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HRRP Target Recognition Based On Soft-Boundary Deep SVDD With LSTM

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***Abstract*—Radar high-resolution range profile (HRRP) target recognition is an active part of radar target recognition (ATR). The current radar HRRP target data has the characteristics of less data volume. At the same time, support vector data description has limited ability to extract the deep features of the signal. To address this issue, we propose a soft-boundary Deep SVDD with LSTM (long short-term memory). The framework consists of an autoencoder, an LSTM neural network layer, and an SVDD hyper-sphere. The autoencoder generates the deep signal features, and the LSTM layer can extract the time-related features. The distance from the feature point to the center of the hyper-sphere is the classification judgment condition. The neural network parameters and the hyper-sphere are trained to be the optimal value. We carry out experiments on a dataset with a small volume. The result and the Received operation characteristic (ROC) curve show that the classifier has good performance. The area under ROC (AUC) value is close to 87%-94%.**

***Index Terms*—Soft-Boundary Deep SVDD; HRRP Target Recognition; LSTM Neural Network; Data Fusion.**

I. Introduction

The high-resolution range profile (HRRP) is the vector sum of the radar echo projected on the ray, which is the sequence of the target scattering intensity distribution [2]. The HRRP image contains rich target feature information, such as the radial position relationship between the scattering centers of the target and the fine structure of the target. Therefore target HRRP image recognition is an active part of radar target detection. Massive ground clutter enters the radar with the target's echo signal in the high signal-to-noise ratio environment. It is not easy to distinguish between signal and clutter [1]. With the development of neural network technology and to overcome the problem of clutter, reference [2] uses a transfer learning framework to address the HRRP recognition problem when the training data have incomplete aspect angles. From unsupervised learning to supervised learning, different deep learning frameworks are applied [7]–[9].

Anomaly detection (AD) and machine learning methods are widely used in various tasks. A recent AD method, support vector data description (SVDD), is getting more popular because of its less need for training samples and prior information, and its better classification performance without the distribution of data than other classification methods [13]. As a combination of AD and machine learning methods, the deep Support Vector Data Description (deep SVDD) can simultaneously learn a feature representation of the data and a data-enclosing hyper-sphere. The deep SVDD is divided into soft-boundary deep SVDD and one-class deep SVDD [12]. For example, reference [4] applies Deep SVDD to malicious traffic detection. Going back to HRRP processing, in an unknown radar target situation, SVDD is used for target recognition [3]. However, suppose the architecture of the model does not comply with certain architecture constraints. In that case, the adaptability will be limited, and the model performance may be affected due to learning sub-optimal features [6]. Therefore, with the help of the Deep SVDD method, the problems of small data volume and weak model generalization ability in HRRP target recognition can be solved.

Long short-term memory (LSTM) network is easier to learn long-term dependence than simple loop architecture, and it can obtain advanced performance on challenging sequence processing tasks. The LSTM network can learn the contextual correlations of HRRPs. Therefore a method that combines LSTM and hidden Markov model (HMM) decision-making is used in HRRP target recognition [5]. Reference [10] proposes a novel Memory-Based Neural Network (MBNN) based on LSTM for HRRP target recognition.

To overcome the limitation in the above feature learning methods for HRRP recognition, a novel target recognition framework based on Soft-Boundary Deep SVDD with LSTM is proposed in this paper. The framework consists of an autoencoder, an LSTM neural network layer, and an SVDD hyper-sphere. The autoencoder can extract the deep feature of the signal. The LSTM layer can extract the time-related features. The distance from the feature point to the center of the hyper-sphere is the classification judgment condition. The whole framework is shown in Fig. 1. Through the training process, the feature extractor and hyper-sphere parameters are trained to fit the classifier. Compared with the previous method, this can effectively extract the signal's depth and time correlation features simultaneously to achieve higher recognition accuracy. Experiment results show that the proposed framework can promote classification accuracy up to 87%-94% in different signal-to-noise rate (SNR) environments.

In this paper, the section arrangements are as follows. The Deep SVDD and LSTM model is shown in section 2. In section 3, the proposed Deep SVDD with training process

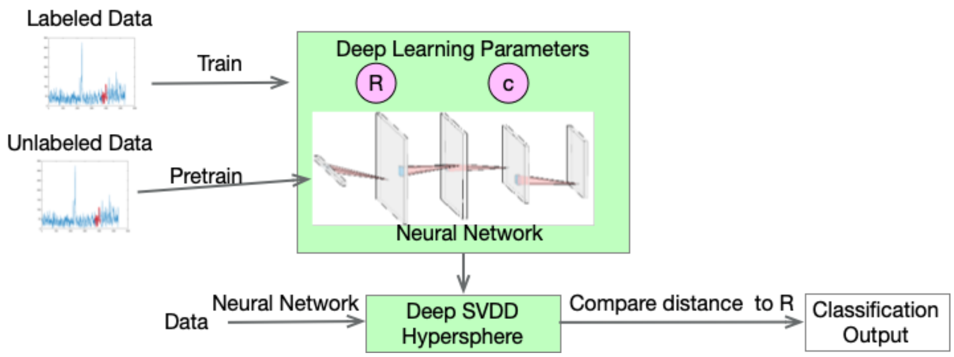

Fig. 1. Deep SVDD with LSTM Framework

including pre-train and optimization work is proposed. Section 4 explains the setup and results of the experiment of the real HRRP dataset. Finally, the article summarizes a conclusion about the whole framework and comments.

II. Soft-Boundary Deep Classification

A. The Deep SVDD Objective

To learn good feature representations of the data together with the soft-boundary classification objective, we employ a neural network that is jointly trained to map the data into a hyper-sphere of minimum volume. The schematic diagram of soft-boundary Deep SVDD is shown in Fig. 2.

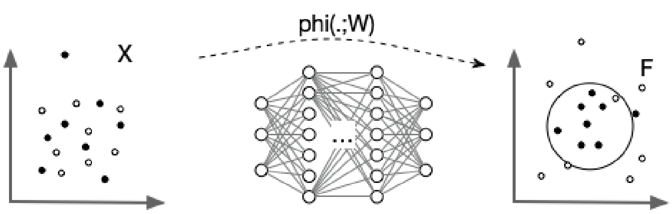

Fig. 2. Schematic diagram of soft-boundary Deep SVDD

According to mapping $\phi(\cdot; W) : X \to F$, the original input space $X \subseteq \mathbb{R}^d$ is mapped to the feature space $F \subseteq \mathbb{R}^p$. In the neural network, ϕ is generated through training, which includs $L \in \mathbb{N}$ hidden layers and set of weights $W = W^1, \ldots, W^L$. The aim of Deep SVDD is to jonitly learn the network parameters W with minimizing the volume of a data-enclosing hypersphere in output space F. The radius R and center c of hypersphere is trained in space F. The soft-boundary Deep SVDD objective as

$$\min_{R,W} R^w + \frac{1}{vn} \sum_{i=1}^{n} max\{0, ||\phi(x_i; W) - c^2|| - R^2\} + \frac{\lambda}{2} \sum_{l=1}^{L} ||W^l||_F^2. \quad (1)$$

Hyperparameter $v \in (0, 1]$ controls the trade-off between the volume of the sphere and violations of the boundary.

The data points are remapped according to the center c of the hypersphere. Furthermore, the positive data points should be close to the center c, and the distance between the center c and positive data points should not be larger than Radius R. We obtain a compact description of origin data through the network, and the feature is mapped to the distance from the center c.

In the most often in soft-boundary classification, the most of train data are assumed as nromal. The Deep SVDD objective is defined as

$$\min_{W} \frac{1}{n} \sum_{i=1}^{n} ||\phi(x_i; W) - c||^2 + \frac{\lambda}{2} \sum_{l=1}^{L} ||W^l||_F^2.$$

Soft-boundary Deep SVDD contracts the sphere by minimizing the mean distance of all data repersentations to the center. Meanwhile, to map the data as close to center c as possible, the neural network must extract the common factors of variation.

B. LSTM Network

Due to gradient vanishing, it is challenging to model long-range dependencies. To address this issue, LSTM is proposed as an extension of the RNN by additionally utilizing a memory cell and three gates: the forget gate, the input gate, and the output gate [15].

The long-term continuous flow path to generate the gradient is the core contribution of the initial LSTM model. The critical extension is to make the power of self-circulation pay attention to the context rather than being fixed. The LSTM block is shown in the Fig. 3, and the corresponding forward propagation formula is as follows:

$$f_i^{(t)} = \sigma(b_i^f + \sum_j U_{i,j}^f x_j^{(t)} + \sum_j W_{i,j}^f h_j^{(t-1)}).$$

The most important component is the state unit $s_i^{(t)}$. Here the weight of the self-loop is controlled by the forget gate $f_i^{(t)}$ (the time t and cell i). Among them, b, U, and W are the bias, input weight, and loop weight in the LSTM cell, respectively. The internal state of the LSTM cell is updated as follows:

$$s_i^{(t)} = f_i^{(t)} s_i^{(t-1)} + g_i^{(t)} \sigma(b_i + \sum_j U_{i,j}^f x_j^{(t)} + \sum_j W_{i,j}^f h_j^{(t-1)}).$$

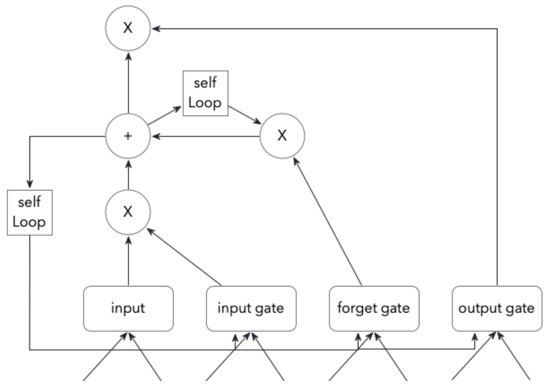

Fig. 3. LSTM Cell

The output of LSTM cell can be closed by output gate $q_i^{(t)}$ with sigmoid cell:

$$h_i^{(t)} = tanh(s_i^{(t)}) q_i^{(t)} \tag{2}$$

$$q_i^{(t)} = \sigma(b_i^o + \sum_j U_{i,j}^o x_j^{(t)} + \sum_j W_{i,j}^o h_j^{(t-1)}). \tag{3}$$

III. Train Precudre

A. Model

The architecture of proposed soft-boundary Deep SVDD with LSTM is shown in Fig. 4, which consists of three parts: encoder, LSTM layer and hypersphere.

The idea behind an autoencoder is to train an ANN to reproduce the identity mapping from a specific information vector to itself, under the topological constraint that one of its hidden layers [11]. The encoder can extract useful feature information and denoise the signal at the same time. This approach shows many excellent effects in many scenarios. We perform a pre-train operation to enable the network to extract helpful information without discarding too much information.

Only one LSTM layer is used because the scale of our network is small. The LSTM layer takes the output of the encoder as input. To simplify the implementation, we initialize the status c with query HRRP data and take the K neighbors as the input of K time steps.

As to hypersphere, the Radius R and center of hypersphere c are trained as the parameters of the network. These parameters are initialized to 0. As the training process, c and R will be updated with each epoch so that the feature points inside the hyper-sphere are positive and others are negative. Finally, a classification module is employed to predict the target label.

For a given test HRRP image $x \in X$, we can naturally define an anomaly score s for soft-boundary Deep SVDD according to the distance from the extracted feature point to the center of hypersphere:

$$s(x) = ||\phi(x : W^*) - c||^2,$$

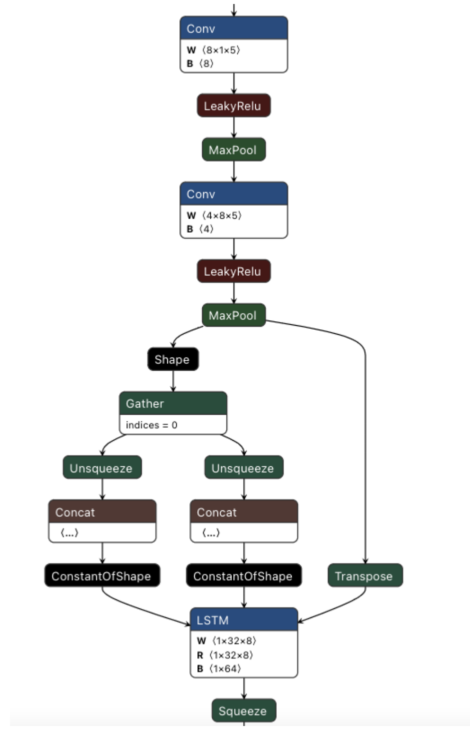

Fig. 4. Model Architecture

where W^* is the parameters of the neural network, according to the slack variable ξ, we can optimize the Radius R of the hyper-sphere.

B. Optimization and Loss

We use stochastic gradient descent (SGD) and its variants, Adam, to optimize the parameters W of a deep network, the c, and R of a hypersphere.

In the preparation stage, we use the encoder and decoder to reproduce the encoding and decoding process. When the encoded signal can be restored, the validity of the encoder is varified. So we use the gap between the restored signal and the original signal to pre-train the encoder. The loss in the pre-train network is defined as

$$Loss = \frac{1}{n} \sum (output - input)^2.$$

In Deep SVDD training process, the performance of the network is depends on the accuracy of classification. The loss function is shown as follows:

$$Loss = \frac{1}{n} \sum (\tanh(dist)_i - labels_i)^2,$$

where the $dist$ is the distance between signal feature vector and c.

$$dist = \sum (output - c)^2 - R^2.$$

To make the classification result generated according to the score lie in the interval [-1,1], we use a layer of tanh function to limit the output of the score. If the output is less than a certain threshold, it will be regarded as a negative label, and if the output is greater than the threshold, it will be regarded as a positive label.

IV. Experiment and Results

The experiment code can be found at GitHub website: https://github.com/Seafood-SIMIT/SVDD-Pytorch-4-HRRP-Radar-Target-Recognition.git.

A. HRRP dataset

The dataset is composed of real HRRP generated by a moving radar platform. The radar platform parameters is shown in TABLE I About the movement information of the radar

TABLE I
The Radar Platform Parameters

parameters	value
Pulse Range Profiles Number	1000
Pulse interval	120ms
Center frequency	35GHz

platform, the target is stationary, the radar platform approaches the target area at a certain speed (30m/s-50m/s) curve, and the beam angle is $2°$. The target attitude is unknown, and the radar trajectory is unknown, also. The picture of the target is shown in Fig. 5. The target size of the vehicle is about $4m \times 2m$.

Fig. 5. Target Truck Outward Appearace

The signal received by radar is in complex form with phase information. After the absolute value operation is performed, the HRRP image of the target is the highlighted part in the Fig. 6. The detection and recognition performance of the algorithm is considered under the condition of no target attitude angle.

There are three training and evaluation data trajectories with different signal-to-noise rates (SNR), and each trajectory contains 1000 sets of continuous pulse range profiles.

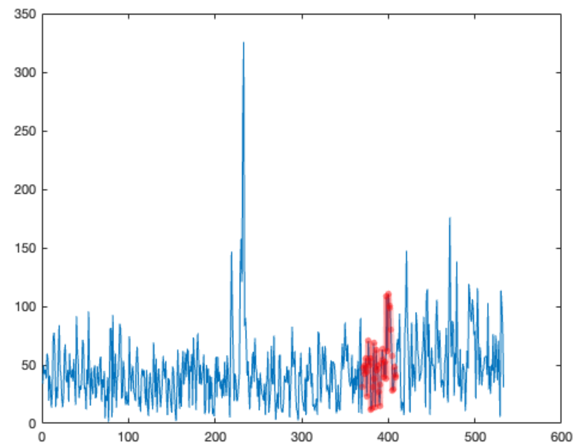

Fig. 6. HRRP data of target

B. Experimental setup

We design three architectures as deep learning parts to find better performance from different feature extraction methods. We perform the classification mission on a LeNet-type CNN framework with leaky ReLU layers, an LSTM framework, and a mixture framework, respectively. For these three neural networks, a batch size of 64 and a learning rate of 3×10^{-3} are used. The weight decay hyperparameter is set to 0.5×10^{-6}. The model is trained during 40 epochs on two Nvidia GTX1080ti GPUs.

The dataset of each experiment is 1000 HRRP images. We randomly selected 30% of them as the validation set. The experiment is also performed on the dataset containing all three HRRP images with different SNR types. In each frame of the HRRP image, we select the target point as the positive sample and the non-target point, that is, the clutter, as the negative sample, with a ratio of 1:3, and use the two as the training input.

C. Results

Receiver operating characteristic (ROC) analysis has been an essential tool for the assessment of classification problems in which the ground truth is a binary reference standard, i.e., two-class classification problems [14]. ROC curve takes true positive rate (TRP) as the horizontal axis and false positive rate (FPR) as the vertical axis. The formula is as follows:

$$TPR = \frac{TP}{TP + FN} \tag{4}$$

$$FPR = \frac{FP}{FP + TN}. \tag{5}$$

Where TP, TN, FP and FN stand for true positive, true negative, false positive and false negative respectively. AUC is the area under the ROC curve, used to describe the classification performance of the model. The training process of radius R is shown in Fig. 7. The Radius can stay at a relatively stable value, about 1.2.

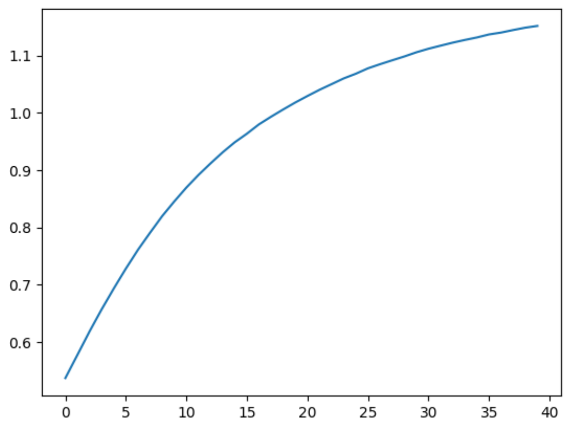

Fig. 7. Radius Training Process

Because we use both positive and negative samples for training, the ROC curve of the model can take into account target detection and clutter interference at the same time.

The result of soft-boundary Deep SVDD with labeled samples during training is shown. The ROC curve of this classifier is shown in Fig. 8. The classifier generalization is not shown

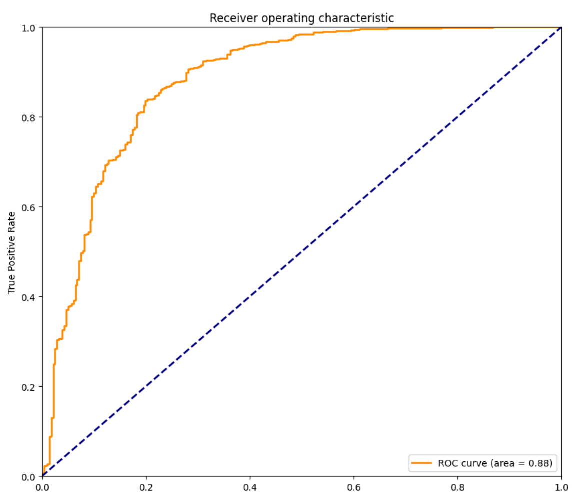

Fig. 8. ROC curve of Results

on the ROC curves. After selecting the threshold from the curve, the performance of the classifier needs to be tested.

The model ROC_AUC value and classification accuracy is illustrated on TABLE.II. In each experiment, we change the dataset from different signal-to-noise ratios. Then the experiment with the whole dataset is performed. In single signal-to-noise ratio data, the classification method that combines CNN and LSTM has better performance. Therefore, we can consider using multiple classifiers in the natural environment

TABLE II
THE CLASSIFICATION PERFORMANCE

		CNN	LSTM	CNN+LSTM
Data1	ROC_AUC	90.66%	87.96%	**91.26%**
	ACC	90.25%	86.92%	**91.08%**
Data2	ROC_AUC	86.65%	87.27%	**88.27%**
	ACC	85.83%	87.33%	**87.5%**
Data3	ROC_AUC	93.90%	85.73%	**94.94%**
	ACC	90.75%	87.42%	**90.92%**
All	ROC_AUC	**86.58%**	85.44%	86.52%
	ACC	**85.97%**	85.47%	85.94%

to deal with multiple target or classification tasks in different signal-to-noise ratio environments.

V. CONCLUSION

The HRRP image recognition is an active part of radar target detection, which belongs to AD. One of the most commonly used AD methods is SVDD. However, the SVDD method has limited ability to extract deep features of the signal. The soft-boundary Deep SVDD is proposed because of the rapid development of neural networks. Considering that the HRRP signal is a one-dimensional timing signal, this paper proposed a novel framework based on soft-boundary Deep SVDD with LSTM. This framework includes an autoencoder, an LSTM neural network, and an SVDD hypersphere. The neural network parameters, the Radius, and the center of the hypersphere are trained to be the optimal value.

Several experiments with sorts of SNR signals are performed to the soft-boundary Deep SVDD with the LSTM model. The dataset used in the experiment has the characteristics of small data volume, so it can be concluded that this model still has better performance even in a small dataset for training. The results show the framework's better performance and ROC curve with the roc_auc value closed to 90%-94%. At the same time, this method also has excellent generalization performance in HRRP radar target recognition.

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