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A Complex Machine Learning Technique For Ground Target Detection and Classification.

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Abstract
A complex ground radar target detection and classification method (CTDCM) based on machine learning algorithms is presented. The method is based on a 3-step analysis: learning step, examined data pre-processing, and target labeling step coupled with classification. The paper in addition describes a feature extraction technique for ground radar images. The learning step requires labeled data for the current classification task in different qualities. The data pre-processing step prepares incoming radar images from a wide range of possible formats for a uniformly converted internal format. The labeling and classification part uses mutual information filtration, labeled data clustering and multiclass Naïve Bayes classifier as a result probability score for a cluster. The described setup was experimentally selected from a variety of classifiers, feature selection methods and data filtration algorithms. One of the principal conditions was linear complexity and minimal computation time together with a low classification error for aircraft onboard usage. Experimental analysis as well as a visual representation of the data are presented. The method was implemented in FPGA onboard DSP unit.

Keywords: machine learning, classification, image analysis, ground radar, programmable logic.

Introduction
Ground radar target detection in general is a difficult task due to a wide variety of observed surfaces, highly variable environments and a broad range of echo levels with numerous unknown parameters.
Target detection using radar images can be performed on pixel level values such as grey representing either the magnitude or squared magnitude of radar echoes. A number of researchers have used artificial intelligence based approaches, such as artificial neural networks and expert systems, for automatic target detection applications [1-8]. However, the success of the neural network approach is related to the complexity of patterns to be classified and amount of data is available to teach it. Other methods such as kernel-based or probability-score methods sometimes do not show best results for target detection on radar data.
This paper focuses on the three-step machine learning approach with ability to predict targets based on low populated data for automatic target detection using radar images. As an example, the detection of aircrafts landed on the ground is presented. 1024×1024 pixel surface scanning radar images were used as sample data. Aircraft labeling was added after first part of target detection. Sample is presented at Fig. 1.

Figure 1: Ground radar image sample.

Method
Classification is categorized into two types: supervised and unsupervised classification. In supervised classification approach, classes are defined by the pre-stored learning data with pre-defined classes for each element of the data. However, in unsupervised classification scheme, the classes are determined using the similarity of classes and the input pattern is assigned accordingly. In our method both types are used: unsupervised step to aggregate similar possible targets into groups (clusters) and then the supervised step to classify each group from the known set of targets.
The first part of target detection is used to label targets from background image. Detection threshold is used as the mutual information $I(X,Y)$ of the data in regions

$$\left[x_0 + x_\delta, x_0 - x_\delta\right] \times \left[y_0 + y_\delta, y_0 - y_\delta\right].$$

Where x_δ and y_δ is local maximum of amplitude F

$$\text{in } x_\delta \in [x_\delta^0, \mathrm{x}_\delta^{\max}], y_\delta \in [y_\delta^0, y_\delta^{\max}],$$

where $x_\delta^0, y_\delta^0, \mathrm{x}_\delta^{\max}, y_\delta^{\max}$ – are functions from average amplitude on observed image F_{mean}. Each step in correcting target bounding is done to move amplitude maximum to the center of target bounding simultaneously not excluding any possible target information from the bounding box. Mutual information $I(X,Y)$ is defined as:

$$I(X,Y)=\sum_{x\in X}\sum_{y\in Y}p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (1)$$

Sigmoid curve is used as a decision rule

$$S(t)=\frac{1}{1+e^{-t}} \quad (2)$$

For the current example, 3 classes of target detection are used – background (low amplitude region), noise target (medium amplitude region) and target (high amplitude region). Labeled possible targets are presented at Fig. 2.

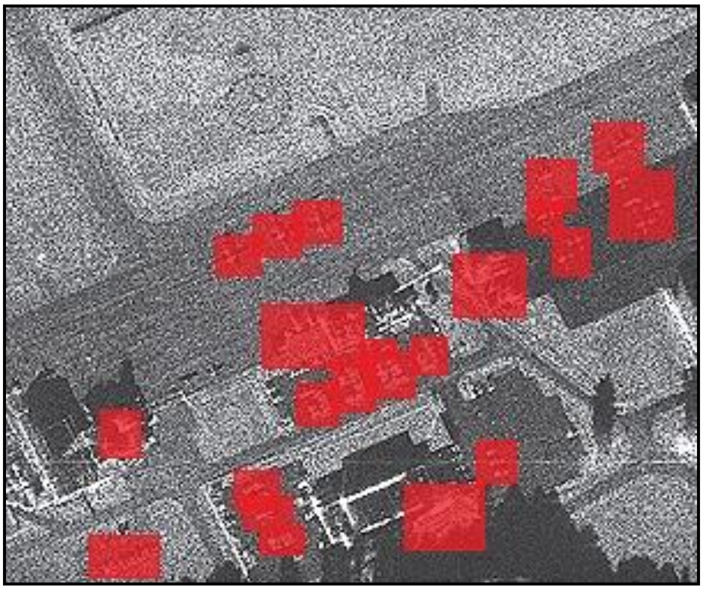

Figure 2: Bounded possible targets.

After labeling by mutual information criteria, the second step is clustering of the labeled possible targets. Clustering involves grouping objects in sets, such that objects within a cluster are as similar as possible, whereas objects from different clusters are as dissimilar as possible. Thus, the optimal clustering is somehow subjective and dependent on the characteristic used for determining similarities, as well as on the level of detail required from the partitions.

For clustering measure, a sum of intra-cluster distances between points in a given cluster C_k containing n_k points is used:

$$W_k=\sum_{k=1}^{K}\frac{1}{2n_k}\sum_{x_i\in C_k}\sum_{x_j\in C_k}\left\|x_i-x_j\right\|^2 \quad (3)$$

To determine the number of clusters (types of targets detected) a gap statistic method is used. Stanford researchers Tibshirani, Walther and Hastie in their paper [9] developed the gap statistic. The idea behind the approach is to find a way to standardize the comparison of $\log W_k$ with a null reference distribution of the data, i.e. a distribution with no obvious clustering. Their estimate for the optimal number of clusters K is the value for which $\log W_k$ falls the farthest below this reference curve. This information is contained in the following formula for the gap statistic:

$$Gap_n(k)=E_n^*\{\log W_k\}-\log W_k \quad (4)$$

The reference datasets are in our case generated by sampling uniformly from the original dataset's bounding box. To obtain the estimate $E_n^*\{\log W_k\}$ we compute the average of 15 copies of $\log W_k^*$, each of which is generated with a Monte Carlo sample from the reference distribution. Those $\log W_k^*$ from the Monte Carlo replicates exhibit a standard deviation $sd(k)$ which, accounting for the simulation error, is turned into the quantity

$$s_k=1,03\cdot sd(k). \quad (5)$$

Finally, the optimal number of clusters K is the smallest k such that:

$$Gap(k)\geq Gap(k+1)-s_{k+1}. \quad (6)$$

Then, we divide labeled targets in K clusters by k-means method:

$$S^*=\underset{S}{\operatorname{argmin}}\sum_{i=1}^{K}\sum_{x\in S_i}\left\|x-\mu_i\right\|^2 , \quad (7)$$

where μ_i – is the mean of points in
$S_i\in S=\{S_1,S_2,...,S_K\}$.

The last step of the CATCM method is supervised two-step recognition: training and classification. In the training mode, the feature extraction/selection module constructs the features, which are representations of the input pattern, and then the classifier is trained in order to segment the feature space, and we propose 1 to 4-pixel area as an average amplitude for each feature. In the classification mode, the trained classifier determines the class of the input pattern using the extracted features. Weighted Naïve Bayes classifier is used for a classification step. Weights $\{w_i,...,w_n\}$ for features are pre-stored in the system for each class of classification process:

$$C=\underset{k\in\{1,..,K\}}{\operatorname{argmax}}\,p(C_k)\left(\prod_{i=1}^{n}p\left(x_i\mid C_k\right)^{w_i}\right)^{\frac{1}{\sum_{i=1}^{n}w_i}} \quad (8)$$

As a competitor for Naïve Bayes 9-layer back propagation neural network has been used. First internal layer uses 100 neurons and others proportionally down to 10 neurons at last internal layer. As an output three classes are used – aircraft, vehicles and background (noise). As a pre-processing, each target transfers into 40x40 pixels target to use as a unified input to the DNN. The neural network diagram is presented on Fig.3.

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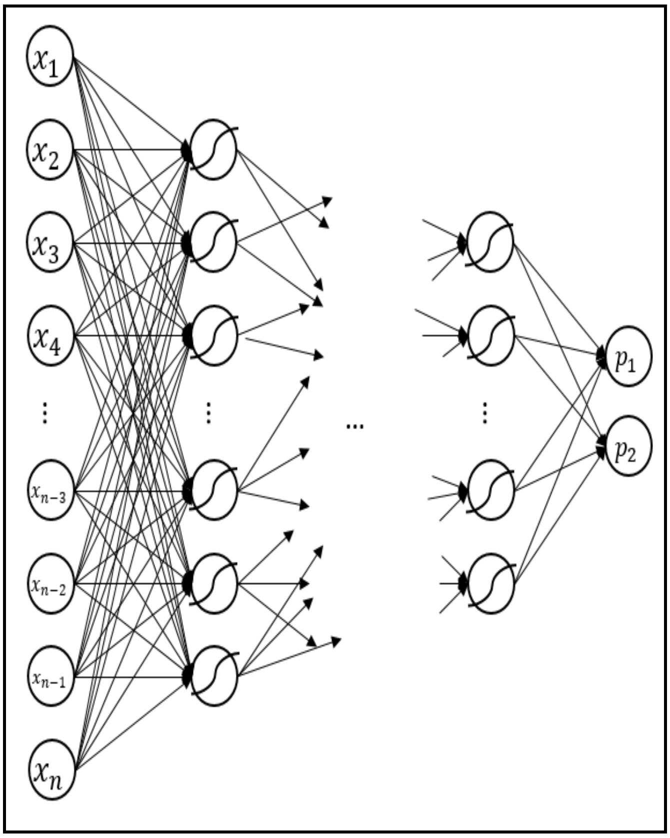

Figure 3: Neural network diagram.

Figure 4: Sort metric for the methods comparison.

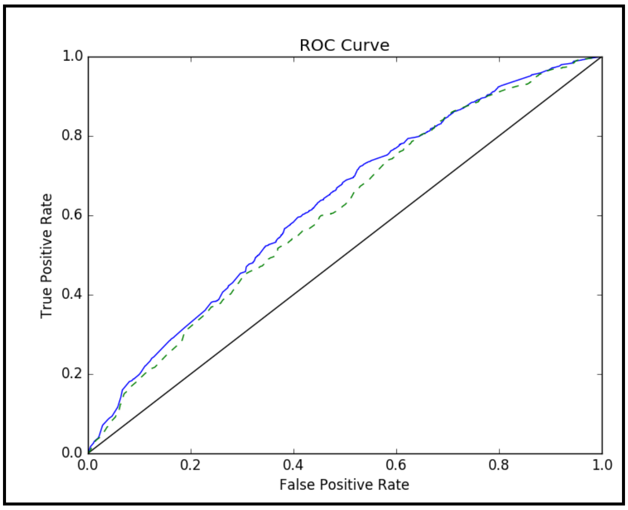

Figure 5: ROC curve for the methods comparison.

Implementation in DSP unit

Implementation of the described method into a radar prototype FPGA DSP unit is a good example of practical application of machine learning techniques. Total space requirement is 10 Mbytes for FPGA binary firmware.

Experimental results

Proposed CTDCM method was tested on numerous radar images with aircrafts and vehicles observed. As a primary quality metrics ROC curve was used as far as a sort metric, that is defined as a sum of $\frac{1}{err}$, where err is a signed distance between classification score and real target. Graphical results for CTDCM with Naïve Bayes and CTDCM-DNN with neural network are presented at Fig. 4 and Fig. 5, numerical results are presented at table 1.

Table 1: Main characteristics of the processing kernel components

	CTDCM	CTDCM-DNN
Classification error	12%	17%
AUC	0.627842	0.609412
Learning time	1.85 secs	Limited to 10 secs
Classification time	2.35 secs	1.15 secs

Conclusion

In this paper, we propose the complex method for target detection from ground radar images with machine learning approach. The basic idea of the method is to apply machine learning algorithms to the problem of target detection. Proposed CTDCM method uses 3-step processing: learning step, data pre-processing, and labeling step coupled with classification. The last step also devided into labeling and classification, which includes clustering labeled data and classification of selected clusters. Clustering as a pre-processing for classification allows holding the performance of the method with high noised data. CTDCM method was implemented in FPGA DSP unit and tested using 3 classes and compared with its deep neural network modification on

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