Quantitative analysis for image segmentation by granular computing clustering from the view of set

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Abstract
As partition method of set, granular computing clustering is applied to image segmentation evaluated by global consistency error, variation of Information, and Rand index from the view of set. Firstly, quantitative assessment of clustering is evaluated from the view of set. Secondly, granular computing clustering algorithms are induced by the distance formulas, the granules with different shapes are defined as the forms of vectors by different distance norms, especially, the atomic granule is induced by a point of space, the union operator realizes the transformation between two granule spaces and is used to form granular computing clustering algorithms. Thirdly, the image segmentations by granular computing clustering are evaluated from the view of set, such as global consistency error, variation of Information, and Rand index. Segmentations of the color images selected from BSD300 are used to show the superiority and feasibility for image segmentation by granular computing clustering compared with Kmeans and fuzzy c-means by experiments.

Keywords
Image segmentation, granule space, granular computing, granular computing clustering

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Introduction
In computer vision, image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.¹ Image segmentation is typically used to locate objects and boundaries in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic.¹ From the viewpoint of the set theory, image segmentation is based on the pixels, and the pixel set is divided into several subsets according to the features of the pixels, such as the RGB feature, YUV feature, and gradient feature. When applied to a stack of images, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms. The practical applications of image segmentation included content-based image retrieval,² machine vision,³ medical imaging,⁴ and object detection.⁵

Clustering for image segmentation is a popular method by which an image is partitioned into multiple segments. Clustering can be considered the most important unsupervised learning problem, which deals with finding a structure in a collection of unlabeled data. Kmeans clustering and fuzzy c-means (FCM) clustering are two important unsupervised algorithms. The K-means algorithm, which is

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computationally difficult Non-deterministic Polynomial hard (NP-hard), is an iterative technique that is used to partition an image into $K$ clusters. FCM is a data clustering technique where in each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek et al. as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. FCM algorithm incorporates spatial information into the membership function for clustering. The spatial function is the summation of the membership function in the neighborhood of each pixel under consideration.

Granular computing (GrC) is a computational model for studying the law of transformation between the micro world and the macro world. From the view of set theory, the transformation from the micro world to the macro world means the GrC from the small granularity to large granularity. As a clustering method, GrC can be used to image segmentation. Image segmentation is the process of partitioning a digital image into multiple segments. A segment is regarded as a granule. The pixels with the similar features are clustered in the same image segments, such as the semantic image segmentation, atrous spatial pyramid pooling (ASPP) is proposed to robustly segment objects at multiple scales. ASPP probes an incoming convolutional feature layer with filters at multiple sampling rates and effective fields-of-views, thus capturing objects as well as image context at multiple scales. The multi-scale is related to multiple granularity, the decision makers perform their exploration and analysis across a range of data scales from local to global, while maintaining a cohesive thematic context of the transition between the different granularity levels. From the view of granular computing, the pixel has the smallest granularity, and the image segment has the larger granularity compared with the granule induced by the pixel.

Granular computing for clustering is an unsupervised clustering method, in which the vector is represented as a granule and the operation between granules is used to realize the transformation between the granules with different granularities. In this paper, image segmentation is implemented by granular computing. Firstly, the granule with the smallest granularity is induced by the vector represented by the features of pixel, the union operator between granules is designed to unite smaller granules into larger granule, and smaller granules contain less pixels than larger granules, the granularity threshold is set to control the union process. Secondly, image segmentation is evaluated by global consistency error (GCE), variation of information (VI), and Rand index (RI) from the view of set.

The rest of this paper is presented as follows: Quantitative assessment of clustering from the view of set section describes quantitative assessment of clustering from the view of set. granular computing clustering (GrCC) are described in Granular computing clustering algorithm section. Experiments section demonstrates the segmentation results of color image selected from BSD300. Conclusions section summarizes the contribution of our work and presents future work plans.

### Quantitative assessment of clustering from the view of set

As the partition method, the data set $S$ is divided into some subsets $S_i (i = 1, 2, \ldots, n)$, which satisfy the following conditions:

1. $S_1 \cup S_2 \cup \ldots \cup S_n = S$
2. $S_i \cap S_j = \emptyset$, for $i \neq j$

For the two partitions $\pi = \{S_1, S_2, \ldots, S_n\}$ and $\pi' = \{S_1', S_2', \ldots, S_m'\}$ of data set $S$, and $N = |S| = |S_1| + |S_2| + \cdots + |S_n| = |S_1'| + |S_2'| + \cdots + |S_m'|$, we evaluate the partitions by the following aspects.

**GCE**

D. Martin proposed several error measures to quantify the consistency between partition by human and partition by algorithm. Let $\pi$ and $\pi'$ be two partitions of set $S = \{x_1, x_2, \ldots, x_N\}$ consisting of $N$ samples. For a given datum $x_i$, consider the classes that contain $x_i$ in $\pi$ and $\pi'$. We denote these sets of data by $C(\pi, x_i)$ and $C(\pi', x_i)$, respectively. Local refinement error (LRE) is then defined at datum $x_i$ as

$$LRE(\pi, \pi', x_i) = \frac{|C(\pi, x_i) - C(\pi', x_i)|}{|C(\pi, x_i)|}$$

where $C(\pi, x_i) - C(\pi', x_i)$ denotes the set differencing operator between sets $C(\pi, x_i)$ and $C(\pi', x_i)$. This error measure is not symmetric and encodes a measure of refinement in one direction only. There are two natural ways to combine the LRE at each point into a measure for the entire set. GCE forces all local refinements to be in the same direction and is defined as

$$GCE = \min \left\{ \frac{1}{N} \sum_{i=1}^{N} LRE(\pi, \pi', x_i), \frac{1}{N} \sum_{i=1}^{N} LRE(\pi', \pi, x_i) \right\}$$

VI work in Meila computes a measure of information content in each of the partitions. The proposed measure, termed the VI, is a metric and is related to
the conditional entropies between the class label distribution of the partitions. The measure has several promising properties but its potential for evaluating results on set where there is one ground-truth clustering by human. The VI is computed by the following steps. Firstly, computing the entropies $E_n(\pi)$ and $E_n(\pi')$ associated with partitions $\pi$ and $\pi'$.

$$E_n(\pi) = -\sum_{i=1}^{n} P(i) \log_2 P(i)$$

where $P(i) = \frac{|S_i|}{N}$

$$E_n(\pi') = -\sum_{i=1}^{m} P'(i) \log_2 P'(i)$$

where $P'(i) = \frac{|S_i|}{N}$.

Secondly, computing the mutual information between partitions $\pi$ and $\pi'$

$$I(\pi, \pi') = \sum_{i=1}^{n} \sum_{j=1}^{m} P(i,j) \log_2 \frac{P(i,j)}{P(i)P(j)}$$

Thirdly, computing the VI

$$VI(\pi, \pi') = E_n(\pi) + E_n(\pi') - 2I(\pi, \pi')$$

**Rand Index** RI was motivated by standard classification problems in which the result of a classification scheme has to be compared to a correct classification. The most common performance measure for this problem calculates the fraction of correctly classified (respectively misclassified) elements to all elements. For RI, comparing two clusters was just a natural extension of the performance measure: instead of counting single elements he counts correctly classified pairs of elements. Thus, RI is defined by

$$RI(\pi, \pi') = \frac{2(N_{11} + N_{00})}{N(N-1)}$$

where $N_{11}$ denotes the numbers of pairs that are in the same cluster under $\pi$ and $\pi'$, $N_{00}$ denotes the number of pairs that are in different clusters under $\pi$ and $\pi'$. RI depends on both the number of clusters and the number of elements, and ranges from 0 to 1. $\pi$ and $\pi'$ are identical when RI equals to 1.

We explain the evaluation of partitions, such as GCE, VI, and RI, taking the segmentation of image I with the size $6 \times 6$. The segmentation labels of the pixels are shown in Figure 1 for the image I. Suppose the segmentation by human is shown in Figure 1(a), the segmentation by algorithm A is shown in Figure 1(b), and the segmentation by algorithm B is shown in Figure 1(c).

From the view of set, the segmentation by human shown in Figure 1(a) is transformed into the set

$$\pi = \{1, 1, 2, 3, 3, 1, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3\}$$

the segmentation by algorithm A shown in Figure 1(b) is transformed into the set

$$\pi_1 = \{2, 2, 3, 3, 1, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3, 1, 1, 2, 2, 3, 3\}$$

the segmentation by algorithm B shown in Figure 1(c) is transformed into the set

$$\pi_2 = \{3, 3, 2, 2, 1, 1, 1, 2, 2, 3, 3, 3, 3, 2, 2, 1, 1, 2, 2, 3, 3, 1, 1, 1, 2, 2, 3, 3\}$$

where the numbers represent the cluster labels in $\pi$, $\pi_1$, and $\pi_2$.

We can calculate the evaluation value of partitions $\pi_1$ and $\pi_2$ induced by algorithm A and algorithm B, such as GCE, VI, and RI.

$$GCE(\pi_1, \pi) = 0.5449 \quad VI(\pi_1, \pi) = 2.4831 \quad RI(\pi_1, \pi) = 0.6238$$

| (a) | (b) | (c) |
|-----|-----|-----|
| 3 3 3 3 3 3 | 1 1 3 1 1 3 | 1 3 3 1 1 3 |
| 3 3 3 3 3 3 | 1 1 3 2 1 3 | 2 2 3 1 3 2 |
| 2 2 2 2 2 2 | 3 3 2 2 3 2 | 2 2 2 3 2 1 |
| 2 2 2 2 2 2 | 3 3 2 3 3 2 | 2 2 2 3 2 1 |
| 1 1 1 1 1 1 | 2 2 1 2 2 3 | 3 1 3 2 2 1 |
| 1 1 1 1 1 1 | 2 2 1 1 1 3 | 3 1 3 2 1 3 |

**Figure 1.** The segmentations by different methods (for example).
GCE(π2, π) = 0.5880 \ VI(π2, π) = 2.8469 \ RI(π2, π) = 0.5952

From the evaluation value of GCE, VI, and RI, we can see the segmentation by algorithm A is better than that by algorithm B, because GCE(π1, π) < GCE(π2, π), VI(π1, π) < VI(π2, π), and RI(π1, π) < RI(π2, π).

**Granular computing clustering algorithm**

GrCC algorithm is the method by which the granules are clusters. For the data set \( S = \{ x_i | i = 1, 2, \ldots, N \} \), we construct GrCC in terms of the following steps. Firstly, the single point in \( S \) is represented as the atomic granules which are indivisible. Secondly, the distance formulas are introduced to determine the union process between two granules. Thirdly, the union operator is designed to update the granules and form GrCC.

**GrCC**

The idea of GrCC is described as follows. Firstly, the granule set (or the clustering set) \( (GS) \) is empty. Secondly, for the first datum \( x_1 \) in \( S \), the corresponding atomic granule is represented as the normal vector \( G_1 = (x_1, 0) \) with the center \( x_1 \) and radii \( 0 \), and the center \( x_1 \) is regarded as the clustering center. The granule \( G_1 \) is move into \( GS \), and the datum \( x_1 \) is removed from \( S \). Thirdly, for the rest data \( x_i (i = 1, 2, \ldots, N) \), \( d_{ij} \) represents the distance metric between the atomic granule \( G_i \) induced by the datum \( x_j \) and the granule \( G_j \), if the \( d_{ij} \) is less than or equal to the user-defined parameter \( \rho \), the granule \( G_j \) in \( GS \) is replaced by the union of granule \( G_i \) and \( G_j \), otherwise the atomic granule \( G_i \) becomes the new member of \( GS \), and \( x_i \) is removed from \( S \) until \( S \) is empty.

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**Algorithm 1. GrCC**

Input: the data set \( S \), the user-defined parameter \( \rho \)
Output: the granule set \( (GS) \)
1. Initialize the granule set \( GS = \emptyset \)
2. For the 1st sample \( x_1 \) in \( S \), form the corresponding atomic granule \( G_1 \), \( GS = GS \cup \{ G_1 \} \) remove the sample \( x_1 \)
3. \( j = 1: |S| \)
4. Compute the distance metric \( d_j \) between the atomic granule \( G_i \) and the \( j \)th granule \( G_j \) induced by the \( j \)th sample in \( S \)
5. Find samples in data set \( S \) whose distance metric \( d_j \) are less than or equal to \( \rho \), the found samples are united into the updated granule \( G_{update} \)
6. \( G_i = G_{update} \), remove the found samples from data set \( S \)
7. If the data set \( S \) is empty, the procedure is terminated, otherwise, go to 2.

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**Representation of granule and granularity**

In reality, the shapes of granules are irregular, the distance between two granules is not easy to be measured, the union granule and the meet granule are related to the shapes of granules. In order to study granular computing, the granule is represented as regular shapes, such as hyperdiamond, hypersphere, hypercube in N-dimensional space. These three shape granules can be represented as the following normal form in the paper.

\[ G = (C, r) \]

where \( C \) is the center of granule, \( r \) is the radius of granule which is generally induced by the distance between two points in N-dimensional space. Different induced form means the different shape of granule. Granularity is the size of granule, such as the radius of granule.

In Figure 2, the normal form granule \( G = (0.1, 0.2, 0.5) \) is hyperdiamond granule shown in Figure 2(a) in \( R^2 \) space, whose center is \((0.1, 0.2)\) and granularity is 0.5 induced by the \( L_1\)-norm. \( G = (0.1, 0.2, 0.5) \) is hypersphere granule shown in Figure 2(b) with center \((0.1, 0.2)\) and granularity 0.5 induced by \( L_2\)-norm distance. \( G = (0.1, 0.2, 0.5) \) is hypercube granule shown in Figure 2(c) with center \((0.1, 0.2)\) and granularity 0.5 induced by \( L_{\infty}\)-norm. From Figure 2, we can see different shape granules have different shapes even if they have the same forms of representations.

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**Figure 2.** Granules with different shapes in \( R^2 \) space.
**Distance measure between granules**

The distance between granules refers to the minimal distance between two points which belong to different granules.

For two hyperdiamond granules $G_1 = (C_1, r_1)$ and $G_2 = (C_2, r_2)$, the distance is

\[
d(G_1, G_2) = \|C_1 - C_2\|_1 - r_1 - r_2
\]

where $C_1$ and $C_2$ are vectors in N-dimensional space and the centers of hyperdiamond granules $G_1$ and $G_2$, $r_1$, and $r_2$ are granularities of hyperdiamond granules $G_1$ and $G_2$.

\[
\|C_1 - C_2\|_1 = |x_1 - y_1| + |x_2 - y_2| + \cdots + |x_N - y_N|
\]

For two hypersphere granules $G_1 = (C_1, r_1)$ and $G_2 = (C_2, r_2)$, the distance is

\[
d(G_1, G_2) = \|C_1 - C_2\|_2 - r_1 - r_2
\]

where $C_1$ and $C_2$ are vectors in N-dimensional space and the centers of hypersphere granules $G_1$ and $G_2$, $r_1$, and $r_2$ are granularities of hypersphere granules $G_1$ and $G_2$.

\[
\|C_1 - C_2\|_2 = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_N - y_N)^2}
\]

For hypercube granules $G_1 = (C_1, r_1)$ and $G_2 = (C_2, r_2)$, the distance is

\[
d(G_1, G_2) = \|C_1 - C_2\|_{\infty} - r_1 - r_2
\]

where $C_1$ and $C_2$ are vectors in N-dimensional space and the centers of hypercube granules $G_1$ and $G_2$, $r_1$, and $r_2$ are granularities of hypercube granules $G_1$ and $G_2$.

\[
\|C_1 - C_2\|_{\infty} = \max\{|x_1 - y_1|, |x_2 - y_2|, \ldots, |x_N - y_N|\}
\]

According to the distance between two granules mentioned above, the distance between two granules is the arbitrary real number. There is margin between two granules when $d > 0$, there is a same point between two granules when $d = 0$, and there is an overlap between two granules when $d < 0$. When $d > 0$, the greater $d$ means the greater margin between two granules, and when $d < 0$, the greater $d$ means the smaller overlap. Figure 3 shows the distance between two granules, including $d < 0$, $d = 0$, and $d > 0$.

**Operations between two granules**

The operations between two granules reflect the transformation between macroscopic and microcosmic of human cognitions. When a person want to observe the object more carefully, the object is partitioned into some suitable sub-objects, namely the universe is transformed into some parts in order to study the object in detail in the view of microscopic. Conversely, there is the same attributes of some objects, we regard the objects as a universe to simple the process in the view of macroscopic. The operations between two granules are designed to realize the transformation between macroscopic and microscopic. Set-based models of granular structures are special cases of lattice-based models, where the lattice union operation $\lor$ coincides with set union operation $\cup$ and lattice meet operation $\land$ coincides with set intersection operation $\cap$.

Union operation $\lor$ and meet operation $\land$ are used to realize the transformation between macroscopic and microcosmic. Operation $\lor$ unites the granules with small granularities to the granules with the large granularities. Inversely, Operation $\land$ divides the granules with large granularities into the granules with small granularities. Union operation $\lor$ and meet operation $\land$ are designed as follows.

Any points are regarded as atomic granules which are indivisible, the union process is the key to obtain the larger granules compared with atomic granules. Likewise, the whole space is a granule with the maximal granularity, the meet process produces the smaller granules compared with original granules. Union operator is used to form GrCC. We explain the union

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**Figure 3.** Distances between two granules in $R^2$ space.
process between two granules by taking hyperdiamond granule as an example.

For two hyperdiamond granules \( G_1 = (C_1, r_1) \) and \( G_2 = (C_2, r_2) \) in \( N \)-dimensional space, the union hyperdiamond granule is

\[
G = G_1 \lor G_2 = (C, R)
\]

The center \( C \) and the granularity \( R \) of \( G \) are computed as follows.

Firstly, the vector from \( C_1 \) to \( C_2 \) and vector from \( C_2 \) to \( C_1 \) are computed. If \( C_1 = C_2 \), then \( C_{12} = 0 \) and \( C_{21} = 0 \). If \( C_1 \neq C_2 \), then \( C_{12} = \frac{C_2-C_1}{\|C_1-C_2\|} \) and \( C_{21} = \frac{C_1-C_2}{\|C_1-C_2\|} \).

Secondly, the crosspoints of \( G \) and \( G_1 \) are \( P_1 = C_1 - C_{12}r_1 \) and \( P_2 = C_1 + C_{12}r_1 \). The crosspoints of \( G \) and \( G_2 \) are \( Q_1 = C_2 - C_{21}r_2 \) and \( Q_2 = C_2 + C_{21}r_2 \).

Thirdly, the center \( C \) and granularity \( R \) of the union hyperdiamond granule \( G \) is computed by algorithm 2.

**Algorithm 2. Computing \( C \) and \( R \) of union hyperdiamond granule \( G \) between hyperdiamond granule \( G_1 \) and hyperdiamond granule \( G_2 \)**

**Input:** \( G_1 = (C_1, r_1) \) and \( G_2 = (C_2, r_2) \)

**Output:** \( G = (C, R) \)

**if** \( n_1 \geq n_2 \)

**if** \( d(C_1, C_2) \leq r_1 - r_2 \)

\( C = C_1 \)

\( R = r_1 \)

**else**

\( C = (P_1 + Q_1)/2 \)

\( R = d(P_1, Q_1)/2 \)

**end**

**else**

\( C = C_2 \)

\( R = r_2 \)

**else**

\( C = (P_1 + Q_1)/2 \)

\( R = d(P_1, Q_1)/2 \)

**end**

Figure 4 shows the union process of the hyperdiamond granule \( G_1 = (0.2, 0.15, 0.1) \) and the hyperdiamond granule \( G_1 = (0.1, 0.2, 0.1) \). The crosspoints of hyperdiamond granule \( G_1 \) and the line crossing vector \( C_{12} = (-0.6667, 0.3333) \) are \( P_1 = (0.2667, 0.1167) \) and \( P_2 = (0.1333, 0.1833) \). The crosspoints of hyperdiamond granule \( G_2 \) and the line crossing vector \( C_{21} = (0.3333, -0.6667) \) are \( Q_1 = (0.0333, 0.2333) \) and \( Q_2 = (0.1667, 0.1667) \). According to algorithm 1, the central vector and granularity of the union hyperdiamond granule \( G \) are \( C = (0.15, 0.175) \) and \( R = 0.175 \), namely \( G = (0.15, 0.175, 0.175) \).

**Image segmentations by GrCC**

RGB is an additive color model in which red, green, and blue light is added together in various ways to reproduce a broad array of colors. Given a color image represented by RGB, image segmentation by GrCC includes the following steps.

Firstly, the data set \( S \) is formed by the pixel values. Secondly, the algorithm GrCC is performed on the data set \( S \). Thirdly, the pixel value is replaced by its cluster center.

**Algorithm 3. Image segmentation by GrCC**

**Input:** the image \( I \) including \( n_1 \) rows and \( n_2 \) columns, the user-defined parameter \( \rho \) of GrCC

**Output:** the segmented image

S1. for \( i = 1:n_1 \)
S2. for \( j = 1:n_2 \)
S3. form the data set \( S \) including the RGB value \( x \) of the pixel \( (i, j) \)
S4. perform algorithm 1, and achieve the center of GrCC
S5. the color vector of the pixel \( (i, j) \) is replaced by center of the granule including data \( x \)
S6. end for \( j \)
S7. end for \( i \)
Figure 5. GCE, VI, and RI of image #135069 selected from BSD300 for different parameter $\rho$. 
Experiments

In order to verify the superiority of image segmentation by GrCC, we compared the proposed segmentation by GrCC with segmentations by Kmeans and FCM, and all the experiments are performed in the same environment, such as Intel PIV PC with 3.2 GHz CPU and 8 GB memory, Microsoft Windows7 and Matlab2008. The performance includes GCE, VI, and RI between the segmentation by human and the segmentation by algorithm. GrCC induced by the distance formula (1) is called as GrCC1, GrCC induced by the distance formula (2) is called as GrCC2, and GrCC induced by the distance formula (3) is called as GrCC3.

Firstly, we select an image (#135069) to compare the segmentation by GrCC with the segmentation by human. For the selection of parameter \( q \), we set \( q \) from 200 to 50 with step 1. The best quantitative assessment values of GCE, VI, and RI and the parameters

Figure 6. Segmentations of image #135069 by GrCC3 under different evaluations.

Figure 7. Segmentations of image #3096 by GrCC3 under different evaluations.
performed the best quantitative assessment values are listed in Table 1. In the table, \( \rho \) represents the parameter of GrCC, \( K \) is the clustering number of FCM and Kmeans. From the table, we can see, the segmentation images obtained by GrCC are closer to the artificial segmentation images than these obtained by FCM and Kmeans because the segmentation images by GrCC have the small GCE, the small VI, and large RI compared with the segmentation images by FCM and Kmeans. For the GrCC algorithms, the GrCC3 is better than GrCC1 and GrCC2.

Figure 5 shows the curve of the evaluation index along with the parameters for GrCC3. From the figure, we can see, there is a mutation point making the evaluation performance of segmented images optimal. The mutation point is the selected granularity threshold \( \rho \). Figure 6 shows the optimal segmented images by GrCC3 evaluated by GCE, VI, and RI. Figure 6(a) shows the segmented image by human, Figure 6(b) shows the segmented image with the minimal GCE by GrCC3, Figure 6(c) shows the segmented image with the minimal VI by GrCC3, and Figure 6(d)
shows the segmented image with the maximal RI by GrCC3.

Secondly, images in BSD300 (www.eecs.berkeley.edu/Research/Projects/CS/vision/bbsd/), which includes original color images and their human segmentations, is selected to perform segmentations by GrCC. images, such Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, are used to evaluate the performance of GrCC3 because segmentation by GrCC3 is better than Kmeans and FCM, and Kmeans.

![Figure 10. Segmentations of image #113016 by GrCC3 under different evaluations.](image)

![Figure 11. Segmentations of image #12003 by GrCC3 under different evaluations.](image)

**Conclusions**

A new evaluation of segmentation of color image is used to evaluate the segmentation from the view of set, and the images selected from BSD300 are used to demonstrate the feasibility and superiority of the evaluations. The segmentation experimental results shown that (1) GrCC segmentation is better than Kmeans and FCM from the aspects of GCE, VI, and RI. (2) GrCC with the distance formula (3) is better than GrCC with
the distance formulas (1) and (2). Some issues still need further study, such as the adaptive selection of granularity threshold $\rho$. In this paper, the benchmark image segmentation set, BSD300, is used to verify the feasibility and superiority of GrCC, image target detected by GrCC will be the future research field.

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