Radar Pattern Classification Based on Class Probability Output Networks

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Abstract. Modern aircrafts 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 propose a method of classifying the radar patterns automatically using the network of calculating the p-values of testing 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 aircrafts or ships. For detecting objects emitting specific patterns of electromagnetic signals, the detected signal patterns should be analysed and categorized according to the types of emitters. In the conventional approach of emitter identification, the key features of radar patterns such as the sequences of frequencies, time of arrivals, and pulse widths 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) [1] 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. 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 [2, 3]. 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 also provides comparable performances with (or better performances than) human experts.

The rest of this paper is organized as follows: in section 2, the problem of radar classification is described, section 3 presents the method of radar pattern classification using the CPON, section 4 shows simulation results for radar pattern classification, and finally, section 6 presents the conclusion.

2 Radar Pattern Classification

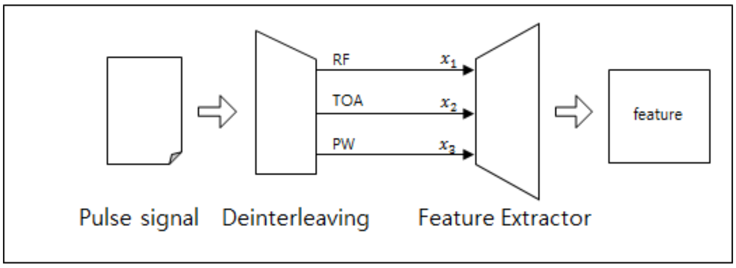

Fig. 1: Extraction from Signal to feature.

The CPON application needs features for classification. The feature is consist of statistic parameters from a sequence of radar pulse signal. The statistic parameter is series of moment from first to fourth moment. For getting statistic parameter, we need to obtain the difference for time interval from parameter of the sequence. The sequence is consist of some pulse parameters, but we take three parameters, RF(Radar Frequency), TOA(Time On Arrival), PW(Pulse Width). Not other parameters are not represent difference for each class, but these three parameters are represent. For more accurate classifying result, we use secondary difference for obtaining classifiable distance. Consistent of primary difference is more ambiguous than consistent of secondary so cannot represent discriminant feature.

Radar signal is compounded of some pulse signals. But not every signal is required for classification. Parameter-over-mounted feature makes inconspicuous itself. Therefore we need to specify most conspicuous feature.

The key feature of classifying pattern is proper features from source. There is key feature for pattern classification. The best of feature for classification is isolated feature from others. If the feature is close or similar to others, the probability of discriminant is under-fitted. So the purpose of design of the feature is to deriving parameter from the signal sequence. there is statistic specification on the sequence of signal. On this specification, we compute moments, mean($\bar{X}$), variance(S^2), skewness(b_1), kurtosis(g_2) for obvious discriminant.

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 uni-modal; 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 y as the classifier's output for the input pattern $\mathbf{x}$:

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

where m represents the number of kernels and w_i, ϕ_i, and θ represent the ith weight, the ith kernel function, and the kernel parameter, respectively. Furthermore, the beta distribution 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:

$$f_Y(y|a,b) = \frac{1}{B(a,b)} y^{a-1}(1-y)^{b-1}, \quad 0 \le y \le 1, \tag{2}$$

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

$$B(a,b) = \int_0^1 y^{a-1}(1-y)^{b-1} dy. \tag{3}$$

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:

$$a = E[Y] \left(\frac{E[Y](1-E[Y])}{Var(Y)} - 1 \right) \tag{4}$$

and

$$b = (1-E[Y]) \left(\frac{E[Y](1-E[Y])}{Var(Y)} - 1 \right). \tag{5}$$

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 [6] 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,

$$f_U(u) = \frac{f_Y(y)}{|dF_Y/dy|} = \frac{f_Y(y)}{|f_Y(y)|} = 1. \tag{6}$$

To check whether the data distribution fits with the proposed Beta distribution, the Kolmogorov-Smirinov (K-S) test [5] of data distribution can be considered as follows:

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

$$D_n = \sup_u |F_U^*(u) - F_U(u)|, \tag{7}$$

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:

$$p\text{-value} = P(D_n \geq t/\sqrt{n}) = 1 - H(t), \tag{8}$$

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

$$H(t) = \frac{\sqrt{2\pi}}{t} \sum_{i=1}^{\infty} e^{-(2i-1)^2\pi^2/(8t^2)}. \tag{9}$$

– 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-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 the clustering algorithm such as the learning vector quantization (LVQ) method [6]. Then, the kernel functions are located at the positions of centroids and linearly combined as the form of (1). The output of (1) is normalized between 0 and 1 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, the kernel functions are assigned to the centroids.

Step 3. Determine the classifier's output for each kernel function and normalized 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 (8). For the detailed description of estimating parameters, refer to [2].

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 kth class C_k; that is, the output of the kth CPON $F_k(y_k)$ for $k$the classifier's normalized output y_k is calculated as

$$F_k(y_k) = P(C_k|Y_k \leq y_k) = F_{Y_k}(y_k), \tag{10}$$

where Y_k represents a random variable for the kth class C_k and $F_{Y_k}(y_k)$ represents its CDF. This output implies the p-value of testing hypotheses of the kth 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

$$l = \arg \max_{1 \leq k \leq K} F_k(y_k). \tag{11}$$

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 ...

- radar data
- classification method
- evaluation criteria: accuracy, precision, recall, F-measure
- simulation results
- analysis of simulation results

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 widiths of emitting signals are analysed 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 CPONs provide the p-values of testing hypotheses of the types of emitters. Through the simulation for radar pattern classification, it has been demonstrated that the proposed method method is comparable with (or better than) human experts.

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