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Automatic Target Classification in SAR Images by Multilayer Back Propagation Neural Network

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Abstract: In this study, a novel descriptive feature extraction method of Discrete Fourier transform and neural network classifier for classification of Synthetic Aperture Radar (SAR) images is proposed. The classification process has the following stages (1) Image Segmentation using statistical Region Merging (SRM) (2) Polar transform and Feature extraction using Discrete Fourier Transform (3) Neural Network classification using back propagation. The algorithm has been applied for the three classes of military manmade objects (metal objects) in SAR imagery is using MSTAR public release database. Experimental results are presente.

Keywords: Back-propagation algorithm, feature extraction, MSTAR database, SAR images, SRM segmentation

INTRODUCTION

Synthetic Aperture Radar (SAR) is a coherent radar system that generates high resolution remote sensing imagery. SAR imagery is used in finding comparatively small mobile or immobile targets for military applications (Bennamoun and Mamic, 2002; Daisheng, 2005). The need is to classify the targets using the SAR images. SAR images containing objects that are small, influenced by speckle still requires efficient classification technique to correctly classify objects. The foci of this study are on providing an advanced classification techniques for SAR images.

METHODOLOGY

The proposed method is used to classify vehicle as tank or armed personal carrier of SAR images. A reference database is maintained with the SAR image, which are released by MSTAR database. In proposed method, the SAR image classification is done by employing feature extraction algorithm to extract the stable, repeatable and distinctive features of the SAR image and then by matching these features with the features of reference images. Proposed method introduces a SAR classification method with rotation invariance (Minoru *et al*., 1992). The rotation invariance feature is represented by the absolute value of Fourier coefficients of polar image of the SAR. Then SAR image can be distinguished by feeding those features into a multi-layered BP neural network. The block diagram of proposed method is represented in Fig. 1.

Image segmentation: In this section, a method for segmenting the object from the SAR image is proposed. Image segmentation is a technique for extracting information from an image. This is generally the first step in image analysis. Segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried depends on the problem being solved. The image segmentation in this study is performed using Statistical Region Merging proposed Richard Nock and Frank Nielsen. The key idea of the Statistical Region Merging model is to formulate image segmentation as an inference problem. Here the merging procedure is based on the theorem 'The independent bounded difference inequality'. It is the reconstruction of regions on the observed image, based on image on which the true regions we seek are statistical regions whose borders are defined from a simple axiom. Second, the model shows the existence of a particular blend of statistics and algorithmic to process observed images generated with this model, by region merging, with two statistical properties. The regions in the query image are merged using the SRM segmentation procedure to obtain the object region from the image. The segmentation procedure output was shown in (Fig. 2) which shows the region merged image and the shows the segmented output.

Polar transform: The segmented SAR image is converted from Cartesian coordinates to logarithmic polar coordinates. The rotation problem under the Cartesian coordinates becomes the translation problem under the logarithmic polar coordinates. The image transform from Cartesian to logarithmic polar

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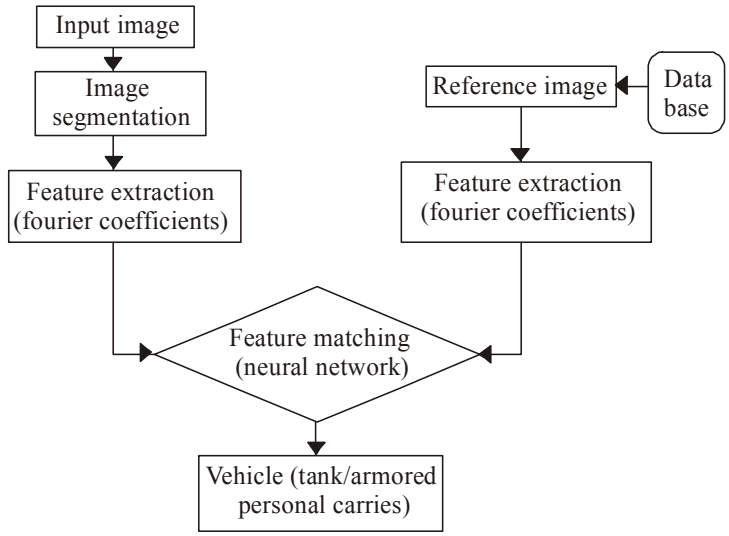
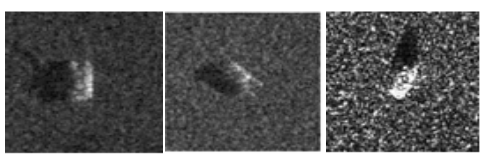


Fig. 1: Block diagram of the proposed metho



(a) (b) (c)

Fig. 2: (a) T72-Tank (b) BMP2-armored personnel carriers (c) BTR60- armored personnel

coordinates is introduced. Suppose the input image can be denoted as f (x, y) under the Cartesian coordinates and as f (r, θ) under the logarithmic coordinates. The coordinates transform from f (x, y) to f (r, θ) can be defined as:

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2}$$

$$\theta = \arctan\left(\frac{y - y_c}{x - x_c}\right) \quad (2)$$

where, 0≤θ≤2π, (xc, yc) x y is the coordinates of center of the image under the Cartesian coordinates. we can see that the rotation problem under the Cartesian coordinates becomes the translation problem under the logarithmic polar coordinates. Using the Eq. (2) polar transform of image is obtained.

Feature extraction: Feature vectors as the input for the neural network. Polar transform is applied to segmented SAR image. The rotation problem under the Cartesian coordinates becomes the translation problem under the polar coordinates. Then the Fourier transform applied to the output of the polar transform. Then the feature vectors will be obtained as shown in Fig. 3.

Fourier transform: The output of the transformation represents the image in the Fourier or frequency

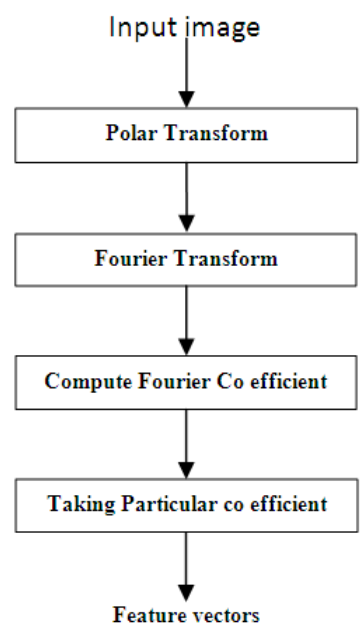


Fig. 3: Feature vector computation

domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image. If f(r, θ) is periodically expanded on the θ direction, then $\hat{f}(r,\theta)$ can be gotten as the follow:

$$\hat{f}(r,\theta) = f(r,\theta + 2m\pi) \quad (3)$$

where, m is any integer and $\hat{f}(r,\theta)$ is expanded into Fourier series by letting r = rk as:

$$\hat{f}(r_k,\theta) = \sum_{m=-\infty}^{m=\infty} a_k^m e^{jm\theta} \tag{4}$$

where,

$$a_m^k = \frac{1}{2\pi}\int_0^{2\pi} \hat{f}(r_k,\theta)e^{-jm\theta}d\theta$$

and rk denotes a certain value along the r axis under the polar coordinates.

After the image is rotated by angle α about its origin and periodically expanded, we can get $\hat{g}(r_k,\theta) = \hat{f}(r_k,\theta+\alpha)$, so its Fourier coefficients is:

$$b_m^{(k)} = a_m^{(k)} e^{jm\alpha} \tag{5}$$

The absolute value of Fourier coefficients will not change after the image is rotated. The absolute values of Fourier coefficients are used as feature vectors, then the feature vectors are rotation invariant. The Fourier coefficients can be used to reconstruct the image under the logarithmic polar coordinates. The number of Fourier coefficients maybe be infinite, but with increasing frequency, the amplitude of the coefficients will be reduced significantly. So the Fourier coefficients above a certain frequency can be ignored. Here fifteen co efficient used as feature vectors (Neagoe and Strugaru, 2008).

Neural network training and classification: Multilayer back propagation neural network is taken as the network architecture for the present application. After choosing the network, the number of neurons in each layer has to be decided. The number of neurons in the output layer is fixed. the neural network input is Fourier co efficient. By applying polar transform to the segmented image and then applying Fourier transform to that, feature vectors are obtained. The number of hidden layers in the network and the number of neurons in each layer is chosen by trial and error method based on the performance function until it reaches the specified goal. The relevant equations for the back-propagation algorithm are presented in the order in which they could be used during training for a single training vector, as follows in which 'w' represents weights and 'f' represents activation functions, θ is the bias term and 'y' represents the target:

- Application of the input vector:

$$xp = (xp1, xp2, \ldots\ldots, xpn)t \tag{6}$$

- Calculation of net input values to the hidden layer units:

$$net_{pj}^{h} = \sum_{i=1}^{N} w_{ji}^{h} x_{pi} + \theta_j^h \tag{7}$$

Calculation of outputs form the hidden layer:

$$i_{pj} = f_j^h\left(net_{pj}^h\right) \tag{8}$$

- Calculation of net input values to the output layer units:

$$net_{pk}^{o} = \sum_{j=1}^{L} w_{kj}^{o} i_{pj} + \theta_k^o \tag{9}$$

- Calculation of the outputs:
-

$$o_{pk} = f_k^o\left(net_{pk}^o\right) \tag{10}$$

- Calculation of the error terms for the output units:

$$\delta_{pk}^{o} = (y_{pk} - o_{pk}) f_k^{o'}(net_{pk}^{o}) \tag{11}$$

- Calculation of error terms for the hidden units:

$$\delta_{pj}^{h} = f_j^{h'}(net_{pj}^{h})\sum_k \delta_{pk}^{o} w_{kj}^{o} \tag{12}$$

- Updating of weights on the output layer:

$$w_{kj}^{o}(t+1) = w_{kj}^{o}(t) + \eta\delta_{pk}^{o} i_{pj} \tag{13}$$

- Updating of weights on the hidden layer:

$$w_{ji}^{h}(t+1) = w_{ji}^{h}(t) + \eta\delta_{pj}^{h} x_i \tag{14}$$

- Then the error term is given as follows:

$$E_p = \frac{1}{2}\sum_{k=1}^{M} \delta_{pk}^2 \tag{15}$$

When this error is acceptably small for each of the training vectors, training can be discontinued.

RESULTS AND DISCUSSION

The proposed method is required to find the feature vectors. The database contains 3 images. BTR60, BMP2, T72 are used as the reference for experimentation. In this study, SAR ATR experiments were performed using the MSTAR database to classify three targets as shown in Table 1. The image data are composed of SAR images chips roughly centered on three types of military vehicles: the T72, BTR60 and BMP2 (the T-72 is a tank and the other two vehicles are armored personnel carriers) as shown in Fig. 2.The segmented image and polar transform image as shown in Fig. 4.

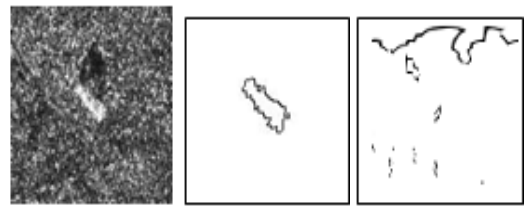
Table 1: Mstar sar database

Database	Image dimension
T72	158x158
BMP2	352x348
BTR60	708x721

Table 2: Fourier co-efficient (I/P parameters)

T72	BMP2	BTR70
47.9948	1046.5079	1264.8211
332.6268	1634.8222	1073.2054
545.7225	318.0122	309.9329
436.0248	3315.7886	540.1821
125.7563	2346.5793	491.8418
141.9366	3002.4739	1066.2805
269.7437	3994.8006	1482.6053
387.7888	2463.0892	1777.4019
349.50656	453.3892	1777.7540
244.9299	2384.8282	1577.3752
266.1169	1995.9141	835.8363
259.77422	1738.8755	1586.5926
125.6576	1821.5125	1727.6994
441.8106	1934.3425	763.3204
635.5895	2341.7658	905.6759

Based on the features extracted from the SAR images, fifteen parameters of Fourier coefficients values are given as input to train the network as shown in Table 2. These input values are compared with those image feed into the network. Then the matching is performed. The network is trained with the parameters corresponding to three types of SAR image, to their respective targets. After training the performance function reaches the goal for all the samples (Neagoe and Strugaru, 2008; Neagoe and Strugaru, 2009; Ruohong, 2008; Sandirasegaram, 2002). The performance function ‘ MSE’ (Mean Squared Error) is plotted against the number of epochs and is shown in Fig. 5. The horizontal line shows the goal and the curve represents the performance function. The Fig. 6 shows the graphical user interface of SAR Image classification. sPerformance is 0.298, Goal is 0.3.



(a) (b) (c)

Fig. 4: a) Original Image b) segmented image c) polar transform image

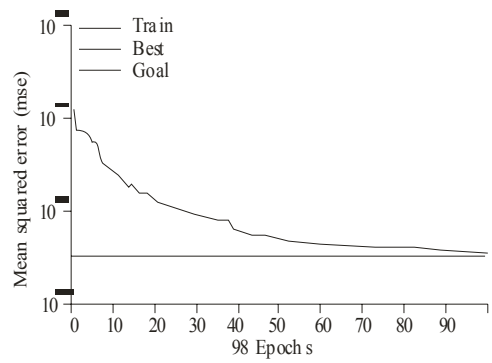


Fig. 5: Plot of performance function vs. number of epochs

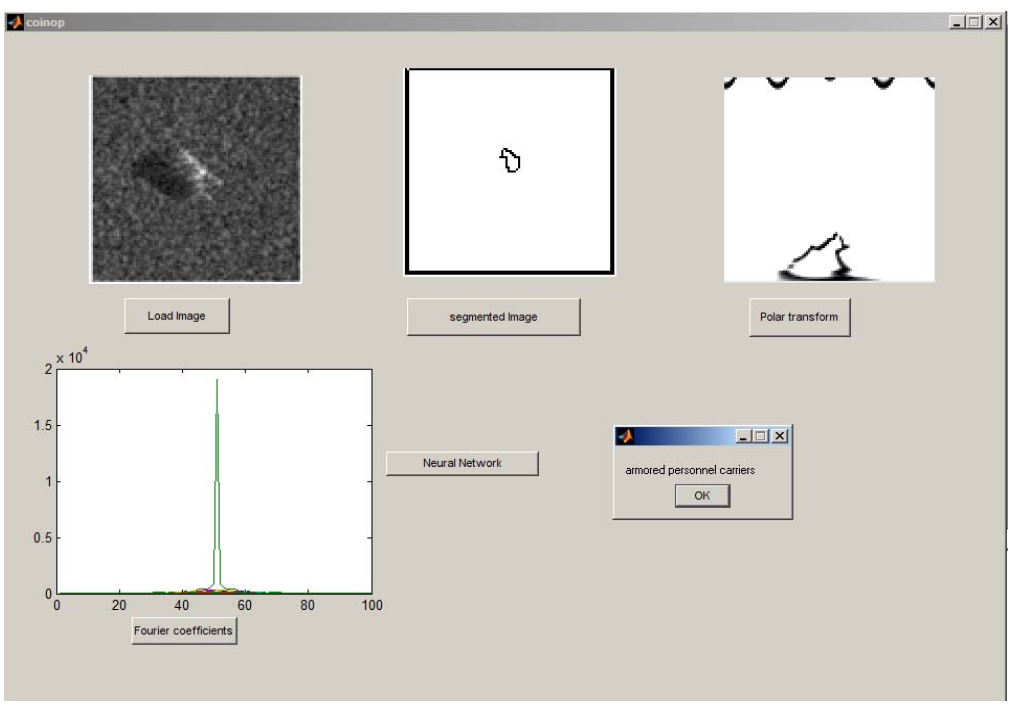


Fig. 6: GUI for SAR image classification using neural network

CONCLUSION

In this study, a new SAR image classification method has been proposed. The image of the SAR is acquired using a MSTAR database. Then the SAR image of the BTR60, BMP2, T72 (armored personnel carriers & Tank) has been subjected to the segmentation process. The Image is segmented using the Statistical Region Merging (SRM) method. After that the feature vectors are extracted using Fourier descriptor and it given in to the neural network. Neural network will trained in to the three types of SAR Images. The classification rate of the proposed algorithm is around 88%. The future study is to Automatic target recognition of SAR images with reduced time.

REFERENCES

Bennamoun, J. and G.J. Mamic, 2002. Object Recognition Fundamentals and Case Studies. Springer, ISBN: 1-85233-398-7.

Daisheng, L 2005. Pattern Recognition and Image Processing. Horwood Series in Engineering Series. ISBN-1-898563-52-7. Minoru, F., O. Sigeru, T. Fumiaki and K. Toshihisa, 1992. Rotation invariant neural pattern recognition system with application to coinrecognition. IEEE T. Neur. Network., 3: 272-279, DOI: 10.1109/72.125868.

Neagoe and G. Strugaru, 2008. A concurrent neural network model for pattern recognition in multi spectral satellite imagery. Proceeding of the World Automation Congress, 2008 (WAC 2008), International Symposium on Soft Computing in Industry (ISSCI'08), Sept. 28-Oct, 2, Hawaii, USA, ISBN: 978-1-889335-38-4, IEEE Catalog No. 08EX2476.

Neagoe and A. Ropot, 2009. A New Neural Approach for Pattern Recognition in Space Imagery. In: Harbour Protection through Data Fusion Technologies, NATO Science for Peace and Security Series-C: Environmental Security, Springer, pp: 283-289.

Ruohong and Y. Ruliang, 2008. SAR target recognition based on MRF and gabor wavelet feature extraction. IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2008), July 2008, 2: 2-907-/2-910.

Sandirasegaram, 2002. Automaic Target Recognition in SAR Imagery using a MLP Neural Network. Technical Memorandum, Defence Research and Development Canada (DRDC), Ottawa, TM, 2002-1.