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MULTI-SOURCE REMOTE SENSING IMAGE FUSION BASED ON SUPPORT VECTOR MACHINE

ZHAO Shu-he, FENG Xue-zhi, KANG Guo-ding, RAMADAN Elnazir
(Department of Urban & Resources Sciences, Nanjing University, Nanjing 210093, P. R. China)

ABSTRACT: Remote Sensing image fusion is an effective way to use the large volume of data from multi-source images. This paper introduces a new method of remote sensing image fusion based on support vector machine (SVM), using high spatial resolution data SPIN-2 and multi-spectral remote sensing data SPOT-4. Firstly, the new method is established by building a model of remote sensing image fusion based on SVM. Then by using SPIN-2 data and SPOT-4 data, image classification fusion is tested. Finally, an evaluation of the fusion result is made in two ways. 1) From subjectivity assessment, the spatial resolution of the fused image is improved compared to the SPOT-4. And it is clearly that the texture of the fused image is distinctive. 2) From quantitative analysis, the effect of classification fusion is better. As a whole, the result shows that the accuracy of image fusion based on SVM is high and the SVM algorithm can be recommended for application in remote sensing image fusion processes.

KEY WORDS: image fusion; SVM; multi-spectral image; panchromatic image

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1 INTRODUCTION

In recent years, many satellites were launched, which provide various types of remote sensing data. The variations of remote sensing platforms have resulted in various data sets of different spatial, spectral and temporal resolutions. That is to say, the data provided is of different kinds and scales (WANG *et al.*, 2001). But it is difficult to obtain high spectral resolution, high spatial resolution and high temporal resolution at the same time in one satellite imaging system. In fact, the sensor images are all losing compression in resolution (HE, 1999). Namely, remote sensing data gained from one sensor can only reflect one or several character of the ground object. Therefore, how to gather the useful information from different images at the same field is an important research task (SUN *et al.*, 1998).

Remote sensing image fusion is an effective way to use the large volume of data from multi-source images. And it can combine multi-sensor, multi-temporal, multi-spectral and multi-resolution images for analyzing. Thus it can overcome the problem of information deficiency during artificial extraction of remote sensing images. In recent years, there are many research works on methods of image fusion. Now the methods of image fusion are divided into three levels, that is, pixel-based fusion, feature-based fusion, decision-level fusion (POHL *et al.*, 1998). And there are many studies on pixel-based fusion and feature-based fusion, for example, JIA Rong-hong *et al.* compared the IHS transformations for integrating SAR and TM images (JIA *et al.*, 1998); LI Jun *et al.* combined wavelet multi-resolution analysis with IHS transformation, put forward a new method of stack fusion (LI *et al.*, 1999); SUN Jia-bing *et al.* studied the image fusion based on wavelet transformation (SUN *et al.*, 1998). These research works have achieved better effects. However, decision-level fusion is one fusion technique of high level, and its effect is the best, yet its difficulty is the most (SUN *et al.*, 1998). Current researches focus mainly on fusion methods such as Bayes rule based on fusion, neural networks based on fusion and Dempster-Shafer theory based on fusion. For example, FANG Yong studied multi-source remote sensing data fusion

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Biography: ZHAO Shu-he (1971 –), male, a native of Shandong, Ph. D. His main research interests include information extraction of high spatial resolution remote sensing data, data fusion of multi-source remote sensing,

based on Dempster-Shafer theory (FANG, 2000); LIU *et al.* studied blur Kohonon neural networks based on image fusion (LIU *et al.*, 2001).

The SVM method is a new pattern recognition technique given by Dr. VAPNIK and his research group (CHAPELLE *et al.*, 1999; VAPNIK, 1995; CORTES and VAPNIK, 1995; BURGES, 1998). It comes from the idea that the optimal separating hyperplane has the best extensive ability in the problem of classifying two kinds of data. In the SVM, input vector is projected into high-dimension feature space nonlinearly. In the new space, the establishment of a linear decision plane will lead to the production of a nonlinear decision plane in original input space. The SVM method has high spread ability under the condition of non-prior knowledge. In remote sensing, SVM can be used to choose features (BARZILAY and BRAILOVSKY, 1999).

In this paper, SVM is applied to remote sensing image fusion, and a new method of image fusion based on SVM is presented. Firstly, the paper introduces the theory of SVM, and a model of remote sensing image fusion based on SVM is built. Then by using high spatial resolution data SPIN-2 and multi-spectral remote sensing data SPOT-4, the image classification fusion is tested. Finally, evaluation of the fusion result is made.

2 REMOTE SENSING IMAGE FUSION BASED ON SVM

2.1 SVM Theory

In recent years, after the success of the SVM in solving real-life problems, the scientist's interest in statistical learning theory has significantly increased (CHAPELLE *et al.*, 1999; SCHOLKOPF *et al.*, 1999). The principle of the SVM-based solution for the learning process is briefly described below (ZHU and BLUMBERG, 2002; ZHANG, 2000).

Suppose that the training data $(x_1, y_1), \ldots, (x_\lambda, y_\lambda), x \in R^n, y \in \{+1, -1\}$, can be separated by a hyperplane. To describe the separating hyperplane, let us use the following form:

$$\begin{aligned} (w * x) - b &\geq 1 \quad \text{if } y_i = 1 \\ (w * x) - b &\leq -1 \quad \text{if } y_i = -1 \end{aligned} \tag{1}$$

Among the separating hyperplanes, the one for which the distance to the closest point is maximal is called the optimal separating hyperplane (OSH). The goal of the learning processing based on SVM is to find the OSH to separate the training data in n dimension by using the criteria described above and then to separate the real data in the same dimension. If we denote $\alpha_i = (\alpha_1, \ldots, \alpha_\lambda)$, the nonnegative Lagrange multipliers associated with constraints Eqation (1), the optimization problem amounts to maximizing

$$W(\alpha) = \sum_{i=1}^{\lambda} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\lambda} \alpha_i \alpha_j y_i y_j x_i x_j \tag{2}$$

with $\alpha_i \geq 0$ and under the constraint $\sum y_i \alpha_i = 0$. Once the vector$(\alpha^0 = \alpha_1^0, \ldots, \alpha_\lambda^0)$ solution of the maximization problem Eqation (2) has been found, the OSH(w_0, b_0) has the following expansion:

$$w_0 = \sum_{i=1}^{\lambda} \alpha_i^0 y_i x_i \tag{3}$$

The support vectors are the points which satisfy $\alpha_i \geq 0$ and Eqation equalize with (1).

For a nonlinear situation, a support vector network tries to map the input vectors into a very high-dimensional feature space Z through some nonlinear mapping chosen a priori. In this space, the construction of an OSH is completed. Therefore, x will be replaced by its mapping in the feature space $\Phi(x)$. Then, Eqation (2) will be changed to Eqation (4):

$$W(\alpha) = \sum_{i=1}^{\lambda} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\lambda} \alpha_i \alpha_j y_i y_j \Phi(x_i) \Phi(x_j) \tag{4}$$

To prevent computational problems, arising from a rapid increase in the number of dimensions of mapped space Φ, an inner product between any two vectors in the feature space $\Phi(x_1)$ and $\Phi(x_2)$ is chosen as a function of two variables in the input space (Eqation (5)):

$$\Phi(x) * \Phi(x_i) = K(x, x_i) \tag{5}$$

then, it will be possible to construct a solution, which is equivalent to the OSH in the feature space, and the nonlinear decision function changes the form to Eqation (6):

$$I(x) = \text{sign}\Big(\sum_{\text{support-vectors}} \alpha_i K(x_i * x) \Big) + b_0 \tag{6}$$

where the $\alpha_i = (\alpha_1, \ldots, \alpha_\lambda)$ is the nonnegative Lagrange multipliers for the optimization process to look for the OSH. $K(x, x_i)$ is an SVM type of kernel, which is chosen to replace the inner product (x_i, x_j).

2.2 Fusion Model Based On SVM

The fusion model of remote sensing image based on SVM is a decision-level fusion model. Its fusion course is as follows.

First of all, the multi-source remote sensing data are preprocessed, and matched to a certain state. Then, using the image classification method based on SVM, each RS data is classified, and the classification results are gained. Finally, the fusion image is achieved by fusing the classification results, according to certain rule. Fig. 1 shows the structure map of the fusion model.

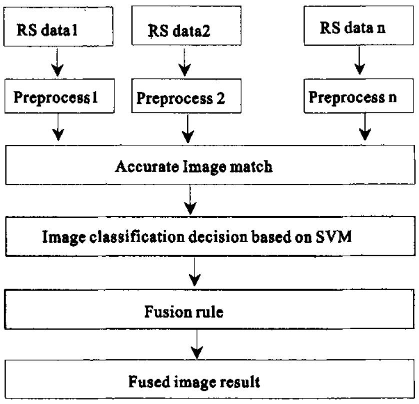

Fig. 1 Structure map of remote sensing image fusion model based on SVM

Remote sensing data indicates that the image comes from different remote sensors such as Landsat TM, SPOT-4, SAR, SPIN-2, IKONOS, etc. The preprocessing stage includes radiant correction, geometry correction, noise removal, etc. And the accurate image match is very important, it will affect the accuracy of fusion image. The image classification decision based on SVM will be done according to section 2. 1. And the image fusion will be made by feature selection of image classification, thus the result can be achieved by fusion of classified images.

3 EXPERIMENT AND DISCUSSION

3. 1 Study Site and Data Preprocessing

The study site is situated in the middle part of Nanjing City. The geo-coordinate is 118°31′ – 119°04′ E, 31°38′ – 32°13′N. In the field, there are hills, lower mountains, and also many water bodies, such as reservoirs, lakes, ponds, etc. It belongs to the typical region of the south of the Changjiang River.

The data set is the SPOT-4 HRV data (12/08/1999) and the SPIN-2 data (08/1999). The SPOT-4 HRV data include four wave bands. Its ground spatial resolution is 20m. And the SPIN-2 data is achieved from the Russian satellite Cosmos, its ground spatial resolution is 2m.

The size of data is 512 × 512 pixels. And the multi-spectral data SPOT-4 and panchromatic data SPIN-2 is preprocessed. It includes radiant correction, geometry correction, etc.

3. 2 Experiment

Using image fusion method based on SVM, the fusion experiment is made by panchromatic data SPIN-2 and multi-spectral remote sensing data SPOT-4. SPOT-4 multi-spectral image, SPIN-2 panchromatic image and the fused image are respectively shown in Fig. 2, Fig. 3 and Fig. 4. The basic steps of classification fusion experiment are as follows:

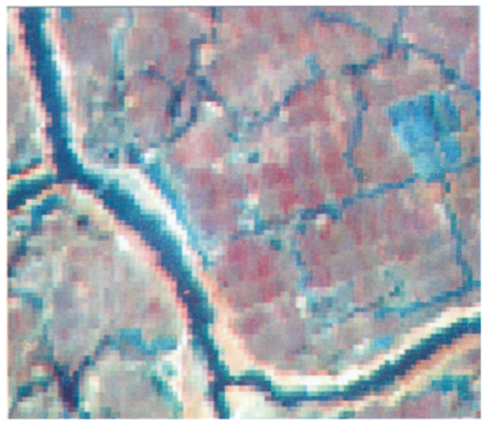

Fig. 2 SPOT-4 multi-spectral image

Fig. 3 SPIN-2 panchromatic image

Fig. 4 Fusion image

(1) Resampling: Multi-spectral remote sensing data SPOT-4, which has been preprocessed, is resampled according to the spatial resolution of panchromatic image SPIN-2 data.

(2) Image matching: The SPIN-2 data is chosen as the criterion image, then about ten pairs of RCPs (Registration Control Points) from the SPOT-4 image and the SPIN-2 image are selected. These RCPs are mainly road intersections, bridges, river corners, etc. Finally we use linear transform method and bilinear interpolation method to match the resampled data SPOT-4 to the SPIN-2 data, and the registration accuracy is up to sub-pixel.

(3) Sample selection: The spatial features in the study site are selected through field investigation and analysis of materials. They include water bodies, residential area, traffic area, cultivated land and bare soils. One hundred and twenty samples data were selected for each spatial feature, then the input sample is processed from zero to one.

(4) High dimension projection: According to the kernel function, the spatial feature samples are projected to high dimension feature space. The kernel function is radial basis function. Equation of kernel function is $K(x,x_i)=\exp\{-|x-x_i|^2/\sigma^2\}$.

(5) Construction of distinguished function: Using SVM, we find the optimal separating hyper-plane between each class feature sample and the others in the feature space. Then the support vector sets of each space feature and the corresponding multiple parameters α_i are gained. Thus the linear distinguish function come to being, which will distinguish the feature class.

(6) Classification decision: The unknown space cells of the original images are projected to feature space through the kernel, and used as the input of distinguishing function. Then the output of any kinds is given. Finally, to judge the cell may belong to the corresponding space feature class through competition.

(7) Classification fusion: feature images of each class are selected, then the images are fused, and finally the fusion image is gained.

3.3 Fusion Result Assessment

3.3.1 Subjectivity assessment

From Fig. 4, the spatial resolution of the fused image is improved compared to the SPOT-4. And it is clear that the texture of the fused image is distinctive. Especially the water bodies and linear objects are prominent. It is easy for us to distinguish linear objects such as cropland boundary, roads, the outline of residential area, bridge, etc. But the information is fuzzy in the original image.

3.3.2 Quantitative analysis

How to evaluate the image fusion resulted in an accurate way has not been solved (WALD *et al.*, 1997) In the paper, 450 test samples were selected to analyze the classification fusion result quantitatively. Table 1 shows the accuracy evaluation of image classification fusion. From the result of classification test, the accuracy of water bodies is the highest, and the accuracy of bare soils is the lowest. But the overall accuracy reaches to 90.8 percent. In the whole, the effect of classification fusion is better, and it can be applied to classification of remote sensing data automatically.

Table 1 Accuracy evaluation of image classification fusion

Class	Number of test samples	Overall classification number	Accurate classification number	Producer accurace (%)	User accuracy (%)
Water bodies	90	89	84	98.8	94.3
Residential area	90	92	82	100.0	89.1
Traffic area	90	86	79	95.5	91.8
Cultivated land	90	91	83	100.0	91.2
Bare soils	90	92	81	100.0	88.0
Total	450	450	409		
Overall accuracy (%)	90.8				

4 CONCLUSIONS

SVM can be used to process complex data and high dimension data. And towards the large volume of data from multi-source image, a method of image fusion based on SVM is presented. At the same time, an experiment of fusion data is made. The result shows that the accuracy of the fusion method based on SVM is high. And the SVM method will have wide application to remote sensing image processing. For future work, it will achieve more effective result if we consider the other information such as geometric shape, texture structure, etc. Finally, we hope that the SVM method will be applied to process super-spectral remote sensing data.

REFERENCES

BARZILAY O, BRAILOVSKY V L, 1999. On domain knowledge and feature selection using a support vector machine[J]. *Pattern Recognition Letters*, 20(5): 475 - 484.

BURGES C J C, 1998, A tutorial on support vector machines for pattern recognition [J]. *Data Mining and Knowledge Discovery*, 2(2): 955 - 974.

CHAPELLE O, HAFFNER P, VAPNIK V N, 1999. Support vector machines for histogram-based image classification [J]. *IEEE Trans. On Neural Networks*, 10 (5): 1055 - 1064.

CORTES C, VAPNIK V, 1995. Support vector networks[J]. *Machine Learning*, 20: 273 - 297.

FANG Yong, 2000. The research of data fusion from multiple sources by evidential reasoning [J]. *Journal of Remote Sensing*, 4(2): 106 - 111 (in Chinese).

HE Guo-jin, 1999. Review of wavelet transform applied to remote sensing image processing [J]. *Remote Sensing Information*, 1: 14 - 17 (in Chinese).

JIA Yong-hong, LI De-ren, SUN Jia-bing, LIU Ji-lin, 1998. Comparison of IHS transformation for integrating SAR and TM images[J]. *Journal of Remote Sensing*, 2(2): 103 - 106. (in Chinese)

LI Jun, ZHOU Yue-qin, LI De-ren *et al.*, 1999. Fusion of high-resolution panchromatic and multispectral images by using wavelet transform[J]. *Journal of Remote Sensing*, 3(2): 116 - 121. (in Chinese).

LIU Chun-ping *et al.*, 2001, "Multi-source remote sensing data fusion using fuzzy self-organization mapping network and modified dempster-shafer evidential reasoning method to classification" [C]. In: *The Second International Conference of Multi-spectral Image Processing & Pattern Recognition of SPIE.* Central China University of Science and Technology, 4556: 71 - 79.

POHL C *et al.*, 1998. Multi-Sensor image fusion in remote sensing: concepts, methods and applications[J] . *International Journal of Remote Sensing*, 19(5): 823 - 854.

SCHOLKOPF B, MIKA S, BURGES C J C *et al.*, 1999. Input space versus feature space in Kernel-based methods[J] . *IEEE Transactions on Neural Networks*, 10(55): 1000 - 1017.

SUN Jia-bing, LIU Ji-lin, LI Jun, 1998. Multi-source remote sensing image data fusion [J]. *Journal of Remote Sensing*, 2 (1): 47 - 50. (in Chinese)

VAPNIK V N, 1995. *The Nature of Statistical Learning Theory* [M]. Springerberlag, New York.

WALD L, RANCHIN T, MANGOLINI M, 1997. Fusion of satellite images of different spatial resolutions: asssessing the quality of resulting Images [J]. *PE & RS*, 63(3): 691 - 699.

WANG Zhi-jun, LI De-ren, LI Qing-quan, 2001. Wavelet theory based Ikonos panchromatic and multi - spectral image fusion [J] . *Acta Geodaetica et Cartographica Sinica*, 30(2): 112 - 116. (in Chinese)

ZHANG Xue-gong, 2000. *The Nature of Statistical Learning Theory*[M]. Beijing: Tsinghua University Press. (in Chinese)

ZHU Guo-bin, BLUMBERG D G, 2002. Classification using ASTER data and SVM algorithms: The case study of Beer Sheva, Israel[J]. *Remote Sensing of Environment*, 80(1): 233 - 240.