Research on the Image Segmentation Quality Assessment Based on Fuzzy Clustering Algorithm

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Abstract

Human are very familiar with images. Image can be captured by optical imaging or human vision system. There is a saying "One picture is worth a thousand words". This means that image contains much information about the things represented by it. With the development of computer technology, digital image technology has been widely used in science research, industry, medical treatment, education, entertainment and communication. Therefore, the research on image technology is of great significance. In this paper, we investigate the problems for evaluating the image segmentation quality with triangular fuzzy information. We utilize the triangular fuzzy weighted average (TFWA) operator to aggregate the triangular fuzzy information corresponding to each alternative and get the overall value of alternatives, then rank the alternatives and select the most desirable one(s) by using the formula of the degree of possibility for comparison between two triangular fuzzy variables. Finally an illustrative example has been given to show the developed approach.

Keywords

Quality Assessment, Triangular Fuzzy Information, Triangular Fuzzy Weighted Average (TFWA) Operator, image segmentation quality.

1. Introduction

With the development of electronic technology and computer technology, digital image technologies are widely used in the field of digital television, digital video camcorders, digital cameras and other digital products. People's need for digital image processing is increasing, In order to meet people's need, to achieve a definite purposes, people pay more attention to the research of the special treatment of the image. hese special processing includes to repairing the damaged parts of images, it makes the restored image close to or reach to the effects original image, it is called as image inpainting. It also includes the technology which can separate the target and background, it is called image segmentation. Image inpainting is to restore the missing or damaged portions of the image in order to make it more legible and to restore its unity in a way that is non-detectable for an observer who does not know the original image. Currently, digital inpainting techniques have found broad applications in image processing, vision analysis, digital restoration of ancient paintings for conservation purposes, text removal and objects removal in images for special effects, restoration of old photographs or films with scratches or ancient paintings for conservation purposes, text removal and objects removal in images for special effects, restoration of old photographs or films with scratches or missing patches, occlusion in computer vision, errors conceal in videos, and so on. Therefore people pay more attention on image inpainting, digital image inpainting technique is becoming an important subject of research academia.In the image processing and image analysis research and application areas, image segmentation is a fundamental and key technology. Image segmentation is to separate the target and background, on this basis, it is possible to further analysis and use of targets, it provides an important basis for the follow-up treatments. The results of its analysis or processing will directly affect the subsequent processing of information. So we say that image segmentation is an important part and key steps from image processing to image analysis. Therefore, study image inpainting and image segmentation is so significance to further development of the theory for digital image processing and further expand the application field of image processing.

There are numerous approaches and applications for unsupervised image segmentation in computer vision. Many different theories are proposed for varying the roles of the unsupervised segmentation. As a low level vision problem, an image can be simplified by oversegmentation using a number of different approaches, such as mode-seeking mean shift, multilevel thresholding, histogram-based neural networks, superpixel algorithms, and various graph-based methods [1–4]. Conversely, semantic segmentation is attempted for simultaneous detection, recognition, and segmentation [5]. Generally, the role of unsupervised segmentation falls between image simplification and full semantic segmentation, where semantically meaningful segments are expected to be found but not necessarily recognized. Segmentation is posed as an image-coloring problem that minimizes specific energy functions. Energy functions can be optimized using stochastic methods such as deterministic annealing and stochastic clustering [6–10]. For graph theoretic segmentation approaches, the spectral method and graph cut are efficient deterministic optimization methods [11–13]. Another traditional segmentation method is the variational method, which evolves boundary contours in a level set framework [14, 15].

The aim of this paper is to develop the appraisal model of the image segmentation quality with triangular fuzzy information. The remainder of this paper is set out as follows. In the next section, we introduce some basic concepts related to triangular fuzzy variables. In Section 3 we introduce the problem deal with appraisal model of image segmentation quality with triangular fuzzy information, in which the information about attribute weights is completely known, and the attribute values take the form of triangular fuzzy information. Then, we utilize the triangular fuzzy weighted average (TFWA) operator to aggregate the triangular fuzzy information corresponding to each alternative and get the overall value of the alternatives, then rank the alternatives and select the most desirable one(s) by using the formula of the degree of possibility for the comparison between two triangular fuzzy variables. In Section 4, an illustrative example is pointed out. In Section 5 we conclude the paper and give some remarks.

2. Preliminaries

In this section, we briefly describe some basic concepts and basic operational laws related to triangular fuzzy numbers.

Definition 1[16-17]. Let $\tilde{a}_j = \left[a_j^L, a_j^M, a_j^U\right]\left(j=1,2,\cdots,n\right)$ be a collection of triangular fuzzy numbers,

$$\begin{aligned}\mathrm{TFWA}_w\left(\tilde{a}_1,\tilde{a}_2,\cdots,\tilde{a}_n\right) &= \mathop{\oplus}_{j=1}^{n} w_j\tilde{a}_j \\ &= \left[\sum_{j=1}^{n} w_j a_j^L, \sum_{j=1}^{n} w_j a_j^M, \sum_{j=1}^{n} w_j a_j^U\right]\end{aligned} \tag{1}$$

where $\omega=\left(\omega_1,\omega_2,\cdots,\omega_n\right)$ is the weighting vector of triangular fuzzy numbers $\tilde{a}_j\left(\tilde{a}_j=\left[a_j^L,a_j^M,a_j^U\right]\right)\left(j=1,2,\cdots,n\right)$ with $\omega_j\in\left[0,1\right], \sum_{j=1}^{n}\omega_j=1$, then function TFWA is called the triangular fuzzy weighted average (TFWA) operator of dimension n.

Definition 2[18]. Let $\tilde{b}=\left[b^L,b^M,b^U\right]$ and $\tilde{a}=\left[a^L,a^M,a^U\right]$ be two triangular fuzzy numbers, then the degree of possibility of $a \ge b$ is defined as

$$p(a \ge b) = \lambda \max\left\{1 - \max\left[\frac{b^M - a^L}{a^M - a^L + b^M - b^L}, 0\right], 0\right\} + (1-\lambda)\max\left\{1 - \max\left[\frac{b^U - a^M}{a^U - a^M + b^U - b^M}, 0\right], 0\right\} \quad (2)$$

where the value λ is an index of rating attitude. It reflects the decision maker's risk-bearing attitude. If $\lambda > 0.5$, the decision maker is risk lover. If $\lambda = 0.5$, the decision maker is neutral to risk. If $\lambda < 0.5$, the decision maker is risk avertor.

From Definition 2, we can easily get the following results easily:

(1) $0 \le p(a \ge b) \le 1, 0 \le p(b \ge a) \le 1$;

(2) $p(a \ge b) + p(b \ge a) = 1$. Especially, $p(a \ge a) = p(b \ge b) = 0.5$.

3. Research on the Image Segmentation Quality Assessment Based on Fuzzy Clustering Algorithm

In recent years, digital image processing has been a top object of study and research in the field of information science, computer science, biomedicine, military science, even social science. Image segmentation is very critical and essential to digital image processing, computer vision and pattern recognition. The quality of image segmentation determines the quality of the final result of image analysis and image understanding. Image segmentation problem can be modeled as different mathematical models, then using different optimization methods to solving it. Recently, immune clonal selection optimization is a new hotspot and new area of research in artificial intelligence researcher. Inspired by biological immune systems which contains a wealth of information processing mechanisms and functions, immune clonal selction optimization may provide novel solutions and approaches to the problem of image segmentation. At present, spectral clustering is widely used in pattern recognition. Compared with traditional clustering, it can group the non-convex and serious overlapping data sets. However, applying it to image segmentation are still several difficulties. In this paper, we investigate the problems for evaluating the image segmentation quality with triangular fuzzy information. We utilize the triangular fuzzy weighted average (TFWA) operator to aggregate the triangular fuzzy information corresponding to each alternative and get the overall value of alternatives, then rank the alternatives and select the most desirable one(s) by using the formula of the degree of possibility for comparison between two triangular fuzzy variables. Let $A = \{A_1, A_2, \cdots, A_m\}$ be a discrete set of alternatives, and $G = \{G_1, G_2, \cdots, G_n\}$ be the set of attributes, $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$ is the exponential weighting vector of the attributes $G_j\,(j = 1, 2, \cdots, n)$, where $\omega_j \in [0,1], \sum_{j=1}^{n} \omega_j = 1$. Suppose that $\tilde{R} = (\tilde{r}_{ij})_{m\times n} = [r_{ij}^L, r_{ij}^M, r_{ij}^U]_{m\times n}$ is the decision matrix, where $\tilde{r}_{ij}$ is a preference value, which takes the form of triangular fuzzy numbers, given by the decision maker for the alternative $A_i \in A$ with respect to the attribute $G_j \in G$.

In the following, we apply the TFWA operator for evaluating the image segmentation quality with triangular fuzzy information.

Step 1. Utilize the decision information given in matrix $\tilde{R}$, and the TFWA operator

$$\tilde{r}_i = \mathrm{TFWA}_\omega(\tilde{r}_{i1}, \tilde{r}_{i2}, \cdots, \tilde{r}_{in}),\ i = 1, 2, \cdots, m. \quad (3)$$

to derive the collective overall preference values $\tilde{r}_i\,(i = 1, 2, \cdots, m)$ of the alternative A_i ,where $\omega = (\omega_1, \omega_2, \cdots, \omega_n)^T$ is the weighting vector of the attributes.

Step 2. To rank these collective overall preference values $\tilde{r}_i\left(i=1,2,\cdots,m\right)$, we first compare each $\tilde{r}_i$ with all the $\tilde{r}_j\left(j=1,2,\cdots,m\right)$ by using (2). For simplicity, we let $p_{ij}=p\left(\tilde{r}_i\geq\tilde{r}_j\right)$, then we develop a complementary matrix as $P=\left(p_{ij}\right)_{m\times m}$ and sum all the elements in each line of matrix P, we have $p_i=\sum_{j=1}^{m}p_{ij}, i=1,2,\cdots,m$.

Step 3. Rank all the alternatives $A_i\left(i=1,2,\cdots,m\right)$ and select the best one(s) in accordance with $p_i\left(i=1,2,\cdots,m\right)$.

4. Illustrative Example

Image segmentation is a process of dividing an image into different regions such that region of interest, but the union of any two adjacent regions isn't homogeneous. Image segmentation is the first step and preprocess in image understanding and object recognition. The basic development process of image segmentation is as follows: the early classical image segmentation algorithms based on image intensity and gradient, the eighties active contour models, the image segmentation algorithms with prior knowledges, color image segmentation. From the development process of image segmentation, we can observe that the machine intelligence and pattern recognition ability of the image segmentation become better and better.The thesis mainly aims at researching the related task of image segmentation, object segmentation including in computer vision. The image segmentation task is to divide the image into a plurality of regions with similar characteristics as the basis, the results of image segmentation is the foundation of image understanding and object recognition, it can also be understood as the primary stage of image understanding and object recognition. In image segmentation, fusing together the consistency of image space and unsupervised clustering algorithm to perform image segmentation process by constructing a probability tree structure, proposing the global segmentation method of vector valued image by constructing the edge detection operator of vector valued image, putting forward a new model of variational form and calculation method of vector valued image with convex property, the level set is applied to a new color image segmentation process, eventually. In the part of image preprocessing, improving and enhancing the existing visual saliency metric method, putting forward the improved visual saliency metric method and multi-scale visual saliency detection algorithm, and applying the improved image preprocessing methods into image segmentation. In the basic methods of image segmentation and object segmentation, putting forward the incremental support vector machine learning methods, including the online incremental learning and online reduction learning method; the incremental support vector machine learning method proposing the variable learning support vector machine, including the incremental learning algorithms and decremental learning algorithms based on the variable learning support vector machine; variable learning support vector machine is improved to adaptive variable learning support vector machine, and these improved support vector machine theories in image segmentation and object segmentation for applied research.. This section presents a numerical example to illustrate the method proposed in this paper. Suppose a company plans to evaluate the image segmentation quality. The experts selects four attribute to evaluate the five possible image segmentation alternatives: ①G1 is the functionality and reliability; ②G2 is the efficiency; ③G3 is the easiness to use; ④G4 is the maintainability and transferability. The five possible image segmentation alternatives $A_i\left(i=1,2,3,4,5\right)$ are to be evaluated by using the triangular fuzzy numbers by the three decision makers under the above four attributes, and construct, respectively, the decision matrices as listed in the following matrices $\tilde{R}_k=\left(\tilde{r}_{ij}^{(k)}\right)_{5\times 4}\left(k=1,2,3\right)$ is shown in Table 1.

Table 1. Decision matrix $\tilde{R}$

	G_1	G_2	G_3	G_4
A_1	(0.43,045,0.48)	(0.43,0.46,0.51)	(0.61,0.67,0.73)	(0.53,0.57,0.62)
A_2	(0.28,0.29,0.32)	(0.38,0.39,0.42)	(0.56,0.57,0.59)	(0.68,0.69,0.73)
A_3	(0.45,0.47,0.48)	(0.64,0.66,0.68)	(0.66,0.67,0.69)	(0.71,0.74,0.75)
A_4	(0.65,0.66,0.67)	(0.68,0.69,0.73)	(0.73,0.76,0.80)	(0.78,0.79,0.83)
A_5	(0.64,0.66,0.69)	(0.65,0.68,0.71)	(0.89,0.90,0.93)	(0.79,0.80,0.86)

To get the most desirable image segmentation alternative, the following steps are involved:

Step 1. We utilize the decision information given in matrix R, and the TFWA operator which has associated attribute weight vector $\omega=\left(0.20,0.40,0.10,0.30\right)^T$ to obtain the overall preference values $\tilde{r}_i$ of the image segmentation alternatives $A_i\left(i=1,2,3,4,5\right)$. The results are shown in Table 2.

Table 2. The overall preference values of the image segmentation alternatives

A_1	A_2	A_3	A_4	A_5
(0.74,0.78,0.83)	(0.76,0.78,0.81)	(0.84,0.86,0.89)	(0.71,075,0.78)	(0.76,078,0.82)

Step 2. According to the aggregating results shown in Table 2 and the formula of degree of possibility (1), the ordering of the alternatives are shown in Table 3. Note that > means "preferred to". As we can see from Table 3, Thus the most desirable image segmentation alternative is A_3.

Table 3. Ordering of the image segmentation alternative by utilizing the TFWA operator

	Ordering
TFWA	$A_3 > A_5 > A_2 > A_4 > A_1$

5. Conclusion

In recent years, because of the ability to acquire images under all-time and all-weather conditions, synthetic aperture radar (SAR) has become an important tool for remote sensing based earth observation. SAR image segmentation and classification are fundamental problems for SAR image processing and interpretation, playing a key role in putting SAR techniques into practical applications. Therefore, it is worthy for studying the theories and methods of SAR image segmentation and classification. One major trend in the development of SAR imaging techniques is the constantly improvement of the spatial resolution. High-resolution(HR) SAR images are able to provide rich ground information. Meanwhile, new problems are also put forward for SAR image segmentation and classification. Compared to low- and middle-resolution SAR images, HR SAR images have unique characteristics: the statistical properties change, texture patterns present in the image, the scenes become very complex, and the data amount is huge. Segmentation and classification methods that are applicable for low and middle resolution SAR images are not able to cope with HR SAR images due to aforementioned characteristics. In this paper, we investigate the problems for evaluating the image segmentation quality with triangular fuzzy information. We utilize the triangular fuzzy weighted average (TFWA) operator to aggregate the triangular fuzzy information corresponding to each alternative and get the overall value of alternatives, then rank the alternatives and select the most desirable one(s) by using the formula of the degree of possibility for comparison between two triangular fuzzy variables. Finally an illustrative example has been given to show the developed approach.

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