A Novel Method for Sea Clutter Suppression and Target Detection via Deep Convolutional Autoencoder

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Abstract: In this paper, we investigate target detection based on the different relevance of sea clutter with a deep learning approach. The proposed method employs deep convolution autoencoder (CAE) to learn the necessary features and classification boundaries using the simulated data without employing any explicit features on the pulsed radar signals. Compared with conventional methods for sea clutter suppression, our algorithm do not need to estimate the covariance matrix of clutters. Specifically, we can automatically remove complex patterns like superimposed clutter from a target, rather than simple patterns like pixels missing at random. The results show that the proposed deep learning approach has very reliable detection performance compared with space-time adaptive processing (STAP), even at low signal-to-clutter ratios.

Key–Words: convolutional auto-encoder, deep neural network, sea clutter suppression, target detection.

1 Introduction

When a radar detects targets on or above the sea surface, it has to overcome the interference from sea echo itself. For many diverse factors, such as radar polarization mode, antenna visual angle, sea state and wind direction, clutter is obviously non-Gaussian and non-stationary, which limits the detection capability of radar [1]. Traditional radar systems have adopted adaptive processing techniques such as constant false alarm rate (CFAR) detectors [2], adaptive arrays, and space-time adaptive processing (STAP) to mitigate the deleterious effects of clutter and jamming[3]. Typically, in adaptive radars the disturbance covariance matrix is estimated using training data collected from cells surrounding the cell under test (CUT).

However, all these estimators are based on the assumption that the training data vectors do not contain interference or targets sharing the same covariance matrix as the primary data. These techniques are quite restrictive since they require the environment to remain stationary and homogenous during their adaptation. In fact, the training data vectors are often contaminated by interfering targets, large clutter discretes, spiky clutter, and other outliers of different types rendering them nonhomogeneous[4]. The conventional involved algorithms cannot satisfy the requirements for higher accuracy and more flexible applications. Therefore, it is eagerly to develop a more effective approach to increase the signal-to-clutter ratio and enhance the detection performance.

During the last decade, inspired by the architectural depth of the brain, deep learning has become a new kind of machine learning method and has been paid increasing attention to[5][6]. The algorithms seek to exploit the unknown structure in the input distribution in order to discover better representations, with higher level learned features defined in terms of lower level features. Recently, deep learning has obtained state-of-the-art results in the area of computer vision and speech recognition. In the field of radar signal processing, using the concepts of deep learning, several new approaches [7, 8, 9] have been proposed. Jarmo [7] employed deep convolutional neural networks (DCNNs) to target recognition based on high range resolution profiles (HRRPs) in multistatic radar systems. Kim [8] has developed the use of DCNNs for human detection and activity classification based on Doppler radar. In[9], Gong proposed a novel change detection algorithm specifically toward analyzing multi-temporal synthetic aperture radar (SAR) images based on deep learning. Experiments on real data sets and theoretical analysis indicate the advantages, feasibility, and potential of deep learning methods. However, most proposed methods ,applying deep learning to the field of radar, are based on the SAR images or the spectrograms of echo doppler, which are essentially in the image level. The main innovative point of our work is directly using deep learning algorithms in radar echo data.

It has been shown in the literature that each bounded continuous function can be approximated by a two-layer neural network with arbitrarily small errors, and any function can be approximated with an arbitrary precision using a three-layer neural network[10]. It can be said that as long as the problem can be expressed as a function of the form, theoretically we can consider deep neural networks as a tool of learning.

In this paper, we present an algorithm for clutter suppression task that combines sparse coding and deep networks pre-trained with denoising convolutional auto-encoder defined by this model, and show that by training on large radar echo databases we are able to outperform the current adaptive processing techniques. The algorithms will first learn a large number of basis functions, and then reconstruct any new input radar echo using a weighted combination of a few of these basis functions. The weights of these basis functions then give a slightly higher-level and more succinct representation of the input, then this representation can be used in target scene restoration task.

The rest of of this paper is organized as follows. Section 2 introduces the pulsed radar detection model and describes the testing environment. In Section 3, the overall architecture and components of our convolutional auto-encoder are proposed in detail. Results are shown in Section 4 to demonstrate the effectiveness of the proposed approach. And conclusions are drawn in Section 5.

2 Signal Amid Clutter Model for Pulse Radar

In this section, we present a mathematical model for targets and sea clutter returns. The relevance of sea clutter between different range and azimuth units is strong. Since the target usually exists in 1 or 2 units, its amplitude is much smaller than that of sea clutter. If $s(t)$ is the signal transmitted in each pulse, the received signal in the kth pulse, $k = 0, 1, ..., K-1$, is given by:

$$g^k(t) = \sigma^k s(t-\tau_0)e^{j2\pi\upsilon_0 t} + \sum_i x_i^k s(t-\tau_i)e^{j2\pi\upsilon_i t} + n(t) \tag{1}$$

where σ^k, τ_0 and υ_0 are the complex reflectivity, delay and Doppler shift, respectively, of the target (if present), τ_i and υ_i are the delay and Doppler shift of the ith scatterer, respectively, and $n(t)$ is additive noise. Note that the complex reflectivity of each scatterer fluctuates randomly with each pulse. This is due to the fact that small changes in range, on the order of the radar wavelength, may cause significant changes in the phase of the received signal. In the scenario we consider, the interference due to clutter dominates the additive noise and we will henceforth neglect the latter. Also, we will focus on range estimation alone; the extension to include Doppler estimation is the subject of ongoing research. The received signal in (2) is sampled at a rate f_s to yield a sequence $g^k[n] = g^k(n/f_s)$. This sampled signal is then matched filtering at each sampling instant to yield the sequence.

The movement of ships in the sea is very complex, and the disturbance from wind and wave will also become more obviously. Therefore, we can not assume a constant target radar cross section (RCS) (non-fluctuating target) when we simulate the ship target. In this paper, target fluctuations are modelled using the Marcum-Swerling IV distribution for the target returns[11]:

$$f(\sigma) = \frac{4\sigma}{\bar{\sigma}^2}\exp(\frac{2\sigma}{\bar{\sigma}}) \tag{2}$$

where σ represents the RCS of targets.

Early studies of detection and waveform design for sea clutter rejection typically assumed Rayleigh model, log-normal model or Weibull model for sea clutter echoes, which all are based on single point statistics [12]. With modern radars, however, the resolution is high enough to resolve the small-scale structure of the sea surface. In this scenario, those traditional models, which derive from the application of the central limit theorem to a large number of independent scattering centers, are no longer appropriate and cannot account for the increased presence of spikes in the returns. This has motivated the K-distribution model [13] for sea clutter whose returns are believed to be the result of two processes. The first process is called $speckle$, which is the result of reflections of the incident beam by multiple independent scattering centers, whose variance follows the Gamma distribution in time-space field. The second process, termed $texture$, is caused by the large-scale structures of the sea such as swell and wind, and modulates the local mean power of the speckle.

The K-distribution model has received empirical as well as theoretical support. It has long been known that sea clutter echoes exhibit temporal and spatial correlation. In particular, the speckle decorrelates rapidly (1-5 ms), while the texture remains correlated over several seconds. In practice, the correlation properties of the clutter are determined by the speckle component. The clutter intensity of the K distribution can be expressed as

$$P(z) = \int_0^\infty P(z|x)P_c(x)dx \tag{3}$$

where

$$P(z|x) = \frac{1}{x}\exp(-z/x) \tag{4}$$

and

$$P_c(x) = \frac{b^v x^{v-1}}{\Gamma(v)}\exp(-bx) \tag{5}$$

Equation (5) is the Gamma distribution for the local clutter power x. The b is the scale parameter, which reflects the average power characteristics of the echo. And the shape parameter is v (always between 0.1 to 10), which reflects the skewness of K distribution.

Table 1: World Meteorological Organization sea state

Code	Wind Speed(m/s)	Characteristics
0	0.0-0.2	Calm (glassy)
1	0.3-1.5	Calm (rippled)
2	1.6-3.3	Smooth (wavelets)
3	3.4-5.4	Slight
4	5.5-7.9	Moderate
5	8.0-10.7	Rough
6	10.8-13.8	Very rough

Taking sea state into consideration is of primary importance to clutter suppression, as high waves and confused seas can easily swamp a vessel. The world meteorological organization uses different wind speeds (Beaufort wind force scale) and wave heights to measure different sea states [14]. Since wind is the main factor affecting sea states, in the following work, we will use the K-distribution simulate different sea states by setting different wind speeds. As shown in Table I, we ignore the heavy sea swell and take the low and moderate sea clutter into the training set of deep learning architecture, which is proposed in the next section.

3 Architecture of Autoencoder

Firstly, we briefly specify the traditional autoencoder(AE) framework and its terminology. Let $\mathbf{y}_i$ be the original data for $i = 1, 2, ..., N$ and $\mathbf{x}_i$ be the corrupted version of corresponding $\mathbf{y}_i$. The deterministic mapping $\sigma(.)$ that transforms an input vector $\mathbf{x}$ into hidden representation $\mathbf{h}_i$, always at a typically lower-dimensional space, is called the *encoder*. Its typical form is an affine mapping followed by a nonlinearity:

$$\mathrm{h}(\mathbf{x}_i) = \sigma(\mathbf{W}\mathbf{x}_i + \mathbf{b}) \tag{6}$$

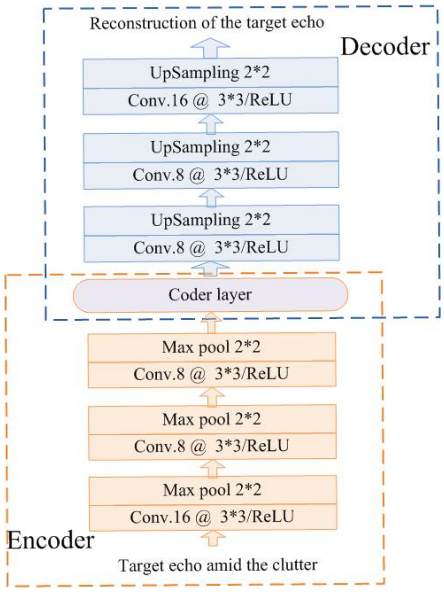

Figure 1: Architecture of the proposed framework.

The resulting hidden representation $\mathbf{h}_i$ is then mapped back to a reconstructed N-dimensional vector $\mathbf{y}_i$ in input space. This mapping is called the *decoder*. Its typical form is again an affine mapping optionally followed by a squashing non-linearity, that is,

$$\hat{y}(\mathbf{x}_i) = \sigma(\mathbf{W}'\mathrm{h}(\mathbf{x}_i) + \mathbf{b}') \tag{7}$$

where $\Theta = \{\mathbf{W}, \mathbf{b}, \mathbf{W}', \mathbf{b}'\}$ represents the weights and biases. Once a layer is trained, its code is fed to the next, to better model highly non-linear dependencies in the input. The autodecoder can be trained with various optimization methods to minimize the reconstruction loss:

$$\theta = \underset{\theta}{argmin}\sum_{i=1}^{N}\|\mathbf{y}_i - \hat{\mathbf{y}}(\mathbf{x}_i)\| \tag{8}$$

By using multiple layers of encoder and decoder, the autodecoder can form a deep architecture and become a Deep Denoising Auto-encoder (DAE) [15]. Fully connected AEs and DAEs both ignore the 2D signal structure. This is not only a problem when dealing with realistically sized inputs, but also introduces redundancy in the parameters, forcing each feature to be global (i.e., to span the entire visual field). However, the trend in vision and object recognition adopted by the most successful models is to discover localized features that repeat themselves all over the input. CAE differs from conventional AEs as their weights are shared among all locations in the input, preserving spatial locality. The reconstruction is hence due to a linear combination of basic signal patches based on the latent code.

The architecture of our convolutional auto-encoder, as shown in Fig.1, is composed of several alternations of convolution and pooling layers, followed by several fully connected layers on the top. The rich nonlinear structure in the CAE can be used to learn an efficient transfer function which removes clutter in radar signal while keeping enough discriminative information to generate good reconstructed features. Unlike patch-based methods [16], we preserve the inputs neighborhood relations and spatial locality in our latent higher-level feature representations.

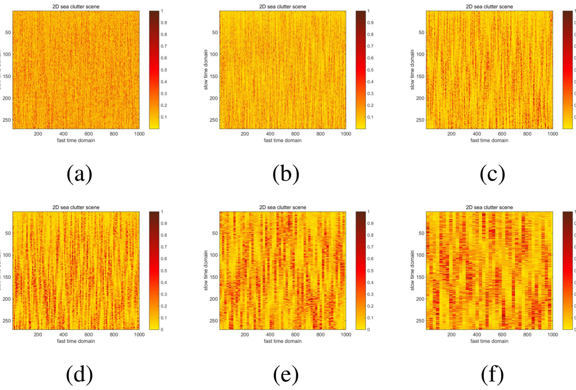

Figure 2: Example of sea clutter scene simulated by K-distribution. (a) sea state degree 1: Very Low (short and low wave) (b) sea state degree 2: Low (long and low wave) (c) sea state degree 3: Light (short and moderate wave) (d) sea state degree 4: Moderate (average and moderate wave) (e) sea state degree 5: Moderate rough (long and moderate wave) (f) sea state degree 6: Rough (short and heavy wave).

4 Results and Related Analysis

In this section, we demonstrated the performance of pulsed radar when using the proposed deep learning architecture in the background of sea clutter. We considered a ground based radar system with ship targets moving in the K-distributed clutter of different sea states. Our training set included six species of sea states (according to Beaufort scale) simulated by K distribution, the clutter scene were shown in Fig.2. The scattering coefficient of the target was obedient to Marcum-Swerling IV statistical properties. We simulated a large training set, hundreds of thousands of radar signal containing targets were collected, including different sea states, target types, target trajectories (input dimensionality $d = 80 \times 100$). The diversity render the problems particularly challenging for current generic learning algorithms. The signal images of time and space field were shown in Fig.3.

In this paper, we used the radar echo signals as the training data of the CAEs network. Only an estimate of the magnitude of radar signal was required here. Note that all the training data and test data were all normalized to zero mean and unit variance. This techniques was to improve the baseline of convolutional auto-encoder system so that the quality of the objectives reconstruction in matched clutter states can be maintained, while the generalization capability to unseen noise can be increased.

We used cross validation to evaluate the performance of the CAEs. We simulated 10000 groups of echo data and targets. 90 percent of them were regarded as train sets, and the rest were test sets. For learning, we used the mini-batch optimizer with an adaptive learning rate method (ADADELTA)[19] and a batch size of 400. The training time with 23 epochs was about 7s using the NVIDA GeForce GTX1080 GPU. We defined the Peak Signal-to-Clutter Ratio ($PSCR = 20\log(\mathrm{Max}_s/\mathrm{Max}_c)$) to be the ratio of the target signal power to the total power of the clutter in the range bin containing the target. Where Max_s and Max_c expressed the maximum amplitude of the signal and clutter respectively. The test target signal was submerged in the clutter of sea state degree 2 with $PSCR = 6dB$ as shown in Fig.3(b). The contour plots and mesh plots of the reconstructed images using different methods were drawn in Fig. 3(c) and Fig. 3(d). It can be seen that the performance of conventional orthodox STAP algorithm [17] is not as effective as which we proposed. From Fig.3(c), we can see that there are still some clutters remained, and the target is not quiet obvious. For Fig.3(d), almost all the clutters are suppressed, and the target is easy to detect. For STAP, it estimates the disturbance covariance matrix using training data collected from cells surrounding the cell. The method requires a high degree of stability and uniformity of the environment. But sea clutter itself has a large clutter block, clutter spikes and other non-stationary characteristics, which damage the reconstruction performance. The presented detection method for static radar via our method is better. It reconstructs the new input target echo and the sea clutter is suppressed well using a weighted combination of a few of these basis functions.

Fig. 4 shows the loss curve of reconstitution for test data. The loss value represents the mean square error between the original data and the reconstruction data [18]. In the figure, we notice that after 50 times iteration the loss value dropped down to 0.06. Using the CAE, we suppressed the clutter and the outputs of the CAEs are quiet similar to the original data. In the radar theory [20], precise reconstruction results often hold with an overwhelming probability. The method

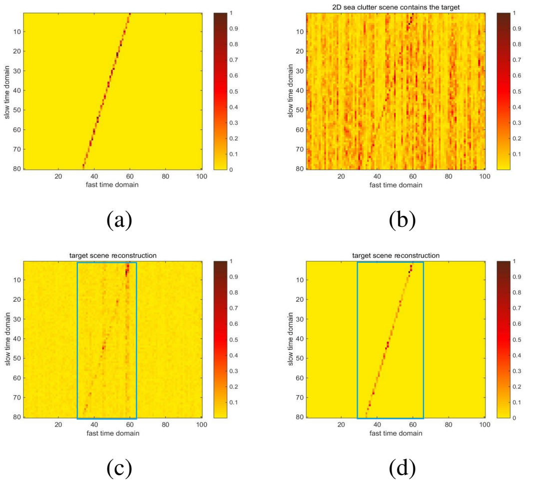

Figure 3: Example of target localization and reconstruction in sea clutter. (a) Simulation of the target trajectory. (b) Target amid the clutter. (c) Results using orthodox STAP algorithm. (d) Results using proposed method on the test set.

shows the better performance in detection probability, accuracy and robustness.

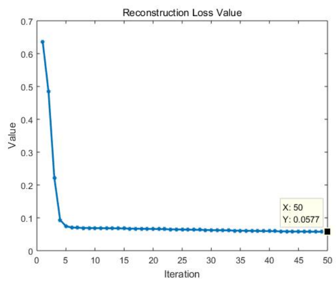

Figure 4: The curve reports the test error rate for CAE trained on problem.

5 Conclusions and Future Work

The traditional radar systems have adopted adaptive processing techniques to mitigate the deleterious effects of clutter and jamming. They need to estimate the disturbance covariance matrix using training data collected from cell under test, which impact the accuracy and flexibility of radar detection. Inspired by the recent great success of deep ConvNets in computer vision and speech recognition, we address the problem of feature extraction by constructing a Convolutional Auto-Encoder to automatically learn hierarchical features from large data sets. The network architecture, training details, and common rules for setting hyper-parameters are described in this paper. Simulation results demonstrate the superiority of based approach over the conventional basic methods in clutter suppression. Inspired by this research, we plan to apply this method to the measured radar data in the future work. Further more, we can take more complex conditions into consideration, such as airborne radar signal, multi-objective scene, weak target detection and so on.

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