Advances in Computational Sciences and Technology
ISSN 0973-6107 Volume 10, Number 4 (2017) pp. 537-548
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http://www.ripublication.com

Ship ISAR Image Classification with Probabilistic Neural Network

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Abstract

Ship detection and classification plays a significant role in naval warfare. Inverse Synthetic Aperture Radar (ISAR) images are being used extensively for feature extraction in ship detection and classification. The classification problem is solved in two steps. The first step is the extraction of features that characterize the target. The second step is to feed the computed feature values to a classifier to assign the target to one of the known classes stored in the database. In this paper, digital image processing techniques are used to extract target features from ship ISAR images for identification and classification. The feature vectors are computed from three different techniques. They are statistical moments, Zernike moments and polar transforms. These feature vectors obtained from the techniques mentioned are given as input to neural network based classifier. Here the Probabilistic neural network is implemented to classify the ship ISAR images. From the results obtained, the classification accuracy was found to be satisfactory with all the feature vectors.

Keywords: ISAR image, Probabilistic Neural Network, image classification.

INTRODUCTION

Radars are used to detect the targets at hundreds of kilometers away, at all weather conditions and without discrimination of day or night. ISAR images are essential radar images mainly used for hotspot identification and classification. ISAR image is a two dimensional image of the target in radar line of sight. High resolution radars with high bandwidth and relative motion between radar and target are the two things essential to obtain an ISAR image. The target has to rotate with uniform speed in circles of smallest possible radius to obtain highly focused ISAR images.

ISAR images that we capture will be at different aspects. Taking this into consideration the feature vectors that we extract from the ISAR images are to be invariant with rotation. In other words the feature vector that represents the target for classification should be same for ISAR images obtained at different aspects with respect to radar. ISAR images obtained at different viewing angles will have different sizes. So there is a need for invariance with scaling for the feature vectors extracted from an ISAR image.

The ship ISAR image looks quite different from optical image of a ship. An ISAR image contains pixel intensity values. Obtaining target characteristics from an ISAR image is a very complex task. The feature vectors that we extract from an ISAR image can be boundary based, pixel intensity based or region based. In this paper the region based and pixel intensity based feature vectors are considered. The Statistical moments and Zernike moments are computed for ISAR images and used as feature vectors for classification. Polar transform technique is applied to ISAR images and the obtained values are taken as feature vector. The feature vectors computed in the above three methods are fed to the probabilistic neural network. The ISAR images of four different targets are classified accurately.

The total work involved in this study can be given by the following four steps.

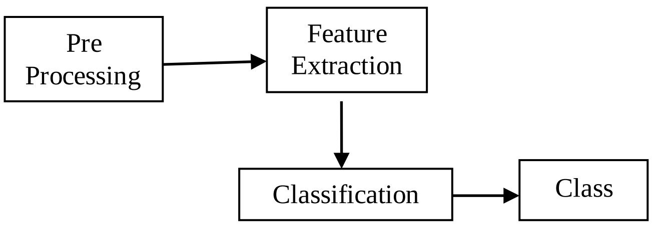

Figure 1: Steps for Ship ISAR image classification

The Zernike Moments are widely used in automatic aerial image recognition [1, 2], face recognition [4] and plant leaf identification [5]. The feature vectors computed using a polar transform show good performance even with a small training data set [1]. The appearance of ISAR images varies with the change of position and orientation. Still the Zernike moments and polar transform based feature vectors give good classification results [2]. The statistical descriptors are used in mammogram analysis [3].

In section II, the description of the three techniques used to calculate feature vectors is given. Section III explains the probabilistic classifier. In section IV numerical values f two feature vectors are given. The classification performance results and implementation details of the classifier using MATLAB Neural Network tool box are given in Section V. Conclusions are given in section VI.

PRE PROCESSING

An ISAR image captured with high resolution radar contains noise, generated due to motion of the target and sea clutter. Hence, preprocessing of the ISAR image is required before applying the digital image processing techniques for feature extraction. The color ISAR image is converted to gray scale image. The gray scale image is 2 dimensional. It is a monochrome image. This means the pixel intensity values are spread across a rectangular or square region. In MATLAB a Gaussian filter is applied to remove noise in the gray image. Finally the gray image is converted to binary image. This conversion is done using MATLB function im2bw ().The Otsu thresholding method is used. These binary images are used to extract feature vectors. A gray scale ISAR image of a target with and without noise is shown in Fig. 2 and Fig. 3 respectively. Fig. 4 shows the binary image.

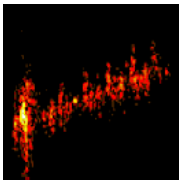

Figure 2: ISAR image

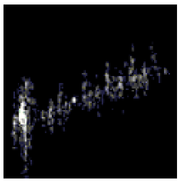

Figure 3: Gray image

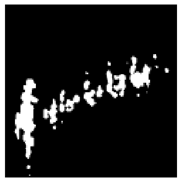

Figure 4: Binary image

Feature Vectors

The target has to continuously rotate for ISAR image formation. That is the radar viewing angle of the target is not constant. This makes the ISAR images that we capture vary continuously. The correct recognition of target based on feature vectors extracted from ISAR images requires the feature vectors to be invariant to rotation. The size of the ISAR image also changes from one aspect to other. This requires that the feature vector to be invariant to scaling also. In this paper, the three feature vectors considered i.e. Zernike moments, polar space and statistical descriptors are rotation and scale invariant.

Polar Transform

To obtain a rotation invariant feature vector, a polar transform can be used to convert the image spatial coordinates to radial coordinates. The calculated two dimensional polar coordinates is converted to one dimension by concatenating the columns. This one dimensional vector is used for classification. The following equations are used for transformation from Cartesian to polar.

$$x = r\cos\theta \qquad (1)$$

$$y = r\sin\theta \qquad (2)$$

$$where\ \theta = \tan^{-1}\frac{y}{x} \quad and\ \ r = x^2 + y^2$$

STATISTICAL DESCRIPTORS

The statistical descriptors are computed from intensity values of image pixels using the following equations.

Mean

$$m = \sum_{i=0}^{n-1} Q_i h(Q_i) \tag{3}$$

Where Q_i is pixel intensity value, $h(Q_i)$ is the histogram of the intensity level in a region, n is the number of intensity levels present in the ISAR image.

Besides mean, five more statistical descriptors standard deviation, smoothness, skewness, uniformity and entropy are evaluated taking the pixel intensity values f the image. How much the pixel intensity values deviate from mean image intensity value is given by standard deviation. It is a measure of average contrast. Smothness measures the intensity in a region. A distribution of image pixel intensity values is given by histogram. Skewness describes how this distribution is. If the distribution is symmetric, the value of skewness is 0. It is positive, when the distribution is skewed to the left. Any random change in intensity values is measured by entorpy. Uniformity tells about how much the pixel intensity values of the image are nearly equal. The equations given below represent the five statistical descriptors.

Standard Deviation:

$$\sigma = \sqrt{\mu_2(Q)} = \sqrt{\sigma^2} \tag{4}$$

Smoothness:

$$r = 1 - \frac{1}{1+\sigma^2} \tag{5}$$

Skewness:

$$\mu_3 = \sum_{i=0}^{L-1} (Q_i - m)^3 \, h(Q_i) \tag{6}$$

Uniformity:

$$U = \sum_{i=0}^{L-1} h^2 \, (Q_i) \tag{7}$$

Entropy:

$$e = - \sum_{i=0}^{n-1} h\,(Q_i) \, \log_2 h(Q_i) \tag{8}$$

Zernike moments

Moments computed from digital images are used for target recognition since they represent global characteristics of images related to geometry and shape. The moments uniquely describe the information contained in the image. Moments are global region based descriptors and can be considered as a combination of area, compactness, irregularity and higher order descriptors together. Zernike moments are preferred to geometric moments or Hu's moments in real world image classification [1]. The advantage of Zernike moments is that they can be used for image reconstruction whereas the Hu's moments cannot be used.The Zernike moments of order n, with multiplicity of phase angle m that can either be negative or positive can be given by Eq. 9.

$$Z_{nm} = \frac{p+1}{\pi} \iint_{x^2+y^2=1} f(r,\theta) V_{nm}^{*} r dr d\theta \tag{9}$$

$$where\ V_{nm}(\rho,\theta) = R_{nm}(\rho) e^{im\theta}, \theta \leq \pi, \rho = 1\ ; \tag{10}$$

$$R_{nm} = \sum_{a=0}^{\left(\frac{n-|m|}{2}\right)} (-1)^a \frac{(n-a)!}{a!\left(\frac{n+|m|}{2}-a\right)!\left(\frac{n-|m|}{2}-a\right)!} \rho^{n-2\alpha} \tag{11}$$

Where R_{nm} is the Zernike/radial basis polynomial with the following conditions satisfied.

- $n \in Z^{+}$
- n-|m| is even
-
- $|m| \leq n$
-
- $\int_0^{2\pi} \int_0^1 V_{nm}^{*}(\rho,\theta)\, \rho d\rho\, d\theta = \frac{\pi}{n+1}\ \delta_{nz}\delta_{mr},$
-
- and $\delta_{zr} = \begin{cases} 1, & z = v, \\ 0, & otherwise \end{cases}$

$V_{nm}(r, \theta)$ represents the Zernike Polynomials of order n with repetition m. The $V_{nm}^{*}(r, \theta)$ denotes the complex conjugate where the Zernike polynomials are defined as functions of the polar coordinates r, θ. The Zernike moments can be computed non recursively by using the relationship between Zernike and geometric moments.

For an image, {f(x, y) $1 \leq I \leq M$, $1 \leq I \leq N$ } can be calculated by substituting the double integration with double summation as shown by the Eq. 12.

$$Z_{nm} = \frac{n+1}{\pi} \sum_{x}^{M} \sum_{y}^{N} V_{nm}^{*}(x,y) f(x,y) \tag{12}$$

The Zernike moments of an image are computed by taking the center of the image as origin and mapping the pixel coordinates to the range of a unit circle i.e. ($x^2 + y^2 = 1$). The Zernike moments up to order 4 and the length of the feature vectors are given in the Table 1 below.

Table 1: Zernike Moments and feature vectors

Order	Moments	No. of elements in Feature vector
0	A_{00}	1
1	A_{11}, A_{-11}	3
2	A_{20}, A_{22}, A_{2-2}	6
3	$A_{31}, A_{3-1}, A_{33}, A_{3-3}$	10

Classifier Design

Probabilistic neural network (PNN) is successfully used for ship identification [9], noise classification [10] and face image classification [6]. In this paper PNN is implemented for ship ISAR image classification. A PNN does have 3 layers of nodes. The figure below shows the architecture for a PNN that can classify two classes, but it can be extended to classify classes greater than two. If the number of elements in the feature vector is N, the input layer will have N nodes, one for each of the input element of a feature vector. Each element in the input feature vector is given as input to all the nodes in the hidden layer. All the hidden nodes are made into groups as shown in Figure 5. Since PNN shown below is designed for two classes, the hidden nodes are made in to two groups, corresponding to two classes. The Gaussian function is evaluated for its associated feature vectors in the same class. At the output node all the Gaussian values compared for one group are summed. The total probability under the sum function is unity and so the sum forms a probability density function. There are two output nodes corresponding to two classes.

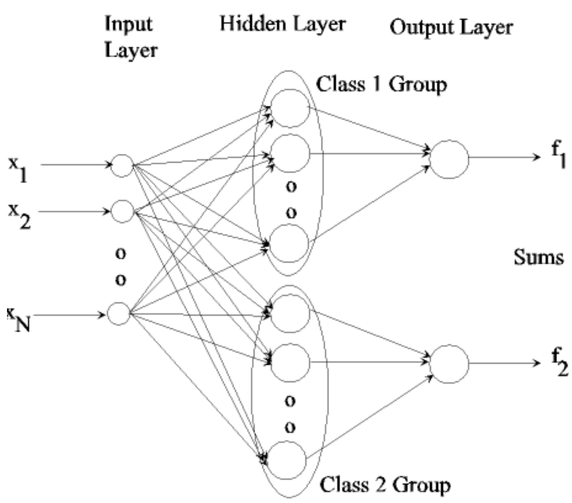

Figure 5: Architecture of Probabilistic Neural Network

Algorithm:

1. Procedure PNN (Train set, Test set, Spread)

2. Input train set and the class information

3. Compute N_i, P (C_i) where N_i – Number of training patterns in each class $C_{i;}$

4. Initializing PNN spread as σ = 0. 25 and set counter = 1.

5. Pick and observation of X_{test} from test set.

6. Do counter = counter + 1.

7. Compute unconditional probability p (X_{test}) and conditional probability P (X_{test} / C_i)

8. Compute posterior probability of X_{test}

9. Compute the average of inputs from pattern units

10. Until counter = M

11. The classification of each pattern vector is made according to the Bayesian Rule.

12. End Procedure

Data Set Generation

To check the suitability of the feature vectors and applicability of the classifier for ship ISAR image classification, large ISAR image data is required. For this study, ship ISAR images of size 30x30 pixels are obtained from open literature. Also, to verify the rotation invariance of feature vectors, each image is rotated by 15° so that 24 images are obtained for each target to cover the aspect range 360°. The feature vectors are obtained for all the rotated images. For four targets the total data set contains 96 images. Out of them, 48 numbers are taken as training set and the remaining 48 as test set.

RESULTS

The rotated images of two targets at angles θ_1 and θ_2 are given in Fig. 6 and Fig. 7. The 1st, 2nd, 3rd, 4th and 5th order Zernike moments are computed and the corresponding lengths of the feature vectors are 3,6,10, 15 and 21. The classification performance of each of the feature vector is compared. The classification with 3rd order Zernike moments is better than that with 2nd order .The performance of Zernike moments of order 3 and above was found to be same when tested for classification. This is shown as case study in section 5. The 3rd order Zernike moments calculated for the ISAR images of two targets at rotation angles θ_1 and θ_2 are given in table 2. In this case the length of feature vector is 10. Computed statistical descriptors are given in table 3. When the six statistical descriptors are considered, the feature vector has 6 elements.

Figure 6: Target 1 at rotation angles θ_1 and θ_2

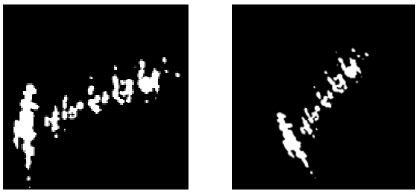

Figure 7: Target 2 at rotation angles θ_1 and θ_2

Table 2: Values of Zernike Moments of order 3

Target 1		Target 2	
target rotation angle θ_1	target rotation angle θ_2	target rotation angle θ_1	target rotation angle θ_2
3.1831	3.1831	0.9549	0.9549
0.2484	0.1242	0.2640	0.2329
0.2484	0.1242	0.2640	0.2329
0.0500	-0.0909	-0.8998	-0.7044
-9.2448	-9.1994	-0.8402	-1.2674
0.0500	-0.0909	-0.8998	-0.7044
-0.0126	-0.0331	-0.5141	-0.3575
-0.9499	-0.4525	-0.4980	-0.5376
-0.9499	-0.4525	-0.4980	-0.5376
-0.0126	-0.0331	-0.5141	-0.3575

All the ISAR images in the data set are transformed to polar space. The coordinates of the two dimension polar coordinates of the each 30x30 pixel image are arranged in to a single dimensional vector and used as a feature vector. The length of the feature vector is 900.

Table 3: Statistical Descriptors

Target 1			Target 2 at an angle	
Rotation	at an angle θ_1	at an angle θ_2	at an angle θ_1	at an angle θ_2
Mean	3.7822	3.7444	6.2811	6.1767
Standard Deviation	19.3431	19.2176	17.7714	17.6784
Smoothness	0.0057	0.0056	0.0048	0.0048
Third moment	0.7016	0.6965	0.4042	0.3838
Uniformity	0.7724	0.7584	0.3649	0.3917
Entropy	1.0532	1.0572	2.7566	2.6534

The performance of the classifier with respect to the considered three feature vectors tested with real world ship ISAR images is given in Table 4 below. From the Table 4 we can observe that the performance of the Zernike moments is better than that of polar space and statistical descriptors. Due to the smaller length, the Zernike moments and statistical descriptors are preferred to polar space. The performance of classifier can be improved by training the neural network with a larger set of images.

Table 4: Feature vectors and Classification accuracy

Feature Vector Type	Feature Vector Length	Classifier accuracy	
		Target 1	Target 2
Zernike moments	10	100%	100%
Statistical Descriptors	6	100%	55%
Polar Transform	900	100%	55%

Case Study:

As a case study, Zernike moments are computed up to 5^{th} order. The obtained feature vectors are given in Table 5.These feature vectors are fed to the classifier. Performance evaluation of the classifier is done and given in Table 6. It is observed that there is misclassification up to order 2. From order 3, the classification accuracy is satisfactory. There is no improvement in the classification with the Zernike moments above order three.

When the 3rd order Zernike moments are considered, the length of feature vector is 10.So the number of input neurons is 10. Since four targets are considered, the number of classes is 4 and hence the number of nodes in the output layer is 4. The spread parameter is taken as 0.25 equal to 1/n where n is the number of classes. When the PNN is trained with the 48 images in the training data set, the PNN has correctly classified the images from the training set. This is shown in Fig. 11. The trained network is tested for images from test set. The classification accuracy matrix given in Table 6 with respect to Zernike moments of order one to order 5 is computed with real world ISAR images.

Table 5: Computed 1st to 5th order Zernike Moments

Order	Values of Zernike moments for different order	Length of feature vector
1	3.1831,0.2484,0.2484	3
2	3.1831, 0.2484, 0.2484, 0.0500, -9.2448	5
3	3.1831, -0.949, 0.2484,-0.9499, 0.2484, -0.0126, 0.0500, -9.2448, 0.0500, -0.0126	10
4	3.1831, -0.949, 0.2484, -0.0126, 0.2484,-0.003, 0.0500, -0.2419, -9.2448, 14.4309, 0.0500, -0.241, -0.0126, -0.003, -0.949	15
5	3.1831, -0.012, -0.003,0.2484, -0.003, -0.0012, 0.2484, -0.241, 0.0727, 0.0500, 14.4309, 1.9810, -9.2448, -0.2419, 1.9810, 0.0500, -0.003, 0.0727, -0.0126, -0.2419, -0.0012, -0.949, 14.4309,-0.949,-0.241	21

Table 6: Classifier accuracy with Zernike Moments

Order	Length of Feature vector	Classifier accuracy	
		Target1	Target2
1	3	75%	100%
2	5	87.5%	100%
3	10	100%	100%
4	15	100%	100%
5	21	100%	100%

CONCLUSIONS

From this paper, one can learn that the three feature vectors Zernike moments, Statistical moments and polar space of the image can be used for classification of ISAR images. Out of three, the dimensions of the feature vectors Zernike moments and statistical moments are very small compared to polar space. The probabilistic neural network classifier is a good classifier that can be used for an ISAR image classification provided the input feature vector is single dimensional. It can be concluded that the performance of the feature vectors and classifier can be established by testing the classier with more realistic ISAR image data.

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