



Information granulation-based fuzzy RBFNN for image fusion based on chaotic brain storm optimization



Cong Li^a, Haibin Duan^{a,b,*}

^a State Key Laboratory of Virtual Reality Technology and Systems, Beihang University (BUAA), Beijing 100191, PR China

^b Bio-inspired Autonomous Flight Systems (BAFS) Research Group, Science and Technology on Aircraft Control Laboratory, Beihang University (BUAA), Beijing 100191, PR China

ARTICLE INFO

Article history:

Received 4 March 2014

Accepted 14 April 2015

Keywords:

Image fusion

Radial basis function neural network (RBFNN)

Brain storm optimization (BSO)

Chaos theory

Optimization

ABSTRACT

Image fusion based on regional feature is a challenging task, which has difficulty in obtaining optimal weight of every image source. In this paper, Information Granulation-based Fuzzy Radial Basis Function Neural Networks (IG-FRBFNN) is utilized to obtain weight of each source image dynamically. In the proposed network, the fuzzy C-means (FCM) clustering is exploited to form the premise part of the rules. Additionally, weighted least square (WLS) learning is adopted to estimate the coefficients of polynomials, which have four types to form the consequent part of the model. Since the performance of IG-FRBFNN is directly affected by some key parameters of the networks, inspired by the chaos theory, chaotic brain storm optimization (CBSO) is proposed in this paper, carrying out the structural and parametric optimization of the network respectively. A series of experimental results demonstrate that the proposed approach performs better compared with the other state-of-the-art approaches.

© 2015 Elsevier GmbH. All rights reserved.

1. Introduction

Image fusion can be simply defined as the process of integrating complementary information collected from multiple sensors, generating a new composite high-quality image to improve the utilization of the image information, and advance the spatial resolution as well as the spectral resolution of the original image. In recent years, with the development of sensors, image fusion is a research focus in the field of image processing and analysis all along, which has successfully applied to numerous fields such as remote sensing [1], surveillance [2], target detection [3], and medical diagnosis [4].

Approximately, according to the stages in the fusion operation, current image fusion schemes can be usually divided into three levels: pixel-level, feature-level and decision-level, a comparison of these three fusion process is shown in Fig. 1. In pixel-level fusion, the image fusion process works directly on the pixels obtained from the multi-sensor's outputs. Compared to other methods, pixel-level fusion retains more original information, and it is the basis of the image fusion on other levels. However, the method of calculating the average pixel-by-pixel of source image would reduce the

contrast of image. Feature level fusion, which based on image feature extracted from the source image, faces difficulty in getting optimal weight of each image source. The regional feature of the image includes regional variance, regional energy, etc. In this paper, the regional variance is exploited to perform image fusion. In decision level fusion, there are some subjective requirements and principles such as Bayesian, Dempster–Shafer evidence theory. In this paper, we will concentrate on the feature-level image fusion, which is usually robust to noise and misregistration [5].

The conventional regional feature fusion method is first characterized by measuring the activeness of the each pixel of the source image, with the method of calculating a certain regional feature of the image's rectangle region, which is centered on the pixel measured. During the last decades, various methods based on regional feature for the purpose of image fusion have been proposed. Recently, by utilizing intelligence technology for image fusion problems, researches get satisfactory experimental results. Li [6] presented a new region-based image fusion scheme using pulse-coupled neural network. Yu [7] proposed a bio-inspired method based on the regional feature to solve the image fusion problem. In our study, Information Granulation-based Fuzzy Radial Basis Function Neural Networks (IG-FRBFNN) is exploited to obtain weight of each source image dynamically for image fusion problems.

The salient features of IG-FRBFNN are as follows. (1) The fuzzy C-means (FCM) clustering is exploited to form the premise part

* Corresponding author at: Bio-inspired Autonomous Flight Systems (BAFS) Research Group, Science and Technology on Aircraft Control Laboratory, Beihang University (BUAA), Beijing 100191, PR China. Tel.: +86 10 82317318.
E-mail address: hbd@buaa.edu.cn (H. Duan).

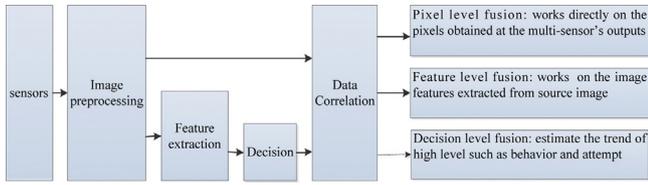


Fig. 1. Comparison of three fusion process.

of the rules. (2) The consequent of the proposed model has four types such as constant (zero-order), linear (first-order), quadratic (second-order), and modified quadratic (modified second-order). (3) The ordinary least square (OLS) or weighted least square (WLS) learning is adopted to estimate the coefficients of polynomials to form consequent part of the model. (4) The optimization algorithm is utilized to carry out the structural and parametric optimization of the IG-FRBNN respectively [8,9].

Recently, swarm intelligence (SI) optimization algorithm such as particle swarm optimization (PSO) [10], ant colony optimization (ACO) [11], and genetic algorithm (GA) [12] have been successfully implemented in numerous fields. These methods have been proven feasible and effective, especially when the objective functions are not deterministic. In this paper, we utilized brain storm optimization (BSO), which is a novel optimization algorithm proposed by Shi [13,14], to optimize IG-FRBFNN for image fusion problem. Unlike other SI, BSO is based on the collective behavior of human being, namely, the brainstorming process [13]. BSO has already proven itself a worthy competitor to its better known rivals. BSO algorithm has been tested on several benchmark functions, and a series of results are presented to verify that BSO algorithm performed reasonably well. However, it is evident that the original BSO runs into local optima easily at times and cannot make full use of global information to update ideas. Thus, inspired by chaos theory [15], a novel variant of BSO algorithm, named chaotic brain storm optimization (CBSO), is proposed in this paper. Moreover, the process of updating individuals is modified to improve the performance of the algorithm.

The rest part of the paper is organized as follows. Firstly, the architecture and learning of the IG-FRBFNN are presented in Section 2. Then, the BSO algorithm and its improved version are introduced in Section 3, followed by Section 4, a series of experimental results are obtained to show the feasibility and effectiveness of our proposed approach. Finally, our concluding and remarks are contained in Section 5.

2. Architecture and learning of the IG-FRBFNN

IG-FRBFNN is a kind of novel network, which is designed by combining the basic principles of RBFNN and the Fuzzy C-Means (FCM) algorithm [16][17]. However, there is still room for improvement, especially for the only use of zero-order polynomials treated as local models to represent the input–output mappings existing in each sub-space, the resulting accuracy of the model might get limited [9]. Therefore, IG-FRBFNN is proposed by Oh et al. [8] to overcome the drawbacks of the conventional FRBFNN. Fig. 2

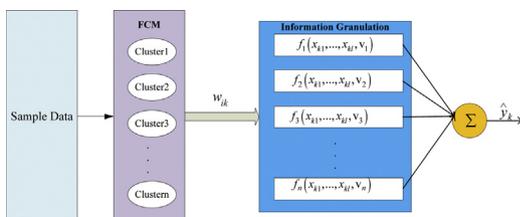


Fig. 2. Architecture of the IG-FRBFNN.

displays the architecture of the IG-FRBFNN. The IG-FRBFNN mainly consists of the following parts:

- (1) Clustering. Fuzzy C-Means (FCM) clustering is exploited to form the premise part of the rules. In this model, the sample data set \mathbf{X} is composed by m vectors, that is, $= \{\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_m\}$, $\mathbf{X}_k = \{\mathbf{X}_{k1}, \mathbf{X}_{k2}, \dots, \mathbf{X}_{kl}, \dots, \mathbf{X}_{km}\}$, $1 \leq i \leq m, 1 \leq j \leq l$, where m represents the number of input data, l is the number of input variables. After clustering, clusters described by the prototypes \mathbf{v}_i , which determines information granules (the centers of individual clusters) and a partition matrix \mathbf{U} representing activation levels (degree of memberships) [9].
- (2) Information granulation. The IG-FRBFNN can be represented as “if-then” fuzzy rules. Besides, there are four types of polynomials to be selected to represent the input–output mappings existing in each sub-space. To simplify the problem, the second-order polynomial (quadratic type) is selected in our study, and the consequent polynomial is described as the following form:

$$f_i(x_{k1}, \dots, x_{kl}, \mathbf{v}_i) = a_{i0} + a_{i1}(x_{k1} - v_{i1}) + a_{i2}(x_{k2} - v_{i2}) + \dots + a_{il}(x_{kl} - v_{il}) + a_{i(l+1)}(x_{k1} - v_{i1})^2 + a_{i(l+2)}(x_{k2} - v_{i2})^2 + \dots + a_{i(2l)}(x_{kl} - v_{il})^2 + a_{i(2l+1)}(x_{k1} - v_{i1})(x_{k2} - v_{i2}) + \dots + a_{i((l+1)(l+2)/2)}(x_{k(l-1)} - v_{i(l-1)})(x_{kl} - v_{il}) \quad (1)$$

We consider the numeric output of the IG-FRBFNN of the following form:

$$\hat{y}_k = \sum_{i=1}^n w_{ik} f_i(x_{k1}, \dots, x_{kl}, \mathbf{v}_i) \quad (2)$$

where w_{ik} denotes the weight of the i th rule and k th data, and \mathbf{v}_i are the prototypes of clusters carried out by the FCM [9].

- (3) The learning of the model. In this study, the weighted least square (WLS) learning method is adopted to estimate the coefficients of polynomials. As presented in Yu’s model [7], the ordinary least square (OLS) is used. However, the experimental condition is indeterminate, leading to the confidence level of the data measured is different. Thus, the estimation accuracy of the OLS is generally not high because the data measured are treated uniformly in the model. Compared with the OLS, the weighting scheme is exploited to process the data with different confidence in the WLS, that is, confidence is high, the weights get bigger; confidence low, takes the smaller weights.

In the WLS, the coefficients of the model are determined by minimizing an overall squared error:

$$J(\hat{\theta}) = \sum_{i=1}^n \sum_{k=1}^m w_{ik} (y_k - f_i(x_k, v_i))^2 \quad (3)$$

where w_{ik} denotes the weight of the i th rule and k th data, y_k is the output of the model.

3. Brain storm optimization and its improved version

3.1. The basic principle of BSO

BSO is a newly-developed and effective algorithm, inspired by the process of the human being’s brain storming [13]. In BSO algorithm, each position within the solution space is called an idea, which is randomly initialized within the search space. Compared with other algorithm, the K-means clustering is exploited in BSO, imitating the methodology of group discussion. During each generation, all the ideas are first divided into k clusters, and the best idea in each cluster is selected as the cluster center, while the quality of

متن کامل مقاله

دریافت فوری ←

ISIArticles

مرجع مقالات تخصصی ایران

- ✓ امکان دانلود نسخه تمام متن مقالات انگلیسی
- ✓ امکان دانلود نسخه ترجمه شده مقالات
- ✓ پذیرش سفارش ترجمه تخصصی
- ✓ امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
- ✓ امکان دانلود رایگان ۲ صفحه اول هر مقاله
- ✓ امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
- ✓ دانلود فوری مقاله پس از پرداخت آنلاین
- ✓ پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات