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Radar Emitter Signals Recognition and Classification with Feedforward Networks

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Abstract

A possible application of neural networks for timely and reliable recognition of radar signal emitters is investigated. In particular, a large data set of intercepted generic radar signal samples is used for investigating and evaluating several neural network topologies, training parameters, input and output coding and machine learning facilitating data transformations. Three case studies are discussed, where in the first two the radar signals are classified in two broad classes – with civil or military application, based on patterns in their pulse train characteristics and in the third one trained to distinguish between several more specific radar functions. Very competitive results of about 82%, 84% and 67% are achieved on the testing data sets.

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1. Introduction

Early radar technology had been secretly developed for military purposes in the 1940s, however nowadays it also have a wide range of civil applications. In the military area, radars (Radar Detection And Ranging) find application in detecting, locating, tracing, and identifying objects, for surveillance, navigation and weapon guidance purposes for terrestrial, marine, and air systems at small to medium and large distances. For civilian purposes, the increasingly wide range of applications includes: traffic control, navigation, weather forecast, pollution control, space observation, and sport systems [1].

Block diagram of a basic radar system is given in Figure 1. Radars are considered “active” sensors, as they use their own source of illumination (a transmitter) for locating targets. The radar range, resolution and sensitivity are generally determined by its transmitter and waveform generator. Although the typical radar systems operate in the microwave region of the electromagnetic spectrum with frequency range of about 200 MHz to about 95 GHz, there are also radars that operate at frequencies as low as 2 MHz and as high as 300 GHz [2]. The lower frequency bands are usually preferred for longer range surveillance, whereas the higher frequencies tend to be used for shorter range applications with higher resolution [1].
Radar detection, classification and tracking of targets against a background of clutter and interference are considered as ‘general radar problem’. For military purposes ‘the general radar problem’ includes searching for, interception, localisation, analysis and identification of radiated electromagnetic energy which is commonly known as radar Electronic Support Measures (ESM). They are considered reliable source of valuable information regarding threat detection, threat avoidance, and in general, situation awareness for timely deployment of counter-measures [3, 4].

A real-time identification of the radar emitter associated with each intercepted pulse train is a very important function of the radar ESM. Typical approaches include sorting incoming radar pulses into individual pulse trains, then comparing their characteristics with a library of parametric descriptions, in order to get list of likely radar types. This can be very difficult task as there may be radar modes for which there is no record in ESM library; overlaps of different radar type parameters; increases in environment density (e.g., Doppler spectrum radars transmitting hundreds of thousands of pulses per second); agility of radar features such as radio frequency and scan, pulse repetition interval etc.; multiplication and dispersion of the modes for military radars; noise and propagation distortion that lead to incomplete or erroneous signals [5].

2. Neural Networks in Radar Recognition Systems

Various approaches and methods have been investigated for radar emitter recognition and identification, where considerable part of the research in the area incorporates Neural Networks (NN), because of their massively parallel architecture, fault tolerance and ability to handle incomplete radar type descriptions and inconsistent and noisy data. NN techniques have previously been applied to several aspects of radar ESM processing [4], including PDW sorting [6, 7] and radar type recognition [8]. More recently, many new radar recognition systems include neural networks as a key classifier [9-12]. Examples of a variety of NN architectures and topologies used for radar identification recognition and classification based on ESM data include popular Multilayer Perceptron (MLP), Radial Basis Function (RBF), a vector neural network [13], single parameter dynamic search neural network [11], and others.

For example, in [5] the authors use initial clustering algorithm to separate pulses from different emitters according to position-specific parameters of the input pulse stream when implementing their “What-and-Where fusion strategy” and then apply fuzzy ARTMAP neural network to classify streams of pulses according to radar type, using their functional parameters. They also do simulations with data set that has missing input pattern components and missing training classes and incorporate a bank of Kalman filters to demonstrate high level performance of their system on incomplete, overlapping and complex radar data. In [14] higher order spectral
analysis (HOSA) techniques are used to extract information from LPI (low probability of intercept) radar signals and to produce 2D signatures, which are then fed to a NN for detecting and identifying the LPI radar signal. The work presented in [15] investigates the potential of NN (MLP) when used in Forward Scattering Radar (FSR) applications for target classification. The authors analyze collected radar signal data and extract features, which are then used to train NN for target classification. They also apply K-Nearest Neighbor classifier to compare the results from the two approaches and conclude that the NN one is superior. In [16] an approach combining rough sets (for data reduction) and NN as a classifier is proposed for radar emitter recognition problem, while [17] combines wavelet packets and neural networks for target classification.

In many cases the NN are hybridized with fuzzy systems, clustering algorithms, wavelet packets, Kalman filters, etc., which in turn leads to recognition systems with increased accuracy and improved efficiency [5, 9, 18].

### 3. Problem Statement and Available Data Set Analysis

Reliable and real-time identification of radar signals is of crucial importance for timely threat detection, threat avoidance, general situation awareness and timely deployment of counter-measures. In this context, this paper investigates the potential application of a NN-based approach for timely and trustworthy identification of radar types, associated with intercepted pulse trains.

For the purposes of this research, a data set composed of 29094 intercepted generic data samples is used. Each of the captured signals is pre-classified by experts in one of 125 categories, based on the main functions the radar emitter performs (surveillance, air defense, air traffic control, weather tracking, etc.).

Each data entry represents a list of 12 recorded pulse train characteristics (signal frequencies, type of modulation, pulse repetition intervals, etc. that will be considered as input parameters), a category label (specifying the radar function and being treated as system output) and a data entry identifier (for reference purposes only) (Table 1).

Table 1. Sample radar data subset. Missing values (i.e. values that could not have been intercepted or recognized) are denoted by ‘Z’. The rest of the acronyms are defined in Table 2.

| ID  | FN | RFC | RFmin | RFmax | PRC | PRImin | PRImax | PDc | PDmin | PDmax | ST  | SPmin | SPmax |
|-----|----|-----|-------|-------|-----|--------|--------|-----|--------|--------|-----|-------|-------|
| 863 | 3D | A   | 5300  | 5850  | F   | Z      | Z      | S   | Z      | Z      | A   | 5.9   | 6.1   |
| 1249| 3D | A   | 1250  | 1350  | F   | Z      | Z      | S   | 2.4    | 2.6    | W   | 3.5   | 4.5   |
| 4891| AT | F   | 2700  | 2900  | F   | Z      | Z      | S   | 0.9    | 1.1    | A   | 2.2   | 2.6   |
| 11080| SS | A   | 8800  | 9900  | F   | Z      | Z      | Z   | Z      | B      | Z   | Z     | Z     |
| 27823| WT | F   | 8800  | 9600  | F   | 2439   | 2564.1 | S   | Z      | Z      | A   | 590   | 610   |

A more comprehensive summary of the data distribution is presented in Table 2, where an overview of the type, range and percentage of missing values for the parameters in the data set is given. The data considered consists of both numerical (integer and float) and categorical values, therefore, coding of the categorical fields will be required during the data pre-processing stage, in order to convert them to numerical representations.

In addition, because of the large amount of missing values for some of the parameters, approaches for handling of missing data should be considered at later stages. Also, in order to reduce the dimensionality of the problem, some statistical pre-processing and feature reduction techniques should also be investigated.
Data Pre-processing

The pre-processing of the available data is of great importance for the subsequent machine learning stage and usually can affect significantly the overall success or failure of the application of a given classification algorithm. In this context, the main objective of this stage is to analyse the available data of inconsistencies, outliers and irrelevant entries and to transform it in a form that could facilitate the underlying mathematical apparatus of the machine learning algorithm and lead to an overall improvement of the classifier’s performance.

4.1. Data Cleaning

For the purposes of the current stage of our research, samples that contain incomplete data (i.e. data that could not have been fully intercepted or recognized) are removed from the investigated data set. As a result, a total of 7693 fully intercepted and recognized radar signals are identified. Subsequently, depending on the experiment to be performed, they are combined by experts into 2 classes (circular, ‘F’ – fixed, etc.) for the purposes of the first two experiments and in 11 classes for the last one.

Although currently not included in our study, the missing data samples contain large amount of valuable information that needs to be explored. Therefore, a comprehensive missing data analysis will be performed for further simulations. Simple missing data handling techniques include listwise deletion, pairwise deletion and mean substitution, however they might lead to a great loss of information and poor or unsatisfactory results. Hence, more advanced approaches, such as multiple imputation (MI) and maximum likelihood (ML) methods that aim to complete the missing data based on statistical analysis should be considered [19].

A randomly selected no missing data sample subset is presented in Table 3. The first column in it (the ID attribute) is retained for referencing purposes only and it is not being presented during the classifier’s training.

Table 3. Sample radar data subset with no missing values.

| ID | FN | RFC | RFmin | RFmax | PRC | PRImin | PRImax | PDC | PDmin | PDmax | ST | SPmin | SPmax |
|----|----|-----|-------|-------|-----|--------|--------|-----|-------|-------|----|-------|-------|
| 983 | A  | F   | 15700 | 17700 | F   | 100    | 142.9  | S   | 0.03  | 0.05  | A   | 0.9   | 1.1   |
| 1286 | SS | A   | 5500  | 5800  | K   | 909.1  | 1111.1 | S   | 0.6   | 0.8   | A   | 1.9   | 2.1   |
| 4846 | SS | F   | 172   | 180   | F   | 2439   | 2564.1 | S   | 1.6   | 1.8   | G   | 28    | 32    |
| 12097 | 3D | D   | 5250  | 5850  | F   | 2703   | 2777.8 | S   | 3     | 3.3   | A   | 5.8   | 6.2   |
| 28059 | WT | F   | 5300  | 5700  | F   | 1127   | 1132.5 | S   | 0.75  | 0.85  | C   | 12    | 60    |
4.2. Data Transformation

This stage of the pre-processing aims to transform the data into a form that is appropriate for feeding to the selected classifier and would facilitate faster and more accurate machine learning. In particular, a transformation known as coding is applied to convert the categorical values presented in the data set to numerical ones. Three of the most broadly applied coding techniques are investigated and evaluated – continuous, binary and introduction of dummy variables.

For the first type of coding, each of the categorical values is substituted by a natural number, e.g. the 12 categories for the RFC input are encoded with 12 ordinal numbers, the 15 PRC categories – with 15 ordinal numbers, etc. A sample continuous coded data subset is given in Table 4. Binary coding, wherein each non-numerical value is substituted by \( \log_2 N \) (where \( N \) is the number of categories taken by that variable) new binary variables (i.e. taking value of either 0 or 1), is demonstrated in Table 5 for 32 categories.

For the last type of coding, the non-numerical attributes are coded using dummy variables. In particular, every \( p \) levels in a categorical variable are represented by introducing \( p \) dummy variables. An example dummy coding for 4 levels is shown in Table 6.

Taking into account the large number of categories presented for the categorical attributes in the input data set (Table 1), continuous and binary codings are considered for transforming the input variables. On the other hand, binary and dummy variable codings are chosen for transforming the output parameters.

Finally, in order to balance the impact of the different input parameters on the training algorithm, data scaling is considered. Correspondingly, each of the experiments conducted in the next section is evaluated using 3 forms of the input data set – the data itself (with no scaling), after normalization (i.e. scaling the attribute values to fall within a specific range, for example \([0 \ 1]\)), and after standardization (i.e. scaling the attribute values to a zero mean and unit variance). A sample binary coded and normalized data subset is given in Table 7.
Table 7. Sample radar data subset with no missing values and binary coding.

| ID    | RFC Enc | RFmin | RFmax | PRC Enc | PRmin | PRmax | PDC Enc | PDmin | PDmax | ST Enc | SPmin | SPmax |
|-------|---------|-------|-------|---------|--------|--------|---------|--------|--------|--------|--------|--------|
| 983   | 0 0 1 1 | 0.228 | 0.249 | 0 0 1 1 | 0.0006 | 0.0003 | 0       | 0.000610| 0.000014| 0 0 0 0 | 0.00025| 0.00030|
| 1286  | 0 0 0 0 | 0.080 | 0.082 | 0 1 1 0 | 0.0056 | 0.0022 | 0       | 0.000303| 0.000363| 0 0 0 0 | 0.00054| 0.00058|
| 4846  | 0 0 1 1 | 0.002 | 0.003 | 0 0 1 1 | 0.0151 | 0.0051 | 0       | 0.000815| 0.000828| 0 0 1 1 | 0.00789| 0.00877|
| 12097 | 0 0 0 0 | 0.076 | 0.082 | 0 0 1 1 | 0.0167 | 0.0055 | 0       | 0.001533| 0.001526| 0 0 0 0 | 0.00163| 0.00170|
| 28059 | 0 0 1 1 | 0.077 | 0.080 | 0 0 1 1 | 0.0070 | 0.0023 | 0       | 0.000379| 0.000386| 0 0 1 1 | 0.00338| 0.01644|

4.3. Data Reduction

Different statistical analysis techniques for dimensionality reduction of the input data are available in the literature. In general, these methods search for a lower dimensional space that can best represent the data. Some of the most broadly used approaches include principal component analysis (PCA), linear discriminant analysis (LDA) and their modifications [19, 20, 21]. However they will be a subject for a further extension of the current work.

5. Classifier Training and Results

Three broader experiments are conducted for investigating the possible application of neural network classifiers for our radar emitter recognition problem. The investigated neural network topologies include one hidden layer, with fully connected neurons in the adjacent layers and batch-mode training. For a given experiment with \( P \) learning samples, the error function is given as:

\[
E_p = \frac{1}{2} \sum_{i=1}^{L} (x_i^p - t_i^p)^2, \tag{1}
\]

where for each sample \( p=1,\ldots,P \) and each neuron of the output layer \( i=1,\ldots,L \), a pair \((x_i, t_i)\) of output and target values, respectively, is defined.

For all of the studies, NN learning with Levenberg-Marquardt algorithm and tangent sigmoid transfer function is used. A split-sample technique with randomly selected 70% of the available data for training, 15% for validation and 15% for testing is followed and mean squared error (MSE) is used for evaluating the learning performance. The stopping criteria is set to 500 training epochs, gradient reaching less than 1.0e-06 or 6 consequent validation check fails, whichever occurs first.

For the purposes of the first study, the categorical attributes of the input data are coded with consecutive integers. In this way a total of 12 input variables are received (Table 4). Two neural network topologies are examined – 12-10-1 (12 neurons in the input, 10 neurons in the hidden and 1 neuron in the output layers) and 12-10-2, where the output parameter is coded as one binary neuron taking values 0 (“Civil”) and 1 (“Military”) for the first topology and 2 binary neurons, taking values 10 (“Civil”) and 01 (“Military”) for the second topology.

The performance of each of the topologies is investigated, evaluated and compared for training with the original data, after normalization and after standardization. The results are summarized in Table 8.

Sample confusion matrices for a 12-10-2 NN classifier with normalized input data and a validation stop after 118 epochs are given in Figure 2. They show the classifier’s performance on the training, validation, testing, and the three kinds of data set combined together. The network outputs are very accurate, as it can be seen by the high number of correct responses in the green squares and the low number of incorrect responses in the red squares. The lower right squares illustrate the overall classifier accuracies, which for the testing set is 81.6 %.
Table 8. Summary of NN classifiers performance for continuous inputs coding and 12-10-X topology with no data scaling, after normalization and after standardization.

| NN Topology | Inputs Scaling | Classification Accuracy |
|-------------|----------------|-------------------------|
| 12-10-1     | no scaling     | 78.12 %                 |
|             | normalization  | 80.82 %                 |
|             | standardization| 80.76 %                 |
| 12-10-2     | no scaling     | 80.14 %                 |
|             | normalization  | 81.60 %                 |
|             | standardization| 82.18 %                 |

Fig. 2. Classification results for 12-10-2 NN classifier with normalized input data. The values in green specify the correctly classified samples for each class (10 - Civil, 01 - Military).

Fig. 3. Classification results for 22-22-2 NN classifier with standardized input data. The values in green specify the correctly classified samples for each class (10 - Civil, 01 - Military).

The second case study investigates two additional NN topologies – 22-22-1 and 22-22-2, where the output parameter is again coded by one binary neuron (0 for “Civil” and 1 for “Military”) for the first topology and by two binary neurons for the second one (10 for “Civil” and 01 for “Military”). Again, the performance of each of the topologies is investigated, evaluated and compared using the original data, after normalization and after standardization. The performance results are summarized in Table 9.

Table 9. Summary of NN classifiers performance for binary inputs coding and 22-22-X topology with no data scaling, after normalization and after standardization.

| NN Topology | Inputs Scaling | Classification Accuracy |
|-------------|----------------|-------------------------|
| 22-22-1     | no scaling     | 81.90 %                 |
|             | normalization  | 83.34 %                 |
|             | standardization| 83.01 %                 |
| 22-22-2     | no scaling     | 81.77 %                 |
|             | normalization  | 83.90 %                 |
|             | standardization| 84.30 %                 |
Similarly to the first case study, a sample confusion matrix is presented in Figure 3 for a 22-22-2 NN classifier trained with standardized input data. A very high accuracy of 84.3 % on the testing data set is achieved after 114 epochs and activation of the validation check stopping criteria (bad performance on the validation data set in six successive iterations).

The final case study investigates a broader output space of 11 classes (4 from the civil and 7 from the military domain) and evaluates a 22-22-11 NN classifier with unscaled, normalized and standardized training data with dummy variable coded outputs. Summary of the obtained results is presented in Table 10 and a sample confusion matrix for the investigated classifier with standardized input training data is given in Figure 4, where a very good recognition rate of 67.49 % can be observed.

| NN Topology | Inputs Scaling | Classification Accuracy |
|-------------|----------------|-------------------------|
| 22-22-4     | no scaling     | 61.94 %                 |
|             | normalization  | 66.70 %                 |
|             | standardization| 67.49 %                 |

Furthermore, additional improvement might be expected, if additional statistical pre-processing techniques, missing data handling routines, NN topologies or training algorithm parameters are investigated.

Although a straight forward comparison to radar classification studies reported by other authors might be misleading, due to the different data sets, model parameters and training methods used, the achieved results are strongly competitive to the ones reported in [5, 13, 14].
6. Conclusion

The application of neural network classifiers for recognition of generic radar data signal train pulse sources is investigated, implemented, tested and validated. Three case studies are presented and several data coding, data transformation and learning parameters are evaluated.

In the first two, all the signals are pre-classified by experts in one of two classes – with civil or military application, whereas the third one tries to distinguish between several more specific radar functions. As a result, very competitive classification performances of about 82%, 84% and 67% respectively, are achieved.

On the other hand, several possible improvements of the taken approach are discussed, such as employing additional statistical techniques for missing data handling and problem dimensionality reduction, as well as varying other training parameters and classifier’s topology. Yet, they and also the classifiers performance on more categories are subject on an ongoing further extension of this work.

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