



Combination of contextual information and optimal texture features for improving the accuracy of SAR image classification

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Abstract

This paper employs the full advantages of contextual information and optimal texture features for improving the accuracy of pixel-based classification. In the proposed novel classification method, first, optimal texture features are selected based on the genetic algorithm (GA) and Jeffries-Matusita (JM) distance criterion. Second, the selected texture features are combined with backscattering SAR data, and a support vector machine (SVM) pixel-based classification is done. Finally, integration of Gaussian Markov random field (MRF) model with SVM classifier obtains final classification map. Comparison of the proposed method with pixel-based classification shows a 13.77% improvement in overall classification accuracy of TerraSAR-X images.

Keywords : synthetic aperture radar (SAR), Markov random field (MRF), Texture features, support vector machine (SVM)

1. INTRODUCTION

Unlike conventional electro-optical imaging sensors, radar imaging is an active system that can transmit microwave signals day and night and in all weather conditions [3]. SAR signals have properties such as a backscatter coefficient that is sensitive to the form, orientation, homogeneity and surface condition of the target and is independent of environmental conditions. Based on these properties, the classification of land cover/ land use can be mentioned as one of the essential purposes of the analysis of remotely sensed data.

A disadvantage of SAR images, however, is the presence of speckles. Therefore, without consideration of the spatial relationship between pixels, the salt-and-pepper effect will be produced in the classification map [2, 5]. To overcome this issue, the incorporation of spatial information has the potential to be used with SAR images. For example, (Jia et al and Wen et al) proposed the combination of various texture features with SAR data in the classification process [4, 6]. Another approach, (Geman and Geman; Dutta et al) offered Markov random fields (MRFs) as a powerful tool for combining contextual information with the image data [1, 7]. The MRF model with the definition of a neighbourhood system attempts to emphasize the label of each pixel will come from its neighbourhood.

The main motivation of this paper is to improve the land use classification accuracy by taking full advantage of spatial information. In this proposed method, the selection discriminating subspace of the texture features is done based on the genetic algorithm (GA), with Jeffries-Matusita (JM) distance as the criterion. Moreover, to achieve the contextual information, the MRF model is added into the SVM based texture-tonal classification. Hence, the proposed approach of utilizing optimal texture features and the MRF model decreases the speckle effect in SAR images and significantly improves the pixel-based classification accuracy.

2. Materials and methods

Shiraz city in the southern part of Iran is selected as the study area. Its location is at 52°29'51" to 52°30'19" E longitudes and 29°36'56" to 29°37'47" N latitudes. The localisation of the study area is shown in Figure 1.

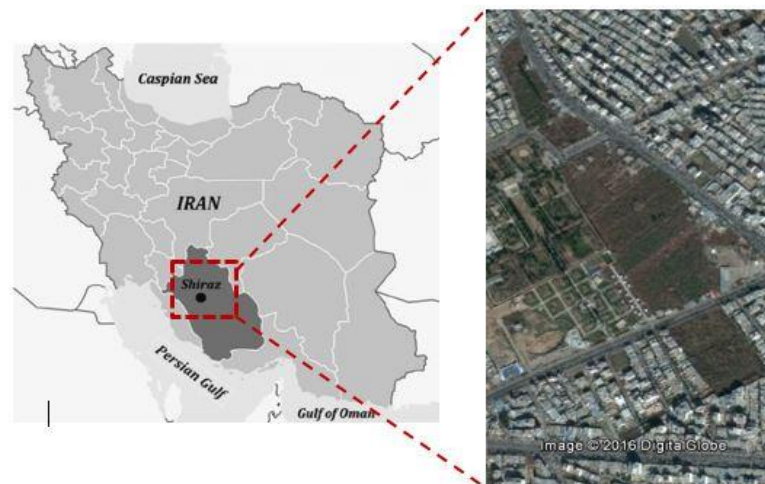


Figure1. The localisation of the study area.

The SAR datasets includes HH and VV polarization images with spatial resolutions of 1m. These images were acquired by the TerraSAR-X satellite with an incidence angle of 52.5 degrees. In this study, a total of three main classes, including road, building and vegetation, were considered. Figure 2 shows HH and VV polarized SAR images.

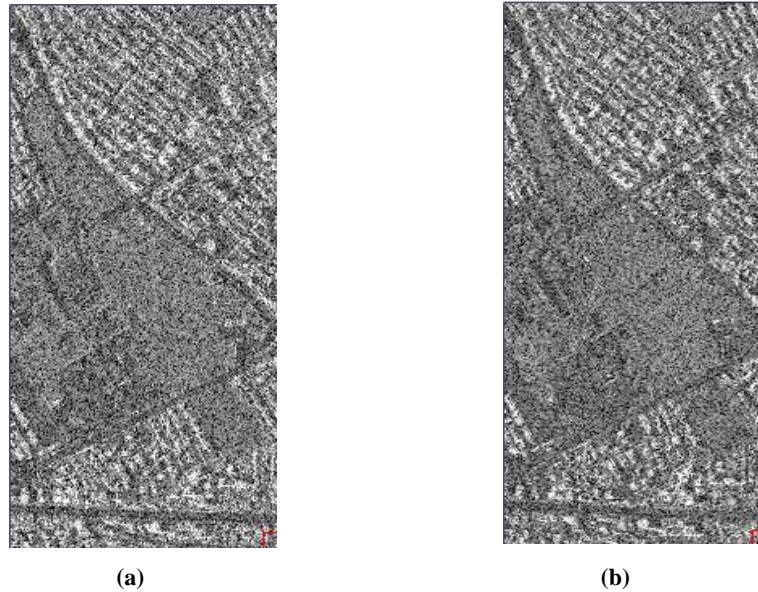


Figure 2. TerraSAR-X images (a) HH polarized image (b) VV polarized image.

The implementation of the proposed method for SAR image classification is shown in Figure 3. After the radiometric calibration and despeckling are completed as the pre-processing steps for SAR images, texture features were extracted using the first-order texture measures and grey-level co-occurrence matrix (GLCM) in four directions, with the angles of 0, 45, 90 and 135 degrees. Then, the mean of each feature based on the GLCM was computed in all directions.

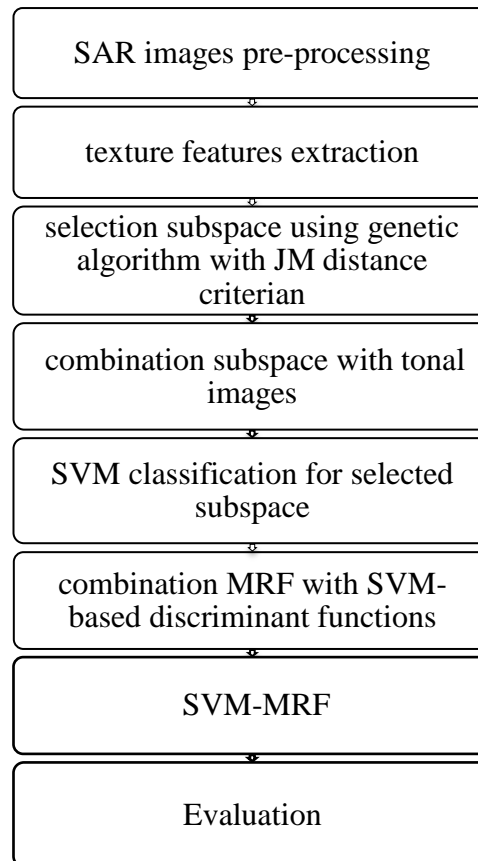


Figure 3. General scheme of the contextual classification.

Due to the correlation of some of the extracted features and the maintenance of discriminative features, in the second step, a feature selection analysis using the GA and JM distance as the criterion was performed. Subsequently, optimal texture features were combined with HH and VV backscattering images, and SVM classification was implemented. Finally, to achieve contextual information, an MRF model was added to the discriminant function of the SVM classifier. In this study, modelling of the neighbourhood information was done using the Gaussian MRF model with a third-order neighbourhood system and iterated conditional modes (ICM).

3. Results and discussion

In this section, the effect of optimal texture feature selection using GA is investigated. Moreover, contextual SVM-texture-MRF classifier performance is compared with that of SVM tonal classification. In the first experimental step, eight texture features of the GLCM and five first-order texture measures were extracted from HH and VV SAR images, which gave the number of $2(8+5)=26$ texture features for both images. The GA selected a set of features by maximizing the value of the JM distance. The classification results for the combination of the selected features with backscattering SAR images have been presented in Table 1.

Table 1. Classification results using selected features

Size of subspace	Accuracy classes (%)			Overall Accuracy (%)	Kappa (%)
	Road	Building	Vegetation		
Tonal images	71.08	87.24	61.52	70.46	54.38
Tonal & 21 texture	79.76	98.19	70.69	79.54	67.58

As it is seen in the above table, by adding texture features to backscattering images, the classification accuracy and the kappa coefficients are increased. Therefore, texture can hold useful information in single polarized SAR images. As well as the adding texture features allow 13.2% increase in Kappa coefficients with respect to the tonal features. Figure 4 shows the classification maps obtained by tonal and texture-tonal classifier.

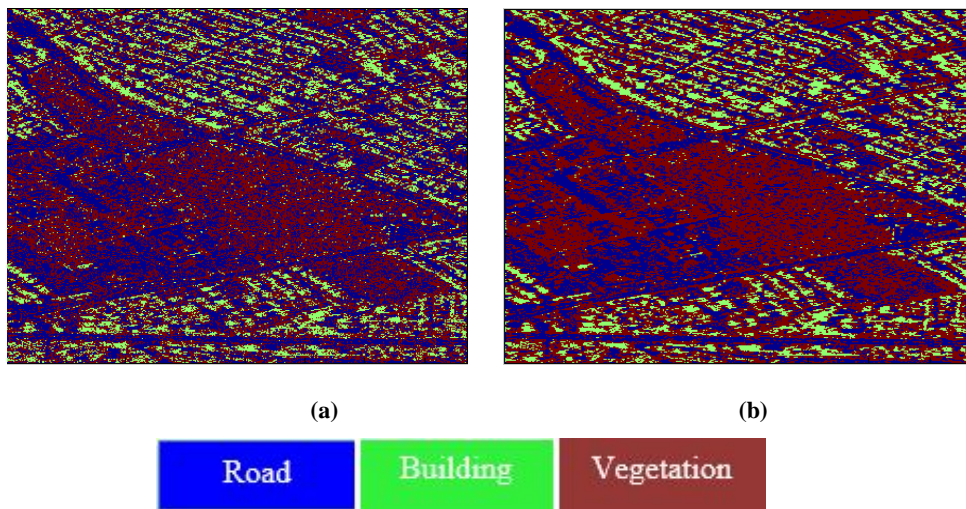


Figure4. Classification map generated by (a) tonal features, (b) tonal & 21 texture features

Non-contextual pixel classifiers, such as in the previous experiment, do not consider the spatial relation among pixels. Therefore, to improve the classification results, the spatial-contextual information is incorporated into SVM classifier. In this study, a combination of tonal images with 21 selected texture features are used for contextual classification. Table 2 shows the results of the SVM-MRF approach for classification.

Table 2. Classification accuracy of SVM-MRF method.

SVM-MRF classifier			
Tonal images-21 selected texture features			
Accuracy Classes (%)	Road	Building	Vegetation
	85.14	97.96	77.22
Overall accuracy (%)	84.23		
Kappa coefficient (%)	75.49		

According to the results, in Table 2, the SVM-MRF classifier improves the classification accuracy and the kappa coefficient by about 5%, and 8%, respectively. This approach increases the vegetation class accuracy from 70.69 to 77.22 and improves the accuracy of the road class by about 6%. Figure 5 shows classification maps using the SVM tonal classification and the proposed method.

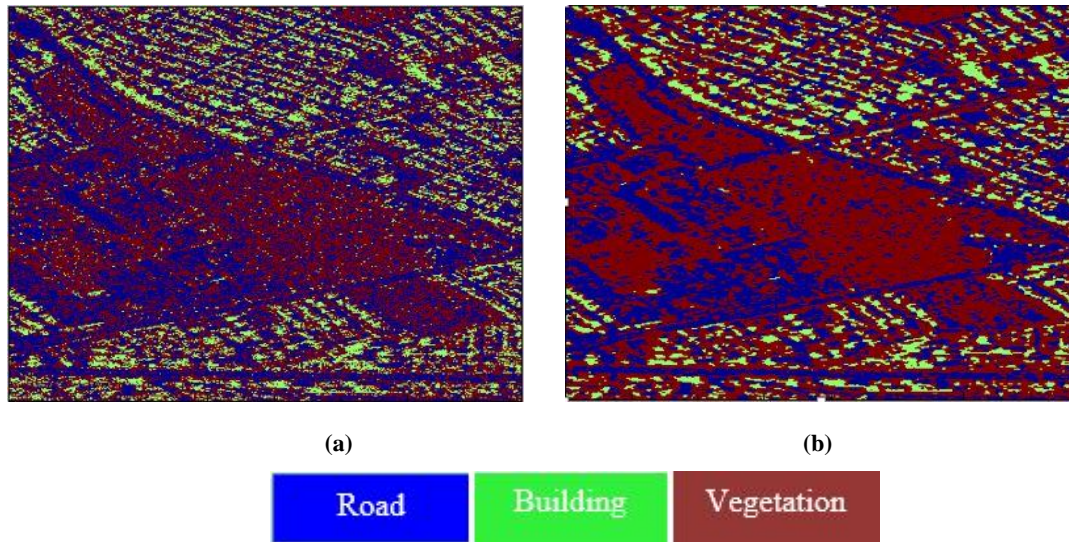


Figure 5. Classification map (a) SVM texture-tonal (b) proposed method

4. Conclusion

The purpose of this paper is to employ a texture-contextual method for the classification of SAR images. The dataset used in this study includes HH and VV polarized SAR images. The proposed method was performed in three experiments. In the first step, after extracting the texture features from first-order measures and the GLCM, optimal features were selected using the GA. The maximizing the value of the JM distance was the criterion function for optimisation. Then, these features were combined with tonal images and the classification of SAR images performed by the SVM. In the third experiment, to take full advantage of spatial information, the Gaussian MRF was introduced in the former stage. The results showed that adding texture features and contextual information to backscattering images improved the classification accuracy and the kappa coefficient significantly. An improvement of 13.34%, 10.72% and 15.7% also was observed in the class accuracy of roads, buildings and vegetation, respectively.

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