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Cloud Model and Tolerance Granular Space-based Image Retrieval Methods

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Abstract: In the existing tolerance granular space models, grid points in each layer are established only taking space position into account, which ignore uncertainties of image texture, such as randomness, fuzziness and relevance. As a matter of fact, it is very important to extract grid points for constructing tolerance granular space, which are tolerance granules' position or center. Therefore, it is very meaningful for the accurate texture feature-description of images to extract grid points well. To address this issue, we firstly apply cloud model to extracting grid points, and establish two new tolerance granular space models. Then, similarity measures based on cloud model and tolerance granule space are presented and two novel image retrieval methods are introduced, including an image texture recognition and a color image retrieval method. Finally, simulation experiments are done on images of image test set chosen from Corel Database, to compare our proposed methods with the conventional color histogram-based image retrieval method, the salient regions and nonsubsampled contourlet transform-based image retrieval method, and tolerance granular-based multi-level texture image retrieval method. The experimental results demonstrate that the proposed methods are indeed efficient and of practical value to many real-world problems.

Keywords: Cloud model, Tolerance granular space, Gray histogram, Grid point

1 Introduction

Along with the rapid development of network technology and digital image acquisition technology, the number of digital images which are from kinds of application areas, such as science, education, medical and industry, has been growing at an alarming speed. A plenty of digital images are produced every day, which contain lots of significant information. Then, a world explosion of digital images is made in the number of digital images. However, it is very difficult to effectively access to images which are distributed all over the world. Thus, it is desirable to exploit an image retrieval technology, which can help people to access and query to images they need quickly and accurately. So far, image retrieval technology contains the text-based image retrieval (TBIR) and the content-based image retrieval (CBIR) [1,2]. TBIR is simple and convenient, while it relies on the manual annotation of all images. That is to say, it demands many people to label images with keywords. Manual annotation not only is a time-consuming work but also is sensitive to human's subjectivity. Along with the expansion of image databases' scales, TBIR is beyond its capacity to effectively organize, manage, and retrieve images. CBIR can objectively index images by computer according to their own visual contents instead of using manual annotation. Thus, CBIR can overcome these shortcomings of TBIR [3,4]. CBIR attracts many researchers' attention and has been a research hot point.

Image features are regarded as the bases of image retrieval, which are extracted as retrieval objects to query in the content-based image retrieval system. Generally speaking, image features contain the low-level visual features and the high-level semantic features [5,6,7]. As a matter of fact, it is quite difficult to extract the latter features from images. In consequence, most of the content-based image retrieval systems base on the low-level visual features, such as color, texture, shape, and spatial relationships, etc. Many objects in an image can be distinguished solely by their textures without any other information. Texture is an important visual feature for image retrieval. Nevertheless, there is no a universal definition of texture. Texture may consist of some basic

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primitives, and may also describe the structural arrangement of a region and the relationship of the surrounding regions [8,9]. Texture may also present gray space distribution law of pixels' neighborhood, which is independent on color or brightness of the image, and can reflect context relationships of the object content [7]. No matter how to define texture, it is the visual information formed by the human's visual and tactile. For human's cognition with uncertainties, such as randomness, fuzziness and relevance, the texture extracted also has these uncertainties [10]. How to extract exactly texture is a main and key research aspect of image retrieval and a large amount of research work in this field has been done. The statistical methods are early proposed for texture retrieval, which utilize the distribution information of gray value of images. Among the statistical methods, gray level co-occurrence matrix and the autocorrelation function are the best known and the most widely used methods to extract texture feature [2]. Contourlet transform and nonsubsampled contourlet transform are usually applied to extract texture. Zhang et al. [6] proposed an image retrieval method based on salient regions and nonsubsampled contourlet transform. Recently, many researchers have been exploring image retrieval by means of Granular Computing (GrC), which applies tolerance granule to representing image texture, and the retrieval results exhibit that these methods are more accurate and efficient [11,12,13].

As an emerging field of study, GrC is consistent with human problem solving based on knowledge structures [14,15]. From the philosophical and theoretical points of views, GrC has been argued that information granulation is essential to human problem solving, and has very significant impact on the design and implementation of intelligent system [16,17]. Consequently, GrC is a basic issue in knowledge representation and data mining. And its research involves many subjects, such as, rough set, fuzzy set, and artificial intelligence, etc [17,18]. GrC is also a useful tool to research complex problem, data mining, and fuzzy information processing, which address to the incomplete, unreliable and inaccurate, inconsistent and uncertain knowledge. The essence of GrC is to represent and process information granule, and its basic idea is that large objects with coarser granularity are divided into several smaller objects with finer granularity to solve the problem in different layers [11,15,16,18]. Zheng [12] proposed that extracting texture feature needs a certain scale in image retrieval, that is, texture of images cannot be observed in coarser scale but can be in much finer scale, which perfectly coincides with principle of structuring tolerance granular space. Thus, some scholars have been applying GrC to image retrieval and a number of research results have been achieved. Zheng [12] mainly explored tolerance granular space in image texture recognition and proposed an image texture recognition method based on tolerance granular space. Considering the loss of color in texture image, Xu et al. [19] introduced a tolerance granular-based multi-level texture feature image retrieval method. Li et al. [13] quantified dynamically the color of image edge by combining tolerance granules, and presented a color image retrieval method based on tolerance granule. An approach to hierarchical classification of images based on tolerance granular space was presented by Yao et al. in [20], which showed the principle that image classification was done from coarse granule to fine granule based on GrC. Xu et al. [11] introduced the rough granular theory, constructed a rough granular space model by defining the granular edges and layered, and proposed an image texture recognition method based on rough granular model. Although those methods above improve the performance of image retrieval, there exist some limitations in extracting image texture when they construct the model. Because during process of construction of granular space model, it need to extract grid points in each layer, which are all impossible position or center and are the basic of building tolerance granular space [11,12,13]. Hence, extracting grid points plays an important role in the construction of tolerance granular space. However, extracting grid points based on space position ignores uncertainties of image texture, such as randomness, fuzziness and relevance. For this reason, the image texture cannot be well described by these methods.

In recent years, lots of scholars have studied the theory of cloud model and utilize it to analyze and extract image texture. Cloud model based on probability theory and fuzzy sets theory was proposed as a cognitive model of uncertainty by Prof. Deyi Li in 1995, considering fuzziness, randomness, and their association relationship [10,21,22,23]. Cloud model applies three numerical characters (expectation Ex, entropy En and hyper-entropy He) to representing a qualitative concept and characterizing randomness and fuzziness of uncertainty. It realizes transformation between a qualitative concept and quantitative datum, and reveals uncertainties of knowledge representation profoundly [21]. Thus, cloud model is very important to understand connotation and extension of qualitative concept, and uncertainties of qualitative concept are vividly described. So far, cloud model has been successfully applied into many fields, for instances, traffic control, image segmentation, remote sensing image classification, etc [21,22,23]. Due to uncertainties existing in images, these uncertainties are not well analyzed and processed by the traditional image retrieval methods. Cloud model can apply digital features to representing simply and accurately uncertainties of the concept and their association relationship between datum. Many research achievements are obtained at present. Wang et al. [21] made a full analysis of backward cloud algorithm based on the theory of probability statistics, and constructed a multi-step backward cloud generator algorithm, which is more precise than the old algorithm of backward cloud. Li et al. [24] presented a classification algorithm based on cloud model and genetic algorithm. Shi et al. [25] introduced a new image segmentation algorithm based on cloud model and fMRI images, in which cloud model was used for dealing with the uncertainties of the fMRI image data. Zhang et al. [26] proposed a new improved edge detection algorithm of images based on cloud model and cellular automata, resolving the problems of edge detection algorithm of images based on fuzzy seasoning or cellular automata. Xu et al. [23] proposed a cloud model-based image region segmentation approach, considering fuzziness and randomness in histogram analysis. Taking uncertainties of images into account, Cui et al. [27] put forward an object detection algorithm based on the cloud model. Zeng et al. [28] presented an ant colony clustering algorithm of image segmentation based on cloud model.

From the discussions above, it is clear that the grid points extracted, based on the space position in the existing model, ignore uncertainties of image texture. However, those uncertainties can be expressed well by cloud model. Therefore, we employ cloud model to extracting grid points in each layer of tolerance granular space model and redefine tolerance relations. And the problems above are solved by cloud model. In this paper, two novel image retrieval methods are introduced, including an image texture recognition method and a color image retrieval method. The rest of this paper is organized as follows. In the next section, some preliminary concepts are briefly reviewed. In Section 3, grid points are extracted by cloud model and the new tolerance relations are redefined. Then two new tolerance granular space models are constructed and two novel image retrieval methods are proposed, an image texture recognition method and a color image retrieval method. In Section 4, simulation experiments are done to evaluate the performances of our methods and the experimental results demonstrate that the proposed methods are indeed efficient and of practical value to many real-world problems. Finally, conclusions are drawn in Section 5.

2 Preliminaries

In this section, we introduce the relation concepts. And this section is divided into two parts as follows: the first part introduces basic concepts of cloud model. In the two parts, we present concepts of tolerance granular space.

2.1 Basic concepts of the cloud model

Cloud model, proposed by Prof. Deyi Li in 1995, is an uncertainty transformation model between qualitative concept and quantitative description. It mainly reflects three kinds of uncertainties, such as fuzziness, randomness, and their association relationship of qualitative concept. In this section, we briefly review several basic concepts about cloud model, such as cloud model, backward cloud generator, and cloud transform. Detailed description and formal definitions of concepts can be found in [21,29,30,31,32].

Let U be a universal set described by precise numbers and C be a qualitative concept related to U. If there exists a number x in U, which randomly realizes the concept C, and the certainty degree of x for C, i.e., $\mu(x) \in [0,1]$, is a random value with stabilization tendency $\mu : U \to [0,1]$, $\forall x \in U$, $x \to \mu(x)$. Then the distribution of x on U is defined as a cloud, and every x is defined as a cloud drop.

Cloud model employs three numerical characters, the expected value Ex, the entropy En, and the hyper-entropy He, to characterizing the qualitative concept at whole, and vividly describing uncertainties of qualitative concept, randomness, fuzziness and relevance. Ex is usually the position corresponding to gravity center of the cloud and the value of Ex can most represent the qualitative concept. That is, Ex in the universe of discourse is fully compatible with the linguistic term. En measures the uncertainty of qualitative concept, and reflects fuzziness and randomness of qualitative concept. In other words, En is the measure of fuzziness of the concept, which describes the double-sided property of qualitative conception and reflects the fluctuation range and the occurrence frequency. The bigger En is, the larger numerical scale accepted by the concept is, and the fuzzier the concept is. He is the measure of the entropy's uncertainties codetermined by employ's fuzziness and randomness. Therefore, He depends on the fuzziness and randomness of Ex and En, reflecting cohesion degree of cloud drops, discrete degree, and thickness of the clouds.

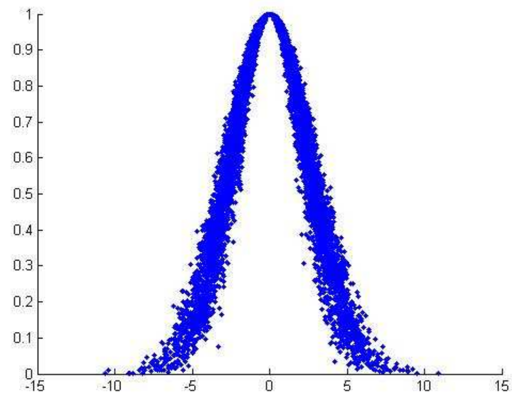

Figure 1 A normal cloud model

There are many kinds of cloud models, such as the normal cloud model, the geometric cloud model, the function cloud model, etc. The normal cloud model is the most common and basic cloud model, which is one of useful tools to characterize qualitative concept. Figure 1 shows a normal cloud model with Ex = 0, En = 5, He = 0.3, and the number of the cloud drops n = 10000.

Backward cloud generator (BCG) is an algorithm based on probability statistics and realizes the uncertain

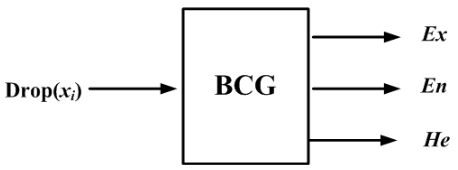

Figure 2 Backward cloud generator

transition from quantitative numerical value into qualitative concept. That is to say, it transforms a certain number of precise data, by statistical methods, into qualitative concept described by three numerical characters $C(Ex,En,He)$. Figure 2 shows the process of backward cloud generator. In actual application, the sample points x_i $(i=1,2,\cdots,n)$ are applied to statistical calculation, and output three numerical characters describing qualitative concept. The detailed procedures of BCG are as follows.

Backward cloud generator algorithm
Input: Sample points x_i $(i=1,2,\cdots,n)$
Output: Concept cloud $C(Ex,En,He)$

Step1: According to sample data x_i, calculate $\overline{X}=\frac{1}{n}\sum_{i=1}^{n}x_i$, the first order absolute central moment $\frac{1}{n}\sum_{i=1}^{n}|x_i-\overline{X}|$, $S^2=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\overline{X})^2$.
Step2: Let $Ex=\overline{X}$, $En=\sqrt{\frac{\pi}{2}}\frac{1}{n}\sum_{i=1}^{n}|x_i-\overline{X}|$, $He=\sqrt{S^2-En^2}$.
Step3: Output concept cloud $C(Ex,En,He)$.
Step4: End.

Cloud transform is a process converting the continuous numerical interval to the discrete concept clouds. Given a universal set U, $X\subseteq U$ is a data attribute, $F(x)$ is frequency distribution function of and is automatically generated as the superposition of a number of different granularity concept clouds, which is discrete and qualitative. And cloud transform formally is

$$F(x)\rightarrow\sum_{i=1}^{n}a_i*C_i(Ex_i,En_i,He_i),\tag{1}$$

where is the amplitude coefficient, is the number of the discrete concept clouds generated.

Let U be a universal set, $C_1(Ex_1,En_1,He_1)$ and $C_2(Ex_2,En_2,He_2)$ are two adjacent concept clouds, if $Ex_1<Ex_2$, then a coarse granularity concept cloud $C_3(Ex_3,En_3,He_3)$ is generated by the following formula

$$C_3=C_1\cup C_2\Leftrightarrow\begin{cases}Ex_3=\frac{Ex_1+Ex_2}{2}+\frac{En_2-En_1}{4}\\ En_3=\frac{Ex_2-Ex_1}{2}+\frac{En_1+En_2}{4}\\ He_3=\max\{He_1,He_2\}\end{cases}\tag{2}$$

This method is called soft-or concept improving.

2.2 Basic concepts of tolerance granular space

In 1962, Zeeman proposed that cognitive activities can be viewed as some kinds of tolerance spaces in the function spaces. Tolerance spaces are used for stability analysis of dynamic system by Zeeman and are constructed by tolerance relations based on distance functions [17]. Tolerance spaces based on distance functions are developed for the analysis of tolerance granulation in this part. In this section, we briefly recall several basic concepts about tolerance granular space, such as tolerance granular space, object set system, tolerance relation, and tolerance granule. And the detailed description of the concepts can be found in [12,17].

Tolerance granular space TG is usually expressed by a quadruple (OS,TR,FG,NTC), where OS is the object set system, TR is a tolerance relation system, FG is the translation function between granules, NTC is a nested tolerance coverage system.

Object set system OS is composed by the objects at difference layers. O_k represents an object at the k^{th} layer. An original object O_1^0 is expressed by an n-dimensional vector, and original object set O_1 is composed by all the original objects. Then 1-order object subset O_1 is a set consisted of original objects. Generally, O_{k+1} is $k+1$-order object subset, construed by objects of the k-order object subset O_k. The object set system is composed by the objects at difference layers, formally $OS=\{\bigcup_p O_p^0\}\cup\cdots\cup\{\bigcup_q O_q^k\}\cup\cdots$, where p, q are the numbers of the original object set O_0 and the k-order object subset O_k, respectively, O_p^0 , O_p^k is the p^{th} original object and q^{th} object of the k-order object subset, respectively.

Tolerance relation system TR is a (parameterized) relation structure, and composed by a set of tolerance relations. The detailed definitions are as follows. A tolerance relation tr, $tr\subseteq X\times X$, is a reflexive and symmetrical binary relation, where X is the original space of object vector and $X\subseteq R^n$. A set $Y\subseteq X$, if $\forall x,y\in Y$, one has that $x\ tr\ y$, then Y is called tolerance class satisfying tolerance relation tr. And in the object space, if there doesn't exist other object z, $z\notin Y$, for $\forall x\in Y$ such that $x\ tr\ z$, then we say Y is the maximum tolerance class. The maximum tolerance class is called as a tolerance granule derived by tr.

Suppose α and β are two n dimensional vectors of X, and $dis(\alpha,\beta|\omega)$ is a distance function, where weight vector $\omega=(\omega_1,\omega_2,\cdots,\omega_n)$ and $\omega_i\geq 0$. $sp(\alpha,\beta|dis,d)$ is called as a simple tolerance proposition, if $sp(\alpha,\beta|dis,d)\Leftrightarrow dis(\alpha,\beta|\omega)\leq d$, where $d\geq 0$, d is called as the radius of $sp(\alpha,\beta|dis,d)$. A compound tolerance proposition $cp(\alpha,\beta|DIS,D)$ is composed by a group of $sp_i(\alpha,\beta|dis_i,d_i)$ related with $\wedge$ and $\vee$, and $0\leq i\leq k$, where $D=\{d_1,d_2,\cdots,d_k\}$, $DIS=\{dis_1,dis_2,\cdots,dis_k\}$, dis_i and d_i are distance function and radius of $sp_i(\alpha,\beta|dis_i,d_i)$, respectively. Tolerance relation

$tr_{cp(\alpha,\beta|DIS,D)}$ induced by the $cp(\alpha,\beta|DIS,D)$ is defined as $(\alpha,\beta) \in tr_{cp(\alpha,\beta|DIS,D)} \Leftrightarrow cp(\alpha,\beta|DIS,D)$.

In a word, proposition cp, weight vector ω, distance function vector DIS and radius vector D are four key elements for a tolerance relation. Tolerance relation system TR is composed by a set of tolerance relations, and many space areas can be described by a tolerance relation system.

Tolerance granule g is usually illustrated by a triple (IG,EG,FG), where IG is the intension of G, EG is the extension of G, FG is the translation function between the intension and the extension. The intension IG is usually expressed by an n-dimensional vector $(ig_1,ig_2,\cdots,ig_n)$, where ig_i is the i^{th} element of IG and $ig_i \in R$. The extension EG contains all the objects and the tolerance granules that are covered by G, formally $EG = \{\bigcup_{i=1}^{a}\{O_i\}\} \cup \{\bigcup_{j=1}^{b}\{G_j\}\}$, where O_i is the i^{th} object, G_i is the i^{th} tolerance granule, a and b are the numbers of objects and tolerance granules, respectively. Tolerance granule $G = (IG,EG,FG)$ can be written more simply as (IG,EG).

In tolerance granular space, tolerance granule on O_k is expressed by G_k^i and is composed by the following two parts:

1) IG_k^i denotes a vector distributed by G_k^i, according to the current task and the context.

2) $EG_k^i(\eta_k^i|tr_k^i)$ is a set which contains all objects and tolerance granules covered by G_k^i. Where η_k^i is a vector, which can be regarded as the impossible position or center of G_k^i, $tr_k^i(cp,\omega,DIS,D)$ is tolerance relation of G_k^i.

3 The novel cloud model and tolerance granular space-based image retrieval methods

In this section, we first describe overview of two novel image retrieval methods proposed, an image texture recognition and a color image retrieval method based on cloud model and tolerance granular space. Then, an algorithm of extracting grid points based on cloud model is presented in the subsection 3.2. Finally, the detailed construction processes of two novel image retrieval methods are expounded in the subsections 3.3 and 3.4.

3.1 Overview of two novel image retrieval methods

The main purpose of this work is to develop novel image retrieval methods on the basic of cloud model and tolerance granular space. What need us to do is to apply cloud model and tolerance granular space to extracting image features for the novel image retrieval methods which can pick up the images they need from the large images database quickly and accurately. And the main idea of the novel image retrieval methods is showed in Figure 3. In the following, overviews of two novel approaches are constructed in detail as follows.

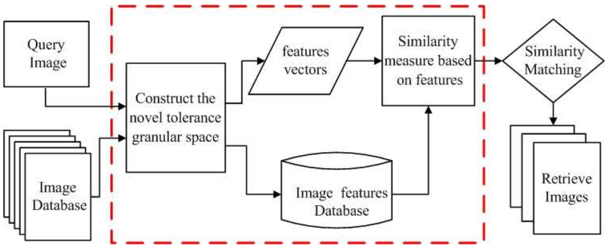

Figure 3 The idea of the novel image retrieval methods based on cloud model and tolerance granular space

First of all, we introduce a novel image texture recognition method based on cloud model and tolerance granular space, denoted by ITRCTS for convenience. In the process of constructing ITRCTS, we first present a tolerance relation system utilizing image gray information and extract grid points in each layer by cloud model. Then, a tolerance granular space model based on gray information of the image is established to extract image texture, by means of cloud model and tolerance granular space. That is, when we construct a tolerance granular space model with a suitable granulation, texture feature is expressed by tolerance granule appropriately. Eventually, we propose a new similarity measure for ITRCTS to evaluate the similarity between two images. The flow chart of texture feature extraction utilizing ITRCTS is shown in Figure 4.

In the following, the idea of the color image retrieval method based on cloud model and tolerance granular space is described. And the process of extracting texture and color features is showed in the Figure 5. For convenience, we can write this method more simply as CIRCTS. Firstly, we utilize image gray information to extract grid points in each layer and redefine tolerance relations with color information of the image. Then, a tolerance relation system is established and a tolerance granular space model with a suitable granulation is constructed. Finally, we propose a new similarity measures for CIRCTS to evaluate similarity between the two images.

3.2 Extract grid points based on cloud model

Grid points are all impossible position or center, which are the bases of building tolerance granular space. Grid points, only on the basic of position, are not well to express uncertainties of texture feature, such as randomness, fuzziness, and relevance. On account of texture feature with the uncertainties, how to extract grid points to present texture feature is a key problem to be solved. And cloud model can well depict these certainties.

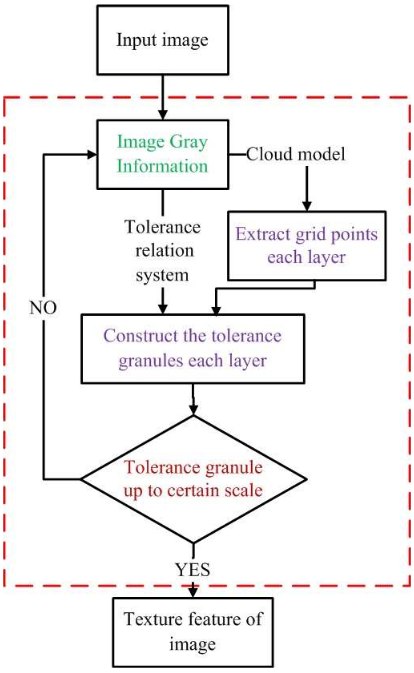

Figure 4 Texture feature extraction utilizing ITRCTS

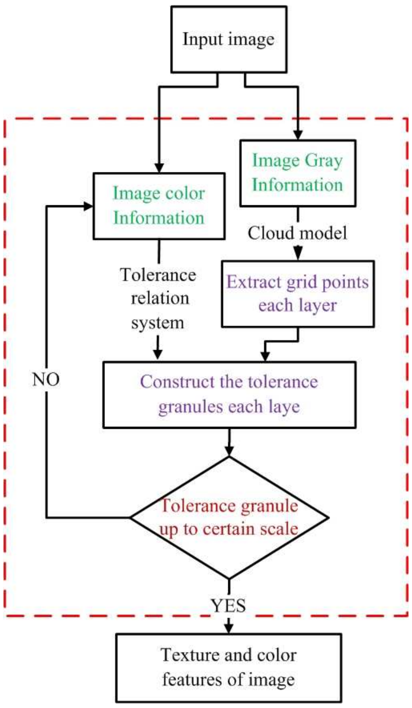

Figure 5 Texture and color features extraction utilizing CIRCTS

Consequently, uncertainties of texture feature are well represented by grid points extracted by means of cloud model.

The detailed process of extracting grid point is represented in the following. Firstly, according to gray information of tolerance granule, a gray histogram is obtained by statistics and is regarded as a gray histogram curve function $F(x)$. Secondly, $F(x)$ is decomposed into several concept clouds by cloud transform. Then, concept clouds are combined into some coarser granularity concept clouds by soft-or concept improving method. And the coarser granularity concept clouds with a finite number are gained. Finally, seek objects from the object set, which have the same value with the expected value of the coarser granularity concept gained, i.e., grid points. The algorithm is introduced as follows in detail.

Algorithm 1 Extracting cloud grid points
Input: Gray information and the number of concept clouds generated K
Output: Three numerical characters of concepts generated $A_i(Ex_i, En_i, He_i)$ and grid points $Grid$, $i = 1, 2, \cdots, K$

Step1: According to gray information, obtain gray histogram, i.e., gray histogram curve function $F(x)$.
Step2: Seek the position peaks of $F(x)$ and these are regarded as Ex_i of concept clouds, $i = 1, 2, \cdots, n$. Then, calculate En_1 of concept cloud with the expected value $Ex_1$and obtain $f_1(x)$ of this concept cloud.
Step3: $F'(x)$ is obtained by $F(x) - f_1(x)$. Repeat Step2 and Step3 till $F(x)$ is divided to n concept clouds $C_i(Ex_i, En_i, He_i)$, $i = 1, 2, \cdots, n$.
Step4: According to soft-or concept improving method, combine the finer concept clouds into some coarser granularity concept clouds $C_j'(Ex_j', En_j', He_j')$, and write down the number of concept clouds obtained N.
Step5: If $N = K$ then output three numerical characters of the the coarser concepts $A_i(Ex_i, En_i, He_i)$, $i = 1, 2, \cdots, K$
else turn to Step4
Step6: Seek objects with the same value from object set as the expected value of the coarser granularity concept clouds gained, put them into the set of grid points $Grid$.
Step7: Output the set of grid points $Grid$.
Step8: End.

3.3 The novel image texture recognition based on cloud model and tolerance granular space

Definition 3.1. A pixel of the image is called as an object, formally $Og_{xy}^0 = (x, y, h)$, where x, y are position coordinate values of the pixel in image, respectively, and h is gray value of the pixel. And an image can be represented by an object set Og_1, denoted by

$$Og_1 = \begin{bmatrix} Og_{11}^0 & Og_{12}^0 & \cdots & Og_{1m}^0 \\ Og_{21}^0 & Og_{22}^0 & \cdots & Og_{2m}^0 \\ \vdots & \vdots & & \vdots \\ Og_{n1}^0 & Og_{n2}^0 & \cdots & Og_{nm}^0 \end{bmatrix}. \quad (3)$$

In the object set, gray information is established by all objects' gray values of object set, and gray histogram is obtained through statistical method. Then grid points are extracted and a tolerance relation system is built, which are applied to construction of a new tolerance granular space model based on cloud model.

Definition 3.2. Let Og^0_{xy}, Og^0_{ij} be two objects of tolerance granules in the same layer, the distance between Og^0_{xy} and Og^0_{ij} is defined as

$$dis_g(Og^0_{xy}, Og^0_{ij}|\omega) = dg(Og^0_{xy}, Og^0_{ij}) = |h_{xy} - h_{ij}|, \quad (4)$$

where $Og^0_{xy} = (x, y, h_{xy})$ and $Og^0_{ij} = (i, j, h_{ij})$.

Definition 3.3. In tolerance relation system, a simple tolerance proposition induced by the distance between two objects is defined as

$$\mathrm{sp_g}(Og^0_{xy}, Og^0_{ij}|dis_g, \omega) = dis_g(Og^0_{xy}, Og^0_{ij}|\omega) \le d. \quad (5)$$

Definition 3.4. In tolerance relation system, a compound tolerance proposition $\mathrm{cp}_g(Og^0_{xy}, Og^0_{ij}|dis_g, D)$ is the union set of the simple tolerance propositions, where $D = \{d_1, d_2, \cdots, d_L\}$.

From Definitions 3.1, 3.2, 3.3, and 3.4, we know that two objects belong to one tolerance granule, if the distance between them is less than the given distance upper limit, i.e., $dis < d$. And radius vector $D = \{d_1, d_2, \cdots, d_L\}$, where L is the number of layers for tolerance granules constructed, d_i is the distance upper limit of the i^{th} layer's tolerance granules. In this part, from top to bottom, a novel space model I for ITRCTS is established. And all original objects constitute the extension of the 0^{th} layer's tolerance granule. Because the intension of tolerance granule is related to other factors, for instances, tasks, the background, the context of tolerance granules, it is not studied in the construction of the model [11,12,13]. It is followed by the detailed procedures to structure the novel space model I for ITRCTS in Algorithm 2.

An image can be divided into L layers by the construction of novel space model I. Then, tolerance granules and their gray indicators can be obtained as well. In the novel space model I, if the expected value of two tolerance granules in the same layer are equal, they can be merged into a compatible coarser granule. And the objects of coarser granule are composed of all objects of two tolerance granules. Gray indicator of coarser granule can be obtained by BCG. Therefore, texture feature is extracted by the novel space model I for ITRCTS. In the process of image retrieval, similarity between query image and image in image database must be calculated and the most similar images with given number are retrieved out of image database. In this part, a novel similarity measure is demonstrated for ITRCTS.

Algorithm 2 The novel space model I for ITRCTS
Input: Image gray information H and recursion number L
Output: Tolerance granules and their gray indicators (Ex_i, En_i, He_i)

Step1: Construct object set Og_1 by image gray information H, and obtain the 0^{th} layer tolerance granule $G^1_0 = (IG^1_0, EG^1_0)$, where $EG^1_0 = (x|x \in Og_1)$.
Step2: Extract granule's grid points $Grid^1_1$ of the 1^st layer utilizing Algorithm 1.
Step3: Calculate tolerance granule $G^1_1 = (IG^1_1, EG^1_1(\eta^1_1|tr^1_1))$ of the 1^{st} layer, where $EG^1_1(\eta^1_1|tr^1_1) = \{x|(x, \eta^1_1) \in tr1_{(cp^1_1, \omega^1_1, DIS^1_1, D^1_1)}{}^1 \wedge (x \in EG^1_0))\}$, and $\eta^1_{k+1} \in Grid^1_{k+1}$.
Step4: Recursively, extract grid points of the $k+1^{th}$ layer by Algorithm 1 based on gray information of the k^{th} layer's tolerance granule G^1_k. Calculate the $k+1^{th}$ layer's tolerance granule $G^1_{k+1} = (IG^1_{k+1}, EG^1_{k+1}(\eta^1_{k+1}|tr^1_{k+1}))$. Where $EG^1_{k+1}(\eta^1_{k+1}|tr^1_{k+1}) = \{x|(x, \eta^1_{k+1}) \in tr^1_{k+1_{(cp^1_{k+1}, \omega^1_{k+1}, DIS^1_{k+1}, D^1_{k+1})}}$ $\wedge(x \in EG^1_k))\}$, and $\eta^1_{k+1} \in Grid^1_{k+1}$.
If $k < L$ then turn to Step4
else turn to Step7
Step5: Calculate gray indicators (Ex_i, En_i, He_i) by BCG.
Step6: Output tolerance granules and their gray indicators (Ex_i, En_i, He_i).
Step7: End.

Definition 3.5. P^k_i, Q^k_i are two tolerance granules with the same expected values in the k^{th} layer of two images P and Q. The histogram intersection matching value of P and Q is defined as

$$H(P,Q) = \frac{1}{L}\sum_{k=1}^{L}\sum_{i=1}^{M}\frac{\min(|P^k_i|, |Q^k_i|)}{\max(|P^k_i|, |Q^k_i|)}, \quad (6)$$

where L is the number of the divided image's layers and M is gray level of the image.

Definition 3.6. P^k_i, Q^k_i are two tolerance granules with the same expected values in the k^{th} layer of two images P and Q. The gray distance between P^k_i and Q^k_i is defined as

$$\begin{aligned} dg(P^k_i, Q^k_i) = {} & [\omega_0(Ex^k_{i1} - Ex^k_{i2})^2 + \omega_1(En^k_{i1} - En^k_{i2})^2 \\ & + \omega_2(He^k_{i1} - He^k_{i2})^2]^{\frac{1}{2}}, \end{aligned} \quad (7)$$

where Ex^k_{i1}, En^k_{i1}, He^k_{i1} are gray indicators of P^k_i , Ex^k_{i2}, En^k_{i2}, He^k_{i2} are gray indicators of Q^k_i, and $\omega = (\omega_0, \omega_1, \omega_2) = (0, 0.7, 0.3)$.

Definition 3.7. The gray distance between P and Q is defined as

$$Dg(P,Q) = \sum_{j=1}^{L}\sum_{i=1}^{M}\frac{dg_t(P^j_i, Q^j_i)}{\max\limits_{0 \le i \le M, 0 \le j \le L}\{dg_t(P^j_i, Q^j_i)\}}. \quad (8)$$

Definition 3.8. A novel similarity measure between images P and Q for ITRCTS is defined as

$$SIM_1(P,Q) = \alpha H(P,Q) + \beta Dg(P,Q), \quad (9)$$

where α and β are weight values of the histogram intersection and gray distance respectively, $0 \leq \alpha \leq 1$, and $\beta = 1-\alpha$.

Property 3.1. $0 \leq SIM_1(P,Q) \leq 1$.

Proof. It follows immediately from formulas (6), (7), and (8), we have that $H(P,Q)$ and $Dg(P,Q)$ are belong to [0,1]. For $0 \leq \alpha \leq 1$ and $\beta = 1-\alpha$, then we can obtain that $0 \leq \alpha H(P,Q)+\beta Dg(P,Q) \leq 1$. Therefore, $0 \leq SIM_1(P,Q) \leq 1$ is obtained. This completes the proof.

3.4 The novel color image retrieval method based on cloud model and tolerance space

Definition 3.9. A pixel of the image is called as an object, formally $Oc^0_{xy} = (x,y,R,G,B,h)$, where x, y are position coordinate values of the pixel in the image, respectively, R, G, B are color values of the pixel in RGB space and h is gray value of the pixel. And an image can be represented as an object set Oc_1, denoted by

$$Oc_1 = \begin{bmatrix} Oc^0_{11} & Oc^0_{12} & \cdots & Oc^0_{1m} \\ Oc^0_{21} & Oc^0_{22} & \cdots & Oc^0_{2m} \\ \vdots & \vdots & & \vdots \\ Oc^0_{n1} & Oc^0_{n2} & \cdots & Oc^0_{nm} \end{bmatrix}. \quad (10)$$

According to Definition 3.9, gray information H obtained is similar to Definition 3.1, and color information C_G is the set containing the color values of R, G, B in RGB color space. In the process of constructing CIRCTS, grid points are extracted taking advantage of gray information H and a tolerance relation system is defined based on color information C_G, which are key elements for the novel space model II for CIRCTS.

Definition 3.10. Let Oc^0_{xy}, Oc^0_{ij} be two objects of tolerance granules in the same layer, the distance between Oc^0_{xy} and Oc^0_{ij} is defined as

$$\begin{aligned} & dis_c(Oc^0_{xy}, Oc^0_{ij}|\omega_c) \\ = & \; dg(Oc^0_{xy}, Oc^0_{ij}) \\ = & \; [\omega_0(R_{xy}-R_{ij})^2 + \omega_1(G_{xy}-G_{ij})^2 \\ & + \omega_2(B_{xy}-B_{ij})^2]^{\frac{1}{2}}, \end{aligned} \quad (11)$$

where$Oc^0_{xy} = (x,y,R_{xy},G_{xy},B_{xy})$, $Oc^0_{ij} = (i,j,R_{ij},G_{ij},B_{ij})$ and weight vector $\omega_c = (\omega_{c0},\omega_{c1},\omega_{c2}) = (1,1,1)$.

Definition 3.11. In tolerance relation system, a simple tolerance proposition induced by the distance between two objects is defined as

$$\mathrm{sp_c}(Oc^0_{xy}, Oc^0_{ij}|dis_c, \omega_c) = dis_c(Oc^0_{xy}, Oc^0_{ij}|\omega_c) \leq d. \quad (12)$$

Definition 3.12. In tolerance relation system, a compound tolerance proposition $\mathrm{cp}_c(Oc^0_{xy}, Oc^0_{ij}|dis_c, D_c)$ is the union set of the simple tolerance propositions, where $D_c = \{d_1, d_2, \cdots, d_{L_c}\}$.

From Definitions 3.10, 3.11, and 3.12, we know that two objects belong to one tolerance granule if and only if $dis < d$. In this part, a novel space model II for CIRCTS, from top to bottom, is established. Because the intension of tolerance granule is related to other factors, for instances, tasks, the background, the context of tolerance granule, the intension of tolerance granule is not discussed in the process to construct the novel model [11, 12, 13]. And all original objects constitute the extension of the 0^{th} layer tolerance granule. The following introduces the detailed procedure to establish the novel space model II for CIRCTS.

Algorithm 3 The novel space model I for ITRCTS
Input: Image gray information H, color information C_G and recursion number L_c
Output: Tolerance granules and their color mean $(\overline{h}, \overline{R}, \overline{G}, \overline{B})$

Step1: Construct object set Oc_1 based on color information C_G, and obtain the 0^{th} layer tolerance granule $G^1_0 = (IG^1_0, EG^1_0)$, where $EG^1_0 = (x|x \in Oc_1)$.
Step2: Extract the granule's grid points $Grid^1_1$ of the 1^{st} layer utilizing Algorithm 1.
Step3: Calculate tolerance granule $G^1_1 = (IG^1_1, EG^1_1(\eta^1_1|tr^1_1))$ of the 1^{st} layer, where $EG^1_1(\eta^1_1|tr^1_1) = \{x|(x,\eta^1_1) \in tr^1_{1_{(cp^1_1,\omega^1_1,DIS^1_1,D^1_1)}} \wedge (x \in EG^1_0))\}$, and $\eta^1_{k+1} \in Grid^1_{k+1}$.
Step4: Recursively, extract grid points of the $k+1^{th}$ layer by Algorithm 1. The $k+1^{th}$ layer tolerance granule $G^1_{k+1} = (IG^1_{k+1}, EG^1_{k+1}(\eta^1_{k+1}|tr^1_{k+1}))$ is obtained, where $EG^1_{k+1}(\eta^1_{k+1}|tr^1_{k+1}) = \{x|(x,\eta^1_{k+1}) \in tr^1_{k+1_{(cp^1_{k+1},\omega^1_{k+1},DIS^1_{k+1},D^1_{k+1})}} \wedge (x \in EG^1_k))\}$, and $\eta^1_{k+1} \in Grid^1_{k+1}$.
If $k < L$ then turn to Step4
else turn to Step6
Step5: Output tolerance granules and their color mean $(\overline{h}, \overline{R}, \overline{G}, \overline{B})$.
Step6: End.

From the above discussion, we know that an image can be divided into L_c layers by the novel space model II. Simultaneously, tolerance granules in each layer, their gray indicators, and their color means also can be obtained. In this model, if two tolerance granules in the same layer have the same gray mean, then they can be merged into a compatible coarser granule, the objects of which are constituted by all objects of the two tolerance granules. And color feature of the new coarser granule is the color mean of all objects in the new coarser granule. Therefore, texture and color features are extracted by the novel space mode II. A novel similarity measure for CIRCTS is demonstrated as follows.

Definition 3.13. P^k_i, Q^k_i are two tolerance granules with the same gray means in the k^{th} layer of two images P and Q, then the texture similarity measure between P_i^k and Q_i^k is defined as

$$sim_t(P_i^k, Q_i^k) = \frac{|EP_i^k \cap EQ_i^k|}{|EP_i^k \cup EQ_i^k|}, \quad (13)$$

where EP_i^k, EQ_i^k are the extension of tolerance granules P_i^k and Q_i^k, respectively.

Definition 3.14. The texture similarity measure between P and Q is defined as

$$SIM_t(P,Q) = \sum_{j=1}^{L_c} \sum_{i=1}^{M} \frac{sim_t(P_i^j, Q_i^j)}{\max\{P_j, Q_j\}}, \quad (14)$$

where, L_c is the number of divided image's layers, M is gray level of the image, P_j and Q_j are the numbers of tolerance granules in the j^{th} layer of images P and Q, respectively.

Definition 3.15. P_i^k, Q_i^k are two tolerance granules with the same gray means in the k^{th} level of the two images P and Q. The color distance between P_i^k and Q_i^k is defined as

$$\begin{aligned} & Dc(P_i^k, Q_i^k) \\ = & [\omega_0(\bar{R}c_{i1}^k - \bar{R}c_{i2}^k)^2 + \omega_1(\bar{G}c_{i1}^k - \bar{G}c_{i2}^k)^2 \\ & + \omega_2(\bar{B}c_{i1}^k - \bar{B}c_{i2}^k)^2]^{\frac{1}{2}}, \end{aligned} \quad (15)$$

where $\bar{R}c_{i1}^k, \bar{G}c_{i1}^k, \bar{B}c_{i1}^k$ are mean values of P_i^k on R, G, B in RGB space, $\bar{R}c_{i2}^k, \bar{G}c_{i2}^k, \bar{B}c_{i2}^k$ are mean values of Q_i^k on R, G, B in RGB space, and $\omega = (\omega_0, \omega_1, \omega) = (1,1,1)$.

Definition 3.16. The color similarity measure between P and Q is defined as

$$SIM_c(P,Q) = \sum_{j=1}^{L_c} \sum_{i=1}^{M} \frac{Dc_t(P_i^j, Q_i^j)}{\max\limits_{0 \le i \le M, 0 \le j \le L} \{Dc_t(P_i^j, Q_i^j)\}}. \quad (16)$$

Definition 3.17. A novel similarity measure for CIRCTS composing color and texture features between images P and Q is defined as

$$SIM_2(P,Q) = \lambda SIM_t(P,Q) + \mu SIM_c(P,Q), \quad (17)$$

where λ and μ are weight values of the color and texture similarity measures, $0 \le \lambda \le 1$, and $\mu = 1 - \lambda$.

Remark In the process of image retrieval, λ and μ can be adjusted for different kinds of images to highlight the corresponding characteristics to gain the relatively good results. Taking Flowers and Horses for example, λ for Flowers is bigger and μ for Horses can be adjusted bigger. Thereby, the satisfied results can be achieved.

Property 3.2. $0 \le SIM_2(P,Q) \le 1$.

Proof. the process of this proof is like Property 3.1.

Remark According the properties 3.1 and 3.2, for any two images P and Q, one has that the bigger is $SIM(P,Q)$, the more similar two images are. Conversely, the less dissimilar two images are. Especially, If one has that $SIM(P,Q) = 0$, two images are different at all. While, if $SIM(P,Q) = 1$, two images are same.

4 Experiments and analysis

In this section, the performances of our approaches are demonstrated. The objective is to evaluate our approaches in terms of retrieval accuracy. Our experiments can be divided into two parts. In the first part, we introduce three evaluation criterions, Precision, Recall, and Precision-Recall graph. In the second part, we compare our approaches with three image retrieval methods, conventional color histogram-based image retrieval method (written by CCH) [33], salient regions and nonsubsampled contourlet transform-based image retrieval method (written by SRNCT) [6], tolerance granular-based multi-level texture image retrieval method (written by TGMT) [19]. These experiments are run on the image test set, images of which are chosen from Corel Database. And these experiments are performed on a personal computer with Windows XP, Intel (R) Core (TM) Quad CPU 3.1 GHz, and 4 GB memory.

4.1 Evaluation criterions

In order to evaluate performance of our approaches, we use Precision (P) and Recall (R) as performance measurements. Precision is the percentage of the relevant images retrieved in the images retrieved in one query. It measures the accuracy of retrieval and is computed by

$$P = \frac{|relevant \quad images \quad retrieved|}{|images \quad retrieved|} \times 100\% \quad (18)$$

Recall is the percentage of the relevant images retrieved of the relevant images in image database in one query. It measures the robustness of the system and is calculated by

$$R = \frac{|relevant \quad images \quad retrieved|}{|relevant \quad images \quad in \quad database|} \times 100\% \quad (19)$$

In order to vividly show performances of our approaches, Precision-Recall graph is also applied to evaluating performances of our approaches at whole. The following is that Precision-Recall graph is described in detail. The x-axis and y-axis represent Recall and Precision rates, respectively. Generally speaking, under the same retrieval condition, the higher numerical values of Precision and Recall are, the better image retrieval method is, for different image retrieval approaches. Otherwise, the worse image retrieval method is.

4.2 Comparative experiments

Corel Database is considered as a widely used local image collection which contains a large number of images of various contents [34,35,36]. Corel Database contains 10, 000 color images and they are gathered from public sources and natural scenes, such as landscapes, flowers, cars, people, horses, buildings, etc. Therefore, we choose images from Corel Database as image test set for our experiments. In order to evaluate performances of our approaches, we compare our approaches with two image retrieval methods that usually are used, CCH and SRNCT, with Precision and Recall. Then, we compare our approaches with an image retrieval method tolerance granule, TGMT, with Precision-Recall graph.

Figure 6 The query image

To evaluate that our approaches is effective, we compare our approaches with two image retrieval methods, CCH and SRNCT with Precision and Recall. In the first place, we let Figure 6 be query image. Figures 7, 8, 9, and 10 exhibit retrieval results of four methods in one query. And each retrieval result contains the most similar 20 images returned from image test set. From Figure 7, 9 images out of returned images using CCH don't belong to buildings. Precision of CCH is 55%, the lowest in four methods. From Figure 8, 7 images out of returned images for SRNCT don't belong to buildings and Precision of SRNCT is 65%. From Figure 9, 8 images out of returned image for ITRCTS don't belong to buildings. Precision of CIRCTS is 60%. From Figure 10, 6 images out of returned images for ITRCTS don't belong to buildings. Precision of CIRCTS is 70%, the highest. Therefore, it can be observed that CIRCTS exhibits the best performance in four methods and ITRCTS surpasses CCH but inferior to SRNCT. Therefore, our approaches are effective in the area of the image retrieval in some degree.

In the following, to test our approaches further, we do a large number of experiments, and calculate the average Precision and Recall of each kind of image according to experiment results. Precision and Recall contrasts of four methods are showed in Tables 1 and 2. From Tables 1 and 2, it is clearly obtained that Precision and Recall of CIRCTS are the highest and ITRCTS surpasses CCH but

Figure 7 The retrieval result using CCH

Figure 8 The retrieval result using SRNCT

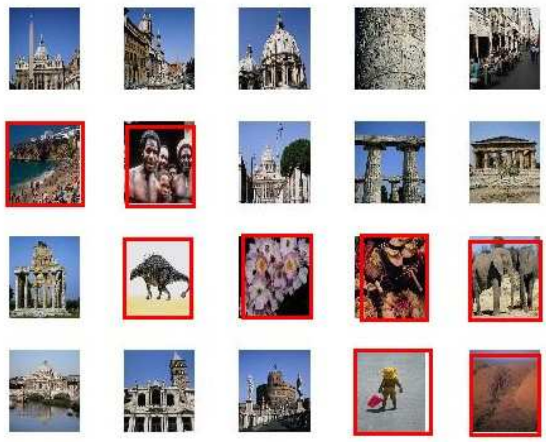

Figure 9 The retrieval result using ITRCTS

Figure 10 The retrieval result using CIRCTS

inferiores to these of SRNCT. As a consequence, it can be observed that CIRCTS exhibits the best performance, the performance of ITRCTS surpass that of CCH but no better than that of SRNCT. Therefore, our approaches are effective in the area of image retrieval in some degree.

Table 1: Precision contrast of four methods

Image Classes	CCH	SRNCT	ITRCTS	CIRCTS
African	0.34	0.37	0.35	0.41
Beaches	0.25	0.33	0.31	0.39
Buildings	0.29	0.35	0.37	0.42
Buses	0.46	0.50	0.48	0.57
Dinosaurs	0.59	0.60	0.61	0.73
Elephants	0.22	0.29	0.28	0.35
Flowers	0.48	0.52	0.50	0.54
Horses	0.53	0.57	0.55	0.61
Mountains	0.28	0.29	0.27	0.37
Food	0.27	0.41	0.39	0.48

Table 2: Recall contrast of four methods

Image Classes	CCH	SRNCT	ITRCTS	CIRCTS
African	0.59	0.62	0.52	0.67
Beaches	0.46	0.54	0.48	0.57
Buildings	0.52	0.57	0.5.5	0.63
Buses	0.73	0.82	0.77	0.86
Dinosaurs	0.75	0.97	0.94	0.98
Elephants	0.38	0.46	0.45	0.76
Flowers	0.67	0.86	0.85	0.89
Horses	0.68	0.95	0.93	0.97
Mountains	0.42	0.47	0.51	0.54
Food	0.53	0.68	0.66	0.78

In the final part, we compare our approaches with TGMT, an image retrieval method based on tolerance granule, with Precision-Recall graph. To get contrastive Precision-Recall graph of three image retrieval methods, which all are based on tolerance granular space, we choose random 10 images each kind of images form Corel Database to experiment and each image is queried for ten times. According to experiment results, Precision and Recall are calculated and the contrastive Precision-Recall graph for three image retrieval methods is showed in Figure 11. From Figure 11, it is obtained that Precision of CIRCTS surpasses that of the other two methods in the same Recall. Precision of ITRCTS is no better than that of TGMT with the Recall between 24% and 35%. However, ITRCTS overmatches the TGMT in the others Interval, when Recall is less than 24% or more than 35%. Thus, the efficiencies of ITRCTS and TGMT are close and ITRCTS is effective in image retrieval.

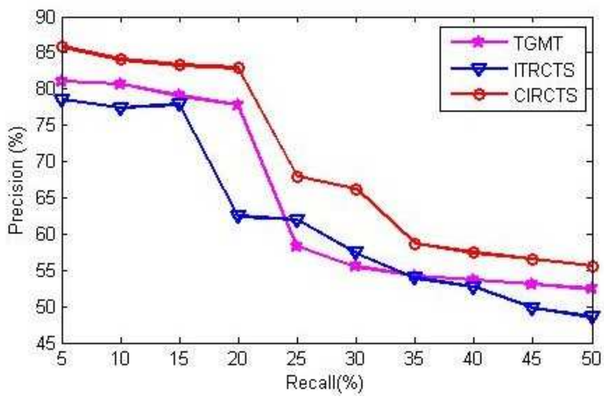

Figure 11 The contrastive Precision-Recall graph for the three image retrieval methods

From the above analysis, our approaches can be effectively pick up images that we need when we retrieve images in some degree. And retrieval result of CIRCTS overmatches that of ITRCTS. In a word, our methods demonstrate that the proposed methods are indeed efficient and of practical value to many real-world problems.

5 Conclusions

In this paper, we analyze cloud model and tolerance granular space, apply cloud model to extracting grid points, construct two novel tolerance granular space models, and present two image retrieval methods based on cloud model and tolerance granular space in the last. Then, simulation experiments show that our approaches are indeed efficient and of practical value to many real-world problems. It is not often observed that cloud model and tolerance granular space are applied to extracting color and texture features of images and image retrieval. Hence, it is a new try and an emerging field to utilize the knowledge of cloud model and tolerance granular space to resolve image retrieval. What's more, it is noted that a novel research method for image retrieval and image processing.

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