^{\mathrm{A}}(\mathrm{B}) = \frac{1}{|\mathrm{B}|}\sum_{x\in \mathrm{B}} \mu_\mathrm{B}(x)\mu_\alpha(\mathrm{A})(x) \tag{4}$$

where |B| denotes the fuzzy cardinality of B

$$|\mathrm{B}| = \sum_{x\in B} \mu_\mathrm{B}(x)$$

## III. FUZZY ATTRIBUTED RELATIONAL GRAPHS AND GRAPH MATCHING

### *A. Fuzzy attributed relational graphs(FARGs)*

A graph $G = (V_G, E_G)$ is an ordered pair of a set of nodes $V_G$ and a set of edges $E_G$. An edge in $G$ connecting nodes u and v is denoted by (u,v), where $(u,v)\in E_G$. A Fuzzy Attributed Relational Graph (FARG) is used to model the vagueness associated with the attributes of nodes and edges. In our application, each node in the FARG represents an object in the image, and each edge between the corresponding two nodes represents the relationship between these objects. All nodes have attributes from the set $A = \{a_i \mid i = 1,\ldots,n_A\}$.

We denote the set of linguistic values (labels) associated with attribute ai by $A_i = \{C_{ik} \mid k = 1,\ldots,n_{a_i}\}$. The value of an attribute ai at node j is a fuzzy set Aji defined over $\Lambda_i$ .For example, the node attribute a1=position_label may be a fuzzy set defined over the linguistic category set $\Lambda_1$ ={up, down, left, right}, and position_label of node j may have membership values, e.g. 0.5, 0.2, 1 and 0 in corresponding to above four position labels, respectively, Aji={0.9, 0.2, 0.1}. Similarly, the node-attribute a2=size_label may be a fuzzy set defined over the set of linguistic values $\Lambda_2$ ={small, medium, large}. We denote the node label of node j by Eq.(5):

$$\lambda(j) = \{(a_i, A_{ji}) \mid A_{ji} \in \Gamma(\Lambda_i); i = 1,\ldots,n_A\} \tag{5}$$

where $\Gamma(\Lambda_i)$ denotes the fuzzy power set of $\Lambda_i$. Each node-attribute ai is allowed to occur only once in $\lambda(j)$ .Edge-attributes are treated similarly. Each edge in the FARG has attributes from the set $R = \{r_i \mid i = 1,\ldots,n_R\}$ .We denote the set of linguistic values associated with edge-attribute ri by $\mathrm{E}_i = \{L_{ik} \mid k = 1,\ldots,n_{r_i}\}$ . The value of an edge-attribute ri for an edge e=(j,k) is a fuzzy set Rei defined over $\mathrm{E}_i$.

### *B. Graph matching*

R. Krishnapuram and R. Medasani presented a a fuzzy graph matching algorithm called FGM [18] that uses ideas from relaxation labeling and fuzzy set theory to solve the sub-graph isomorphism problem. To extend FGM to FARGs, we need to define the compatibility $u_{ij}\in[0,1]$, which is a quantitative measure of the (absolute) degree of match between node $i\in V_A$ and node $j\in V_B$, given the current fuzzy assignment matrix $U$. We start with the definition of compatibility $u_{ij}$ as Eq.(6):

$$u_{ij} = w_{ij}^{0.5}\sum_{\substack{k=1\\(k\neq i)}}^{n+1}\sum_{\substack{l=1\\(l\neq j)}}^{m+1}\frac{m_{kl}m'_{kl}}{n_j^B}$$

$$i = 1,\ldots,n+1, and \quad j = 1,\ldots,m+1 \tag{6}$$

where $w_{ij}$ is the degree of match between (the attributes of) node $i\in V_A$ and node $j\in V_B$, $m_{kl}\in[0,1]$ is the matching score between the edge $(i,k)\in E_A$ and edge $(j,l)\in E_B$, M is the matrix $[m_{kl}]$, $M' = [m'_{kl}]$ is the crisp assignment matrix closest to M atisfying the constraints by Eq.(1) for $i = 1,\ldots,n+1$ and $j = 1,\ldots,m+1$, and $n_j^B$ is a normalization factor equal to the number of edges (with nonzero weights or attribute values) that are incident on node $j\in V_B$. Note that $M'$ that acting as a filter so that each edge in graph B which is incident on node j will contribute to $u_{ij}$ only once. In other words, out of the double summation in Eq.(5), only terms survive. Also, $w_{ij}$ is raised to the power 0.5 for enhancement purposes..

## IV. EXPERIMENTAL RESULTS

### A. The Data Set

Experiments were performed with radiographic images from the IRMA (Image Retrieval in Medical Applications) dataset [19]. This is a growing collection of radiographic images acquired in RWTH Aachen University of Technology Hospital, Germany. It is used as reference for medical image retrieval tasks. It currently contains 15363 arbitrarily selected anonymous radiographic images for which the ground truth information is provided. The radiographs span 193 categories and depict various anatomic specimens of patients of various ages, genders, and pathologies[20].

We selected 4341 medical images from 10 familiar radiographs categories, including cranium, brain, spine, arm, chest, abdomen, leg, pelvis, liver and hands, to implement our experiments. Table 1 is the statistics of the 10 categories we used and the corresponding explanations.

### B. Experiment Ⅰ

In the first experiment, we conducted experiments to compare the performance between our approach and traditional methods. To be consistent with previously published methods, we used the implementations provided by the authors for each method that we tested, including their suggested distance thresholds. Finally, the comparison is made by the precisions and recalls of each method on all the medical image categories.

Figure 2 shows the mean average retrieval precision of different methods over all radiographic categories along with those of previous works. Our method presents a new fuzzy set framework combining Markov random field

TABLE I.
STATISTICS OF THE 10 FAMILIAR RADIOGRAPHS CATEGORIES

| Category | Explanation | No. in *db* |
|---|---|---|
| CRANIUM | round part of the skull that contains people’s brain | 654 |
| BRAIN | organ inside the head | 923 |
| SPINE | row of small bones that are connected together down the middle of the back | 526 |
| ARM | two long parts of the body that are attached to people’s shoulders | 112 |
| CHEST | the top part of the front of the body, between the neck and the stomach | 627 |
| ABDOMEN | the part of the body below the chest that contains the stomach, bowels | 307 |
| LEG | one of the long parts that connect the feet to the rest of the body | 198 |
| PELVIS | the wide curved set of bones at the bottom of the body that the legs and spine are connected to | 204 |
| LIVER | a large organ in the body that produces bile and cleans the blood | 619 |
| HANDS | parts of the body at the end of people’s arms | 171 |

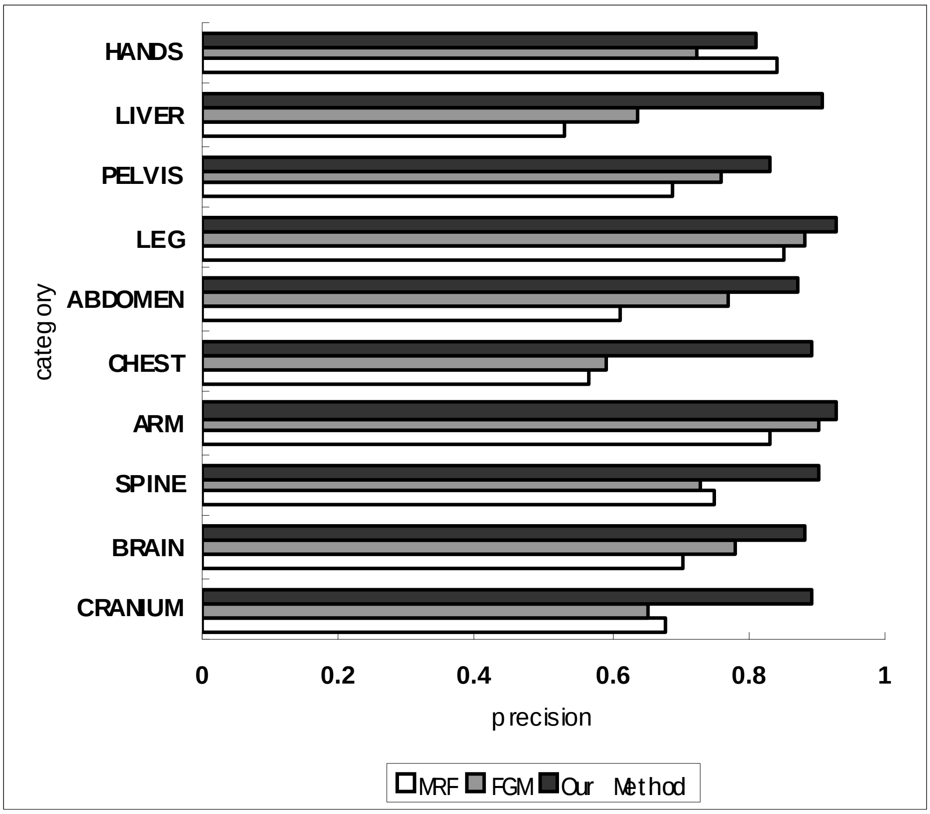



Figure 2. Mean average retrieval precision[%] for each category by using different methods. The different shades of color denote different method and the blocks of bars denote different category

(MRF) and morphological idea, uses the Fuzzy Attributed Relational Graphs (FARGs) to model the vagueness associated with the attributes of image objects and their relationships. It solves the problem of "all-or-nothing" definition that leads to unsatisfactory results in several situations, and does better work on image retrieval precision than traditional methods.

Here we applied the correlation analysis for the different tasks individually and for all tasks jointly. On the one hand, "HANDS", "LEG" and "ARMS" are among the three simplest structure classes and show high retrieval accuracy for all methods. On the other hand, "LIVER", "CHEST", "ABDOMEN" and "CRANIUM" are rather different classes that contain complicated geometric relationships of different objects, and our method show higher retrieval accuracy distinctly than other two models. Thus, the impact of fuzzy set is much stronger whereas other, more prominent examples might not even be included in the testing data.

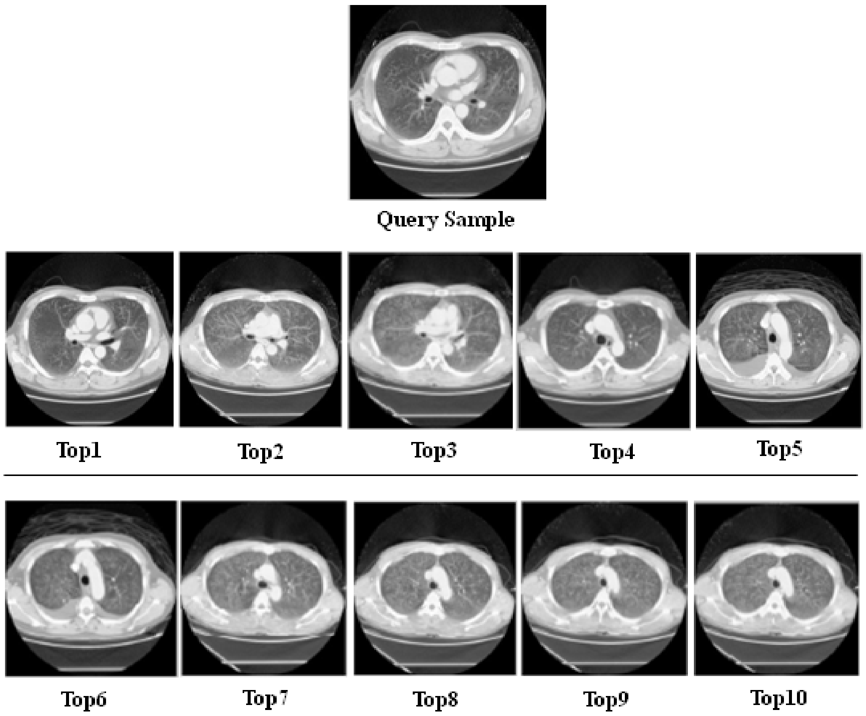



Figure 3. The top 10 retrieval results about liver category using our method

For example, Figure 3 and Figure 4 have shown the top-10 image retrieval results, according to FARGs obtained by our method, that are closest to the query sample(e.g. liver and chest) respectively. It can be seen that the prototypes capture the diversity of the data set very well.

*C. Experiment* Ⅱ

In the second experiment, we conducted experiments to compare the performance between our approach and classic SVM, TSVM (Transductive SVM) method. We performed several relevance feedback experiments to evaluate the effectiveness of above approaches over a part of IRMA dataset that containing 3218 medical image from 29 category. We designed an automatic feedback scheme to simulate the retrieval process conducted by real users. In each iteration, the system marks the first three incorrect images from the top 100 matches as irrelevant examples, and also selects at most 3 correct images as relevant examples (relevant examples in the previous iterations are excluded from the selection). The evaluation measures used in CBIR have been greatly affected by those used in text-based information retrieval [21]. A straightforward and popularly used measure is the PR-graph which depicts the relationship between precision and recall of a specific retrieval system. This measure is used in this paper. Concretely, for every recall value ranging from 0.0 to 1.0, the corresponding precision value is computed and then depicted in the PR-graph.

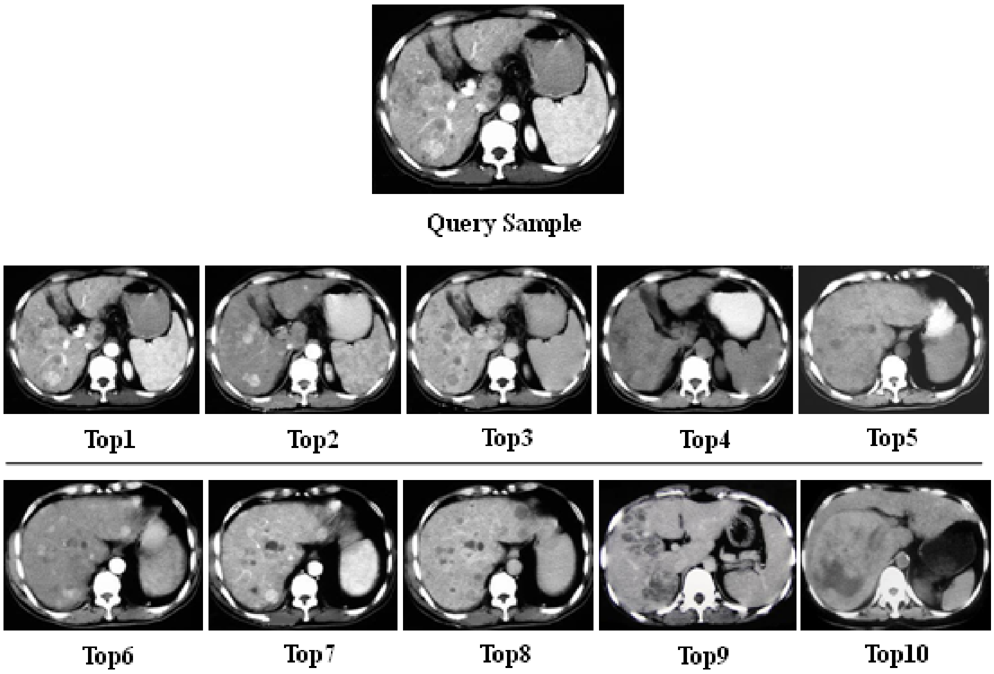
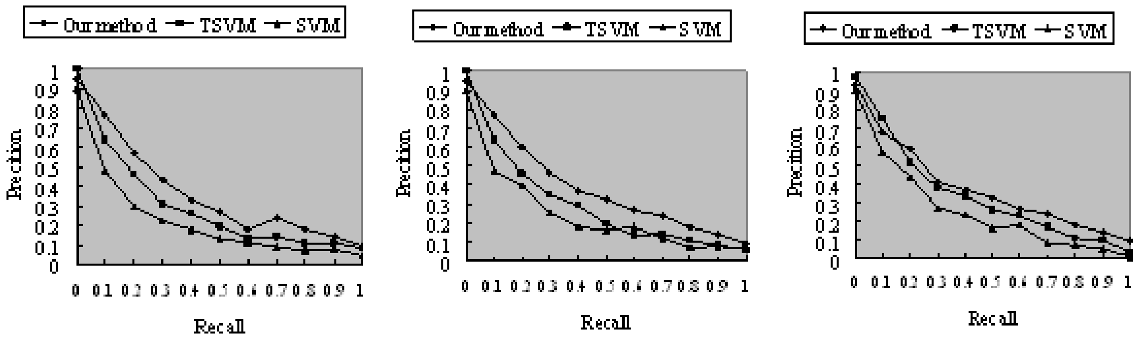



Figure 4. The top 10 retrieval results about chest category using our method




(a) at the 0th round (b) at the 4th round (c) at the 8th round

Figure 5. Average PR-graphs of SVM, TSVM, and our method at the 0th, 4th, and 8th relevance feedback round

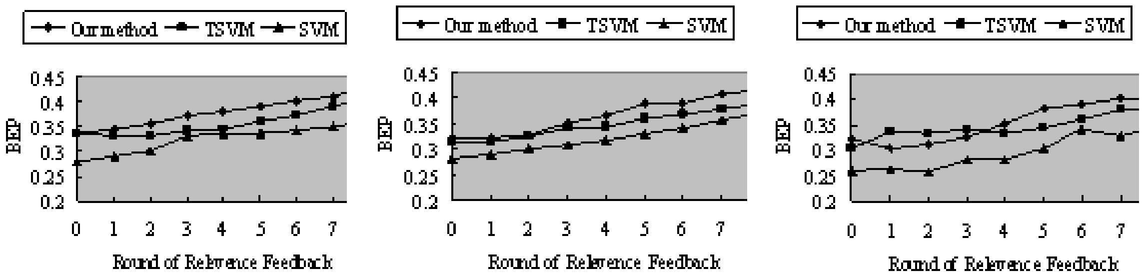
The general PR-graphs at the 0th, 4th and 8th round of relevance feedbacks are shown in Figure 5 (a) to (c) respectively. Here note that the performance at the 0th round corresponds to the performance before starting relevance feedback, that is, the retrieval performance with only the initial query.

A deficiency with the PR-graph is that it can hardly reflect the changes of the retrieval performance caused by relevance feedback directly. Therefore, another graphical measure is employed in this paper. Usually, a CBIR system exhibits a trade-off between precision and recall, to obtain high precision usually means sacrificing recall and vice versa. Considering that in CBIR both the precision and recall are of importance, here BEP (Break-Event-Point) is introduced into CBIR as an evaluation measure. By definition, if the precision and recall are tuned to have an equal value, then this value is called the BEP of the system [13]. The higher the BEP value, the better the performance. Through connecting the BEPs after different rounds of relevance feedback, a BEP-graph is obtained, where the horizontal axis enumerates the round of relevance feedback while the vertical axis gives the BEP value.

The general BEP-graphs are presented in Figure 6 (a) to (c), which also implies the performance of our method is always the best

## V. CONCLUSIONS

Uncertainty pervades every aspect of CBIR. This is because image content cannot be described and represented easily, user queries are ill-posed, the similarity measure to be used is not precisely defined, and relevance feedback given by the user is approximate. To address these issues, fuzzy sets can be used to model the vagueness that is usually present in the image content, user query, and the similarity measure. This allows us to retrieve relevant images that might be missed by traditional approaches.




(a) 200 CT images (b) 500 CT images (c) 1000 CT images

Figure 6. Average BEP-graphs of SVM, TSVM, and our method using 200, 500 and 1000 CT image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**Hui LIU**, works in Dept. of Computer Science & Technology, Shandong University of Finance and Economics, Jinan, China, and Digital Media Technology Key Lab of Shandong Province, Jinan, China. Her research interests include computer application based on CT image.

**Guochao SUN**, works in Central Hospital of Binzhou, Binzhou, China. His research interests include medical image analysis, computer-aided diagnosis.