

# A Fuzzy Reasoning Method for Multi-views Image Registration

Tianzhen DONG

Laboratory of Fuzzy Information Analysis and Intelligent Recognition, Harbin Engineering University, Harbin, China  
Email: dongtianzhen@hrbeu.edu.cn

Tingquan DENG<sup>a</sup> Jiashu DAI<sup>a</sup> Wei XIE<sup>a</sup> Jinhong YANG<sup>a</sup> Qiang FU<sup>b</sup>

a. Laboratory of Fuzzy Information Analysis and Intelligent Recognition, Harbin Engineering University, Harbin, China

b. Agricultural Electricity Bureau of Naiman District, Tongliao Inner Mongolia, China

Email: {tq\_deng, daijiashu2008, xiaoguantingran, yangjinhong.66, fuqiang.nm}@163.com

**Abstract**—Image registration is the key of target measurement, pattern recognition and computer vision. In view of characteristics of images from spatial multi-views, the principle of coarse-to-fine is used to study the registration of multi-view images. Based on image segmentation, taking uncertainty of information from multi-view images into consideration, we regard robust regional features including area, dominant hue, n-order geometric moments as descriptors of connected regions and then fuzzify the connected regions. By introducing fuzzy implication, matching degree between connected regions in multi-views images is calculated. Then the best matching relation between connected regions is built via fuzzy reasoning. Finally, the feedback correction is used to matching relationship between feature points of connected regions. Then the adaptive accurate registration between multi-view images is achieved. The validity of proposed method is demonstrated through experiments.

**Index Terms**—image registration, fuzzy implication, computer vision, pattern recognition

## I. INTRODUCTION

Image registration is the important foundation of multi-view image processing and fusion, object detection and recognition and computer vision. Recently, many researchers have studied on image registration and alignment of medical images, large-scale scene images and satellite remote sensing images. The basic idea is to detect feature information of different viewpoint images, calculate the similarity measures among the selected features and establish the feature matching relationship and transformation model between different viewpoint images[1-13]. Due to the diversity of images to be processed, incompleteness of information and other factors, as well as the different applications, the present registration methods mainly have been based on feature points, line segments and regions, and thus both the complexity of process and results of registration also have greatly difference. Lowe utilized the invariant feature of points in image, such as rotation invariance, translation invariance and scale invariance to match gray

images[14]. Eric et al, introduced the global texture description vector  $G$  into the original SIFT feature vector  $L$ , and used  $\omega$  to adjust the weight of the  $L$  and  $G$ , thus achieved image registration using global information[15]. Since this method has been taken account of not only local neighbourhood information of feature points but also extracted the global texture characteristics, the matching had a relative reasonableness. According to transformation model for color images formed by Von Kries, Wu et al established color invariant space, used SIFT algorithm to achieve the feature point detection in this space, obtained the corresponding matching between feature points based on second-order local differential model(LDP) and RANSAC algorithm and established the transform relationship between all multi-view images[16]. These image registration methods based on feature points have better results on rotating and zooming images, but they have been difficult to achieve precise registration on image deformation such as twisting and flipping. Moreover, the distribution of feature points will be influenced by object structure and texture which causes the transform unreasonable. Due to the deformation rule between different viewpoint images matching based on line segment is difficult to grasp, therefore has not an effective image registration method based on line segment. Peter et al, proposed a multi-mode image registration method based on multi-resolution regional features[17]. Ming et al, established matching relationship between regions using regional SIFT descriptors[18]. Zhen et al, achieved region matching accorded to the collaborative optimization between regions and invariant moments[19, 20]. These region-based registration methods have better results on translation, rotation and scaling of rigid body, however, when targets appear distorted in different viewpoint images or non-rigid deformation, the matching errors are larger.

This paper combines characteristics of space multi-view images and mutual relationship, based on the usage of image segmentation divide the image into some connected regions, extract robust region features of connected regions including region's area, shape eccentricity, dominant hue, n-order geometric moments, and then fuzzify these features. Meanwhile, by introducing fuzzy implication, fuzzy matching degree

Supported by the Natural Science Foundation of Inner-Mongolia Autonomous Region China under grant 2012M0931.

Corresponding author: DONG Tianzhen

E-mail: dongtianzhen@hrbeu.edu.cn

between connected regions in different viewpoint images is calculated, so as to get the best match between regions. Finally, the matched feature points between connected regions matched each other are used to feedback correction and fitting establish spatial transform relationship between connected regions, thus achieved the precise registration between different viewpoints images. The method provided a theoretical basis for multi-view color image registration, also has important theoretical and practical significance in the field of underwater object tracking, military surveillance and virtual scene reconstruction, etc.

## II. CONNECTED REGION MATCHING BASED ON FUZZY REASONING

### A. Basic Operations of Fuzzy Logic

Fuzzy set theory and fuzzy logic are efficient mathematical tools to solve uncertainty problems and play important roles in image processing, machine vision and intelligent control.

Suppose that  $T$  is the binary function on  $[0,1]$  satisfying, for arbitrary  $r, s, t \in [0,1]$ , if

- a)  $T(s, t) = T(t, s)$
- b)  $T(r, T(s, t)) = T(T(r, s), t)$
- c) If  $s \leq t$ , then  $T(r, s) \leq T(r, t)$
- d)  $T(1, s) = s$

then  $T$  is called a triangular norm, briefly t-norm. Both  $T(s, t) = \min(s, t)$  and  $T(s, t) = \max(0, s+t-1)$  are two usually used t-norms[21].

Fuzzy implication is the basis and important component of fuzzy logic and fuzzy reasoning. Fuzzy implication is the generalization and fuzzification of classic logical implication which can be characterized by a binary function on  $[0,1]$ . It is non-increasing with respect to the first variable and non-decreasing about the second variable. In theories and applications, fuzzy implication and t-norm  $T$  are normally contacted by the following form

$$I(s, t) = N(T(s, N(t))) \tag{1}$$

$$I(s, t) = \sup\{r \in [0,1] | T(s, r) \leq t\} \tag{2}$$

Where  $N(x)$  is the negation of  $x$ , usually  $N(x) = 1 - x$ . Then (1) and (2) are respectively called the negative implication and residual implication of t-norm  $T$ , denoted by  $I_S$  and  $I_R$ .

Let  $U$  be a non-empty set called university of discourse. A fuzzy set on  $U$  is determined by a mapping  $\mu$  from  $U$  to  $[0, 1]$ . For arbitrary  $x \in U$ ,  $\mu_F(x) \in [0, 1]$ , briefly denoted by  $F(x)$ , indicates the degree of  $x$  belonging to fuzzy set  $F$ .

The degrees of intersection and inclusion of two fuzzy sets can be quantitatively described by t-norm and fuzzy implication. Assume that  $F_1$  and  $F_2$  are two fuzzy sets on university  $U$ , the intersection degree between  $F_1$  and  $F_2$  is

$$\bigwedge_{x \in U} T(F_1(x), F_2(x)) \tag{3}$$

Meanwhile, the inclusion degree of  $F_1$  in  $F_2$  is defined by

$$\bigwedge_{x \in U} I(F_1(x), F_2(x)) \tag{4}$$

Thus,  $\bigwedge_{x \in U} I(F_1(x), F_2(x)) \wedge \bigwedge_{x \in U} I(F_2(x), F_1(x))$ , namely

$$\bigwedge_{x \in U} (I(F_1(x), F_2(x)) \wedge I(F_2(x), F_1(x)))$$

can characterize the degree of fuzzy set  $F_1$  equal to  $F_2$ , where t-norm  $T$  can be selected flexibly according to actual needs and the negative implication or residual implication of  $T$  is selected as the fuzzy implication.

### B. The Basic Features of Connected Regions and Their Fuzzy Analysis

Several connected regions of irregular shape are obtained by using some kind of image segmentation method to the multi-view images. Due to the influence of observation views and illumination the corresponding connected regions after segmentation are not completely the same between multi-view images. The robust regional features including area, shape eccentricity, dominant hue and n-order geometric moments are selected as the descriptors of connected regions in this paper. A method of fuzzy reasoning is introduced to match the connected regions in multi-view images.

The total number of pixels in a connected region is regarded as its area. The feature of area is fuzzified using fuzzy linguistic variables (fuzzy sets) such as smaller, small, medium, large and larger. Assume that the minimum and maximum areas of connected regions are  $S_{min}$  and  $S_{max}$  respectively, the area is fuzzified to  $m_s$  fuzzy linguistic variables. Taking the relative local stability of connected regions into account, we characterized each fuzzy set by a trapezoidal fuzzy number, namely

$$\lambda(s) = \begin{cases} \frac{m_s(s-S_{Min})}{S_{Max}-S_{Min}} - i & S_{Min} + Max[0, \frac{(i-1)(S_{Max}-S_{Min})}{m_s}] < s < S_{Min} + \frac{i(S_{Max}-S_{Min})}{m_s} \\ 1 & S_{Min} + \frac{i(S_{Max}-S_{Min})}{m_s} \leq s \leq S_{Min} + \frac{(i+1)(S_{Max}-S_{Min})}{m_s} \\ \frac{-m_s(s-S_{Max})}{S_{Max}-S_{Min}} + (i+2) & S_{Min} + \frac{(i+1)(S_{Max}-S_{Min})}{m_s} < s < S_{Min} + Min[\frac{S_{Max}-S_{Min}}{m_s}, \frac{(i+2)(S_{Max}-S_{Min})}{m_s}] \\ 0 & Otherwise \end{cases} \tag{5}$$

In the above formula  $s$  means the area of connected regions,  $i$  is the label of fuzzy sets and  $i = 0, 1, \dots, m_s - 1$ . We take the case of  $m_s = 5$  for example and the fuzzy sets are illustrated in Figure 1.

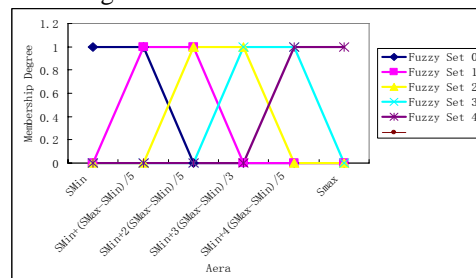


Fig.1 Five trapezoidal fuzzy sets corresponding to the area of connected regions.

The fitting elliptical eccentricity is defined as the shape eccentricity of connected regions which can characterize the region shape objectively. The shape eccentricity of connected regions is fuzzified into  $m_e$  fuzzy linguistic variables (fuzzy sets) such as relatively oblate, oblate, relatively round and round. The feature of  $n$ -order geometric moments of connected regions with translational and rotational invariance reflects the regional information distribution objectively. The 2-order

geometric moment is generally utilized which can be divided into  $m_m$  fuzzy linguistic variables (fuzzy sets). We can fuzzify the 2-order geometric moment to five fuzzy linguistic variables such as smaller, small, medium, large and larger.

The dominant hue of connected regions means the average hue level of pixels in each connected region. The dominant hue is represented by  $m_c$  fuzzy linguistic variables (fuzzy sets), namely  $F_l^c$  ( $l=0, \dots, m_c-1$ ), such as red, yellow, green, cyan, blue and brown according to human's vision. To guarantee the relative stability of region hue, the trapezoidal fuzzy number is adopted to characterize each fuzzy set. Here we take the description of six dominant hues (namely red, yellow, green, cyan, blue and brown) as example and the membership functions of fuzzy sets are showed in Figure 2. Note that the first fuzzy set, representing *red* is composed of two parts.

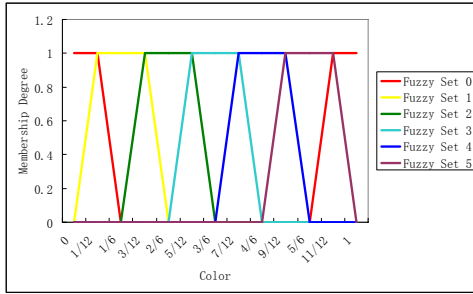


Fig.2 Six trapezoidal fuzzy sets corresponding to the dominant hue of connected regions

For connected regions in multi-view images the membership values of each region to the corresponding fuzzy sets are calculated respectively according to their area, dominant hue, shape eccentricity and  $n$ -order geometric moments.

C. Fuzzy Matching between Connected Regions

Due to the uncertainty of the corresponding regional evolution between multi-view images, fuzzy implication is introduced to calculate the similarity degree between connected regions according to the fuzzified features such as area, shape eccentricity, dominant hue and  $n$ -order geometric moments. Then the similarity degree of two connected regions can be measured objectively via the proposed fuzzy implication.

Assume that  $R_A$  and  $R_B$  are connected regions, the fuzzy similarity degrees with respect to the area, shape eccentricity, dominant hue, and  $n$ -order geometric moment between  $R_A$  and  $R_B$  are respectively defined as follows

$$r^s(R_A, R_B) = \bigwedge_{i=0}^{m_s-1} [I(F_i^s(R_A), F_i^s(R_B)) \wedge I(F_i^s(R_B), F_i^s(R_A))] \quad (6)$$

$$r^e(R_A, R_B) = \bigwedge_{j=0}^{m_e-1} [I(F_j^e(R_A), F_j^e(R_B)) \wedge I(F_j^e(R_B), F_j^e(R_A))] \quad (7)$$

$$r^c(R_A, R_B) = \bigwedge_{k=0}^{m_c-1} [I(F_k^c(R_A), F_k^c(R_B)) \wedge I(F_k^c(R_B), F_k^c(R_A))] \quad (8)$$

$$r^m(R_A, R_B) = \bigwedge_{l=0}^{m_m-1} [I(F_l^m(R_A), F_l^m(R_B)) \wedge I(F_l^m(R_B), F_l^m(R_A))] \quad (9)$$

After calculating the fuzzy similarity degrees of all features between two regions, the similarity degree between two regions is considered as the compositions of all fuzzy similarities. To fuse all similarities, we take

their weighted multiplication as the fuzzy similarity degree between connected regions  $R_A$  and  $R_B$  formulas follows

$$r(R_A, R_B) = [r^s(R_A, R_B)]^{w_s} \cdot [r^e(R_A, R_B)]^{w_e} \cdot [r^c(R_A, R_B)]^{w_c} \cdot [r^m(R_A, R_B)]^{w_m} \quad (10)$$

Where  $w_s, w_e, w_c, w_m$  denote weighted indexes of the four previous features, which are used to balance the importance between four features.

Two connected regions with the largest similarity degree in multi-view images are regarded as the optimally matching connected regions. Thus, we can reason the best matching region  $R_i^o$  in images to be registered corresponding to the connected region  $R_i^s$  in original image. Namely that

$$R_i^o = \arg \underset{R_q^o}{Max} [r(R_i^s, R_q^o)] \quad (11)$$

$M$  in (12) is the number of connected regions in images to be registered. Conversely, for each connected region  $R_i^o$  in images to be registered its matching connected region  $R_{tr}^s$  in original image can be obtained in a similar way. If and only if connected regions  $R_i^s$  and  $R_{tr}^s$  indicate the same region, we say that  $R_i^s$  and  $R_i^o$  are mutual matching connected regions.

There may be the dilemma that any mutual matching regions couldn't be found for several connected regions between original image and its candidate registration images due to the influence of factors such as the illumination, the angle of view and the target depth of field. These regions unable to match are finally emerged into their adjacent regions with a long boundary which have been matched already. Then the registration of connected regions between multi-view images is achieved.

III. MULTI-VIEWS IMAGE REGISTRATION

Based on connected regional matching, we firstly extract the corners and inflections on edges as well as the local extremes within regions as feature points. Then, Gaussian multi-scale analysis method is used to create the matching relations between feature points and establish the space transform between regions[14]. In theory, the space transform between connected regions  $T_p$  consists of a series of affine transforms rather than a simple space transform due to the effects of camera site, the depth of objects, equipment error and so on.

A spatial transform between two pixels is presented for each connected region as follows:

$$X_o = T_p X_s \quad (12)$$

where  $X_s=(x_s, y_s, 1)^T$  and  $X_o=(x_o, y_o, 1)^T$  stand for pixel coordinates of the original image and the image for registration respectively. Since an image is a two-dimension surface, the transform matrix  $T_p$  forms as

$$T_p = \begin{pmatrix} t_{00} & t_{01} & t_{02} \\ t_{10} & t_{11} & t_{12} \\ 0 & 0 & 1 \end{pmatrix} \quad (13)$$

By considering the nonlinear characteristic of real spatial transform and computational complexity, the

elements in transform matrix  $T_P$  are taken as the one-order polynomials with respect to  $x_s, y_s$ :  $t_{ij}(x_s, y_s) = a_{ij}x + b_{ij}y_s + c_{ij}$ .

Thus, the transform from  $X_s$  to  $X_o$  is expressed as

$$\begin{pmatrix} x_o \\ y_o \\ 1 \end{pmatrix} = T_P \bullet \begin{pmatrix} x_s \\ y_s \\ 1 \end{pmatrix} = T_A \bullet \begin{pmatrix} x_s \\ y_s \\ 1 \end{pmatrix} + T_E \quad (14)$$

where  $T_A = \begin{pmatrix} a_{02} + c_{00} & b_{02} + c_{01} & c_{02} \\ a_{12} + c_{10} & b_{12} + c_{11} & c_{12} \\ 0 & 0 & 1 \end{pmatrix}$  determines

the affine transform, and  $T_E$  is the correction term for a connected region defined as

$$T_E = \begin{pmatrix} (x_s & y_s & 1) \\ (x_s & y_s & 1) \\ 0 \end{pmatrix} \begin{pmatrix} \frac{a_{01} + b_{00}}{2} & 0 & 0 \\ \frac{a_{01} + b_{00}}{2} & b_{01} & 0 \\ 0 & 0 & 0 \\ \frac{a_{11} + b_{10}}{2} & 0 & 0 \\ \frac{a_{11} + b_{10}}{2} & b_{11} & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_s \\ y_s \\ 1 \\ x_s \\ y_s \\ 1 \end{pmatrix}$$

Based on the matching relations between feature points ( $P_{sk}, P_{ok}$ ), the transform matrix  $T_A, T_E$  for connected regions of multi-view images are fitted by minimizing the error function  $E(A)$ , that is

$$\min[E(A)] = \min[\sum_{k=0}^N \|P_{Ok} - T_P \bullet P_{Sk}\|] \quad (15)$$

where  $N$  is the number of matched pair of feature points in the connected region.

In fact, the feature point matching process inevitably exist the matching error. In order to reduce this error, bidirectional transformation and feedback compensation is used to amend the space transform between images. Therefore, space transformation between connected regions can be precisely determined.

Thus, the space transform between multi-view images consists of all transforms for connected regions. Since there are overlaps and gaps between adjacent transformed regions, interpolation is used to solve this problem. Then the space transform (i.e. matching relationship) between multi-view images is established.

#### IV. COMPARATIVE EXPERIMENTS AND ANALYSIS

The experiments are conducted on actual multi-view photography of Adornment. And fuzzy implication is taken as the Lukasiewicz implication

$$I(u, v) = \text{Min}\{1, 1 - u + v\} \quad (16)$$

Since there is not a widely accepted analysis method for multi-views color image registration based global information, SIFT-GC and LDP-SIFT are used for comparative experiments. The matched feature points are used to determine space transformation, and the transformed image and the image for registration are overlapped to verify the result of registration. The experimental results are shown as figure 3 and table 1.

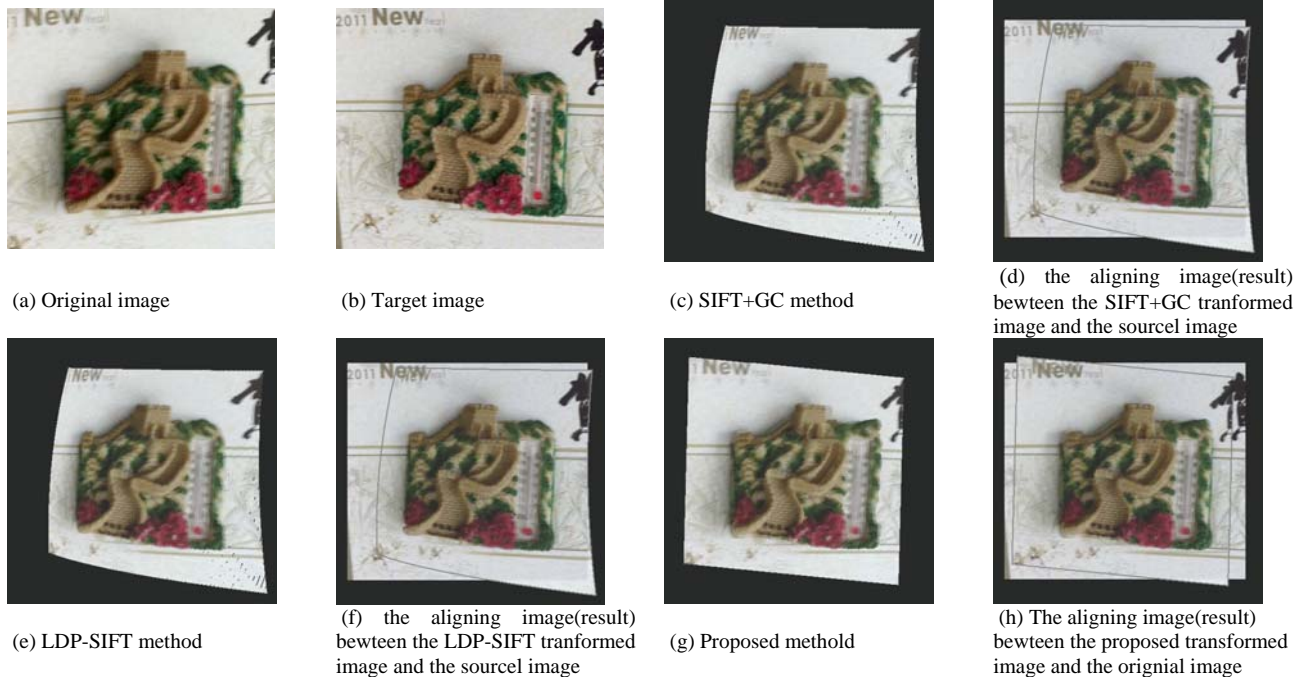


Fig.3 The comparative results of image registration

TABLE I  
THE RESULTS OF REGISTRATION

Items	SIFT-GC	LDP-SIFT	The proposed method
The number of matched points	90	92	136
The distribution of matched points	relatively concentrated	relatively concentrated	well-distributed
The visual effect of transformed images	distortion	distortion	Relatively realistic

The results of registration for natural multi-view images show that the proposed method can obtain more matching feature points than other methods. And the space distribution of feature points is relative uniform while those of other methods suffer from the effects of the shape of object, texture structure and so on. Since the feature points of both SIFT-GC and LDP-SIFT are isolate points, one cannot determine relevance between them. Thus, there is only one space transformation fitted in an image, which cannot reflect real space transformation between multi-view images, especially when an object is provided with dark depth of field which will lead to image distortion shown as figure 7(c),(e). The proposed method creates a space transform for each connected region based on connectivity theory, which can preserve the shape characteristic of objects and reduce the effect of the depth of field to some extent. The obtained transform can reveal the real space transformation and lead to high matching precision between multi-view images.

V. CONCLUSION

Combining with the characteristics and mutual relationship of multi-view images, regional area, regional shape eccentricity, dominant hue and n-order geometric moments are introduced and fuzzied as regional descriptors the proposed method based on the usage of image segmentation. Fuzzy implication is employed to calculate fuzzy matching degree between multi-view images. Then, the best matching relation is reasoned. Finally, matching relations between feature points of connected regions and their feedback corrections are used to establish the transforms between connected regions and achieve accurate registration between multi-views images. matching relationship between feature points of connected regions. Experiments show that compared with SIFT-GC and LDP-SIFT algorithms the proposed method has much advantage in the number and distribution of feature points and can well establish the matching relationship between multi-view images.

REFERENCES

[1] A. Ardehsir Goshtasby and S. Nikolov, "Image fusion: Advances in the state of the art," *Information Fusion*, vol. 8, pp. 114-118, 2007.  
 [2] B. Zitová and J. Flusser, "Image registration methods: a survey," *Image and Vision Computing*, vol. 21, pp. 977-1000, Oct 2003.  
 [3] X. Min and P. K. Varshney, "A Subspace Method for Fourier-Based Image Registration," *Geoscience and Remote Sensing Letters, IEEE*, vol. 6, pp. 491-494, 2009.

[4] O. Samritjarapon and O. Chitsobhuk, "An FFT-Based Technique and Best-first Search for Image Registration," in *Communications and Information Technologies, 2008. ISCIT 2008. International Symposium on*, 2008, pp. 364-367.  
 [5] Y. Dong, Zhang, S. Hua, Wang, L. Wu and Y. Kai. Huo, "Multi-channel Diffusion Tensor Image Registration via adaptive chaotic PSO," *Journal of Computers*, vol. 6, pp. 825-829, Apr 2011.  
 [6] G. Hong and Y. Zhang, "Wavelet-based image registration technique for high-resolution remote sensing images," *Computers & Geosciences*, vol. 34, pp. 1708-1720, Dec 2008.  
 [7] C. Yin, Liu, X. Qiong, Zhang, X. Feng, Li, Y. Ni, Liu and J. Yang, "Gaussian Kernelized Fuzzy c-means with Spatial Information Algorithm for Image Segmentation," *Journal of Computers*, vol. 7, pp. 1511-1518, Jun 2012.  
 [8] S. Xiang, Zhang, "Augmented Reality on Long-wall Face for Unmanned Mining," *Journal of Computers*, vol. 6, pp. 1213-1221, Jun 2011.  
 [9] X. Yang, "Progressive Unbiased Image Registration Using Mean Shift," *Journal of Electronics & Information Technology*, vol. 34, pp. 393-397, Feb 2012.  
 [10] H. Luan, F. Qi, Z. Xue, L. Chen, and D. Shen, "Multimodality image registration by maximization of quantitative-qualitative measure of mutual information," *Pattern Recognition*, vol. 41, pp. 285-298, Jan 2008.  
 [11] Y. Fan and L. Han, Zhang, "Multiresolution 3D Image Registration Using Hybrid Ant Colony Algorithm and Powell's Method," *Journal of Electronics & Information Technology*, vol. 29, pp. 622-625, Mar 2007.  
 [12] K. Kee Baek, K. Jong Soo, and C. Jong Soo, "Fourier Based Image Registration for Sub-Pixel Using Pyramid Edge Detection and Line Fitting," in *Intelligent Networks and Intelligent Systems, 2008. ICINIS '08. First International Conference on*, 2008, pp. 535-538.  
 [13] S. Marsland, C. J. Twining, and C. J. Taylor, "A minimum description length objective function for groupwise non-rigid image registration," *Image and Vision Computing*, vol. 26, pp. 333-346, Mar 2008.  
 [14] D. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," *International Journal of Computer Vision*, vol. 60, pp. 91-110, Nov 2004.  
 [15] E. N. Mortensen, D. Hongli, and L. Shapiro, "A SIFT descriptor with global context," in *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, 2005, pp. 184-190 vol. 1.  
 [16] C. Pan, Wu, Y. Zong, Wang, and T. Xin, Lin, "Color Image Registration Algorithm Using Local Derivative Pattern Approach," *Journal of Xi'an Jiaotong University*, vol. 45, pp. 1-8, Oct 2011.  
 [17] P. Bunting, F. Labrosse, and R. Lucas, "A multi-resolution area-based technique for automatic multi-modal image registration," *Image and Vision Computing*, vol. 28, pp. 1203-1219, Aug 2010.  
 [18] L. An, Ming and D. Hua, Ma, "Region-SIFT Descriptor Based Correspondence Between Multiple Cameras," *Chinese Journal of Computers*, vol. 31, pp. 650-661, Apr 2008.  
 [19] G. Zhi, Zheng and F. Zeng, Wang, "A Region Based Stereo Matching Algorithm Using Cooperative Optimizations," *Acta Automatica Sinica*, vol. 35, pp. 469-477, May 2009.  
 [20] Q. Yong, Xia, D. Zheng, Liu, and Y. Jing, Yang, "Application of Moment Invariant Approach in Region Matching," *Journal of Computer Aided Design & Computer Graphics*, vol. 17, pp. 2152-2156, Oct 2005.

- [21] Y. Fei, B. Yan, Fei, and X. Hong, Li, "Fuzzy Implication Operatora And Their Construction," *Journal of Beijing Normal University (Natural Science)*, vol. 39, pp. 606-611, May 2003.



**Tianzhen Dong** received his M.S. degree from Herbin Engineering University, Herbin, China, in 2007. He is currently a candidate for Ph.D. degree in College of Computer Science and Technology, Harbin Engineering University. He research interests include computer vision, pattern recognition as well as machine intelligence and Machine Perception.



**Tingquan Deng** received his B.S. degree in Mathematics, M.S. degree in Applied Mathematics, and Ph.D. degree in Fundamental Mathematics from Harbin Institute of Technology, Harbin, China, in 1987, 1990 and 2002, respectively. He was a visiting scholar from Center for Mathematics and Computer Science, Amsterdam, the Netherland from 1999 to 2000 for one year and a postdoctoral research fellow in Department of Automation, Tsinghua University, Beijing, China from 2003 to 2005. Currently, he is a professor in College of Science as well as in College of Computer Science and Technology, Harbin Engineering University, Harbin, China. His research interests include uncertainty theory, image processing and pattern recognition, and data mining and machine learning.