

Radar Pattern Classification Based on Class Probability Output Networks

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Abstract. Modern aircraft and ships are equipped with radars emitting specific patterns of electromagnetic signals. The radar antennas are detecting these patterns which are required to identify the types of emitters. A conventional way of emitter identification is to categorize the radar patterns according to the sequences of frequencies, time of arrivals, and pulse widths of emitting signals by human experts. In this respect, this paper presents a method of classifying the radar patterns automatically using the network of calculating the p -values of testing the hypotheses of the types of emitters referred to as the class probability output network (CPON). Through the simulation for radar pattern classification, the effectiveness of the proposed approach has been demonstrated.

Keywords: Radar pattern · Classification · One class · Class probability · Beta distribution

1 Introduction

In modern days, radars are essential devices to detect objects such as aircraft or ships. For detecting objects emitting specific patterns of electromagnetic signals, the detected signal patterns should be analyzed and categorized according to the types of emitters. This emitter identification plays an important role especially in the electronic warfare [1]. The robust performances of emitter identification becomes more important in complex environments of emitters and landscapes. In the conventional approach of emitter identification, the key features of radar patterns such as the sequences of radar frequencies (RFs), time of arrivals (TOAs), and pulse widths (PWs) are used to extract the emitter parameters and these parameters are compared with tabulated emitter parameters. However, this process usually requires high computational complexity and needs to be verified by human experts. In this respect, an approach of automatic classification of radar patterns is proposed to obtain the conditional class probability for the given radar pattern.

There are various ways of implementing pattern classifiers. The most popular way is using the discriminant function whose value indicates the degree of confidence for the classification; that is, the decision of classification is made by selecting the class that has the greatest discriminant value. In this direction, the support vector machines (SVMs) [2] are widely used in many classification problems because they provide reliable performances by maximizing the margin between the positive and negative classes. However, more natural way of representing the degree of confidence for classification is using the conditional class probability for the given pattern. In this context, the class probability output network (CPON) in which the conditional class probability is estimated using the beta distribution parameters, was proposed [3]. This method is implemented on the top of a classifier; that is, many-to-one nonlinear function such as the linear combination of kernel functions. Then, the classifier's output is identified by beta distribution parameters and the output of CPON; that is, the conditional class probability for the given pattern is calculated from the cumulative distribution function (CDF) of Beta distribution parameters. In this computation, the output of CPON represents the p -value of testing a certain class. For the final decision of classification, the class which has the maximum conditional class probability is selected. As a result, the suggested CPON method is able to provide consistent improvement of classification performances for the classifiers using discriminant functions alone. For the detailed descriptions of CPONs and CPON applications, refer to [3, 4]. In this approach, the selected features of radar patterns are used as the input to the classifier of many-to-one mapping nonlinear function and the output distribution is identified by beta distribution parameters to obtain the p -value of testing the type of emitters. As a result, the proposed method provides the p -values of testing hypotheses of the types of emitters and the better performances of classification than other classifiers using the discriminant function.

The rest of this paper is organized as follows: in Sect. 2, the problem of radar classification is described, Sect. 3 presents the method of radar pattern classification using the CPON, Sect. 4 shows simulation results for radar pattern classification, and finally, Sect. 5 presents the conclusion.

2 Key Features for Radar Pattern Classification

The proposed method is intended to identify radar patterns from various emitters. In this approach, it is assumed that the radar has the ability to monitor a region of microwave spectrum and to extract pulse patterns. The whole process of emitter identification (or radar pattern classification) is illustrated in Fig. 1. In this diagram, the feature extractor receives pulses from the microwave radar receiver and processes each pulse into feature values such as azimuth, elevation, intensity, frequency, and pulse width. These data are then stored and tagged with the time of arrival of the pulse. Then, the clustering block is grouping radar pulses into groups in which each group represents radar pulses from a single emitter. For each group of radar pulses, the pulse extraction block is analyzing the pulse repetition patterns of an emitter by using the information of

time of arrivals. Finally, from the information of pulse repetition patterns, input features for the classifier are computed and the decision for the classification of emitters is made based on extracted key features.

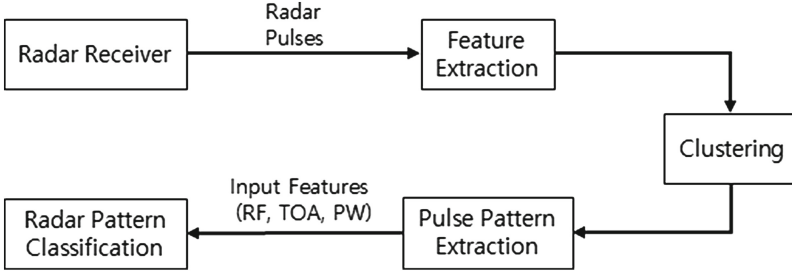


Fig. 1. Process of emitter identification

In the proposed approach, the selected key features are RFs, TOAs, and PWs. Then, for each sequence of key feature values $x_i, i = 1, \dots, n$, the statistical measures such as the mean \bar{x} , variance s^2 , skewness, and kurtosis are determined by

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i, \tag{1}$$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2, \tag{2}$$

$$\text{skewness} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left(\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2\right)^{\frac{3}{2}}}, \text{ and} \tag{3}$$

$$\text{kurtosis} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2\right)^2} - 3. \tag{4}$$

These statistical feature values are calculated for every sweep of received radar signals. Then, as a result, 12 feature values are used as the input to the classifier and the decision of emitter identification is made by using the CPON.

In this approach, the distributions of these feature values are analyzed and the centroids representing the types of emitters are determined as the center points for the distributions of radar patterns. Then, these distributions are used for the decision of determining the specific emitter type in the CPON.

3 Class Probability Output Networks for Emitter Identification

In many classification problems, it is desirable that the output of a classifier represents the conditional class probability. For the conditional class probability, the distribution of classifier's output can be well approximated by the beta

distribution under the assumption that the output of classifier lies within a finite range and the distribution of classifier’s output is unimodal; that is, the distribution has one modal value with the greatest frequency. This assumption is quite reasonable for many cases of classification problems with the proper selection of kernel parameters of a classifier. Here, we consider the following discriminant function \hat{y} as the classifier’s output for the input pattern \mathbf{x} :

$$\hat{y}(\mathbf{x}) = \sum_{i=1}^m w_i \phi_i(\mathbf{x}|\theta), \tag{5}$$

where m represents the number of kernels and w_i , ϕ_i , and θ represent the i th weight, the i th kernel function, and the kernel parameter, respectively.

In the proposed CPON, the probability model represents the conjugate prior of the binomial distribution; that is, in our case, the conditional class probability in binary classification problems. In this context, we consider the following Beta probability density function (PDF) of a random variable Y as the normalized classifier’s output:

$$f_Y(y|a, b) = \frac{1}{B(a, b)} y^{a-1} (1 - y)^{b-1}, \quad 0 \leq y \leq 1, \tag{6}$$

where a and b represents the parameters of beta distribution, and $B(a, b)$ represents a Beta function defined by

$$B(a, b) = \int_0^1 y^{a-1} (1 - y)^{b-1} dy. \tag{7}$$

Here, we assume that the classifier’s output value; that is, \hat{y} is normalized between 0 and 1. One of the advantages of the Beta distribution is that the distribution parameters can be easily guessed from the mean $E[Y]$ and variance $Var(Y)$ as follows:

$$a = E[Y] \left(\frac{E[Y](1 - E[Y])}{Var(Y)} - 1 \right) \tag{8}$$

and

$$b = (1 - E[Y]) \left(\frac{E[Y](1 - E[Y])}{Var(Y)} - 1 \right). \tag{9}$$

Although this moment matching (MM) method is simple, these estimators usually don’t provide accurate estimations especially for smaller number of data. In such cases, the maximum likelihood estimation (MLE) or the simplex method for searching parameters [5] can be used for more accurate estimation of Beta parameters. If the data distribution follows a Beta distribution and the optimal Beta parameters are obtained, the ideal cumulative distribution function (CDF) values of the data $u = F_Y(y)$ follow an uniform distribution; that is,

$$f_U(u) = \frac{f_Y(y)}{|dF_Y/dy|} = \frac{f_Y(y)}{|f_Y(y)|} = 1. \tag{10}$$

To check whether the data distribution fits with the proposed Beta distribution, the Kolmogorov-Smirnov (K-S) test [6] of data distribution can be considered as follows:

- First, determine the distance D_n between the empirical and ideal CDF values:

$$D_n = \sup_u |F_U^*(u) - F_U(u)|, \tag{11}$$

where $F_U^*(u)$ and $F_U(u)$ represent the empirical and theoretical CDFs of $u = F_Y(y)$; that is, the CDF values of the normalized output of a classifier. In this case, $F_U(u) = u$ since the data $u = F_Y(y)$ follow an uniform distribution if the data y follows the presumed (or ideal) Beta distribution.

- Determine the p -value of testing the hypothesis of Beta distribution:

$$p\text{-value} = P(D_n \geq t/\sqrt{n}) = 1 - H(t), \tag{12}$$

where $t = \sqrt{nd_n}$ (the value of a random variable D_n) and the CDF of the K-S statistic $H(t)$ is given by

$$H(t) = \frac{\sqrt{2\pi}}{t} \sum_{i=1}^{\infty} e^{-(2i-1)^2 \pi^2 / (8t^2)}. \tag{13}$$

- Make a decision of accepting the hypothesis of beta distribution H_0 using the p -value according to the level of significance δ :
 accept H_0 , if $p\text{-value} \geq \delta$; reject H_0 , otherwise.

In the construction of CPON for radar pattern recognition, first, the centroids as the representative of the radar pattern data are obtained in the feature space by a clustering algorithm such as the learning vector quantization (LVQ) method [7]. Then, the kernel functions are located at the positions of centroids and linearly combined as the form of (5). The output of (5) is normalized between 0 and 1 by using the linear scale and the normalized classifier’s output distribution is approximated by the Beta distribution parameters. In this training of classifiers, the Beta distribution parameters as well as the kernel parameters are adjusted in such a way that the classifier’s output distributions become closer to the ideal Beta distributions. The algorithm of constructing the CPON for radar pattern classification is described as follows:

- Step 1.** For the features of radar patterns, centroids are determined by the clustering algorithm such as the LVQ method. In this application, one centroid is assigned to a specific emitter. For more complicated distributions in the feature space, more than one centroids can be assigned.
- Step 2.** Then, for each centroid, a kernel function is assigned.
- Step 3.** Determine the classifier’s output for each kernel function and normalize the output value between 0 and 1 using the linear scale.
- Step 4.** The distribution of classifier’s normalized output is identified by Beta distribution parameters. In this estimation of Beta parameters, the kernel parameters such as the kernel widths are adjusted in such a way of maximizing the p -value of (12). For the detailed description of estimating parameters, refer to [3].

After the CPON is trained, the classification for an unknown pattern can be determined by the beta distribution for each class. First, for the unknown pattern, the normalized output y for the classifier is computed. Here, if the normalized value is greater than 1, we set that value as 1; on the other hand, if the value is less than 0, we set that value as 0. Then, the conditional class probability is determined by the CPON output as the CDF value for the classifier's normalized output.

For multi-class classification problems, the CPON can be constructed for each classifier's output. Then, the following conditional probability for the k th class C_k ; that is, the output of the k th CPON $F_k(y_k)$ for k th classifier's normalized output y_k is calculated as

$$F_k(y_k) = P(C_k | Y_k \leq y_k) = F_{Y_k}(y_k), \quad (14)$$

where Y_k represents a random variable for the k th class C_k and $F_{Y_k}(y_k)$ represents its CDF. This output implies the p -value of testing hypotheses of the k th class C_k . Then, the final decision can be made by selecting the class with the maximum p -value; that is, for K classes, the selected class C_l is determined by

$$l = \arg \max_{1 \leq k \leq K} F_k(y_k). \quad (15)$$

From the above equation, the final decision of the type of emitter is made.

4 Simulation

To demonstrate the effectiveness of the proposed method, the simulation for radar pattern classification was performed for the radar data patterns generated from the emitter simulator developed by LIGNex1. This simulator was designed to accommodate the variation of key features such as the RFs, TOAs, and PWs of real emitters. In this benchmark data, there were 50 sets of emitter types (or classes) in which each data set included 100 sequences of emitter patterns containing the features of RFs, TOAs, and PWs. For the evaluation of the proposed method, 10-fold evaluation method was used: 10 disjoint sets of 90% of data as training data and the rest 10% of data as test data were used. Then, the average performances of the following accuracy for 50 classes were determined:

$$\text{Accuracy} = \frac{1}{50} \sum_{i=1}^{50} \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i}, \quad (16)$$

where TP_i , TN_i , FP_i , and FN_i represent the true positive, true negative, false positive, and false negative of the i th classifier, respectively.

However, in this evaluation of classification performances, the accuracy measure can be misleading particularly in the multi-class and/or unbalanced data. From this point of view, the following exact match ratio (EMR) for n test patterns were also determined:

$$\text{EMR} = \frac{1}{n} \sum_{i=1}^n I(\mathbf{x}_i), \quad (17)$$

where \mathbf{x}_i represents the i th test pattern and $I(\mathbf{x}_i)$ represents the following indicator function:

$$I(\mathbf{x}_i) = \begin{cases} 1 & \text{if } L(\mathbf{x}_i) = D(\mathbf{x}_i) \\ 0 & \text{otherwise.} \end{cases}$$

Here, $L(\mathbf{x}_i)$ and $D(\mathbf{x}_i)$ represent the class label and the decision label of the classifier for the i th test pattern, respectively; that is, the EMR represents the ratio of correct decision of the classifier.

To compare the performances of the CPON-based method, the k-nearest neighbor (kNN) and SVM classifiers using the Scikit-learn package [8] were also trained for the same training data and evaluated for the same test data. In this simulation, the same features of RFs, TOAs, and PWs were also used for the training and testing the classifiers. In the case of SVM, 50 binary (one-against-rest) classifiers were trained and tested for the given data. The simulation results for emitter identification were summarized in Table 1.

Table 1. Simulation results for emitter identification

Classifier	kNN	SVM	CPON
Accuracy	0.9944	0.9934	0.9861
EMR	0.7952	0.6734	0.9622

These simulation results have shown that (1) three classifiers were good in the accuracy measure, (2) the SVM was not a good choice for these multi-class data from a view point of the EMR measure, and (3) the proposed method provided the best performance in the EMR measure compared with other classifiers. This implies that the proposed statistical features of the RFs, TOAs, and PWs are quite effective to identify the characteristics of the emitter types and the proposed CPON-based classification is also an effective approach for the problems of emitter identification. Furthermore, the proposed CPON-based method is also able to provide p -values for testing the types of emitters. In practice, this information of p -values helps us to make a decision whether the received radar pattern is a new type of emitter or one of known types of emitters. For example, if the maximum p -value is less than some threshold value (the usual value is 0.05), then there is a high probability that the received radar pattern comes from a new type of emitter. This ability of finding a new type of emitter is also an important issue in emitter identification problems.

5 Conclusion

A new method of radar pattern classification was proposed based on the class probability output network (CPON). In the proposed method, the sequences of key features such as the frequencies, time of arrivals, and pulse widths of emitting signals are analyzed and statistical measures of these features such as

the mean, variance, skewness, and kurtosis are extracted and used as the input to the CPON. Then, the CPON is used to construct a hypothesis of specific emitter from the distributions of these features. As a result, the proposed CPON provides the p -values of testing the hypotheses of the types of emitters. Through the simulation for radar pattern classification, it has been demonstrated that the proposed method provides the better performance of classification than other classifiers using the discriminant function. From the classification performance of the proposed CPON-based emitter identification, it is expected to be comparable with human experts. Furthermore, the proposed CPON-based method is able to provide the information for making a decision whether the received radar pattern comes from a new type of emitter.

References

1. Schleher, D.: Introduction to Electronic Warfare. Artech House, New York (1986)
2. Vapnik, V.: Statistical Learning Theory. Wiley, New York (1998)
3. Park, W., Kil, R.: Pattern classification with class probability output network. *IEEE Trans. Neural Netw.* **20**(10), 1659–1673 (2009)
4. Rosas, H., Kil, R., Han, S.: Automatic media data rating based on class probability output networks. *IEEE Trans. Cons. Electron.* **56**(4), 2296–2302 (2010)
5. AbouRizk, S., Halpin, D., Wilson, J.: Fitting beta distributions based on sample data. *J. Constr. Eng. Manag.* **120**(2), 288–305 (1994)
6. Rohatgi, V., Saleh, A.: Nonparametric statistical inference. In: *An Introduction to Probability and Statistics*, 2nd edn. Wiley, New York (2001)
7. Kohonen, T.: Improved versions of learning vector quantization. In: *IEEE International Joint Conference on Neural Networks*, vol. 1, pp. 545–550 (1990)
8. Pedregosa, F., et al.: Scikit-learn: machine learning in Python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011)