

A new method for Anomaly Detection and Target Recognition

Gurcan Lokman, Guray Yilmaz

Abstract— Use of unmanned Aerial Vehicles (UAVs) has gained significant importance in the recent years because they are capable of to be used in in civilian and military purposes for reconnaissance, surveillance, disaster relief, among other tasks. In this paper we present new automated anomaly detection and target recognition methodology that can be used on such a UAV. The standard paradigm for anomaly detection and target recognition in hyperspectral imagery (HSI) is to run a detection or recognition algorithm, typically statistical in nature, and visually inspect each high-scoring pixel to decide whether it is an anomaly or background data. A new method of anomaly detection and target recognition in HSI was studied based on a Neural Network (NN). Two multi-layered neural networks are used for anomaly detection and target recognition. The first phase of the model is used to detect anomalies in HSI. The second phase of the model is to use determine whether the anomaly is a predefined target or not. Both networks are trained in accordance with its intended purpose, so increase in performance is provided. This method can be a suitable solution for applications where the unmanned aerial vehicles used.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), also known as drones, are aircraft either controlled by ‘pilots’ from the ground or increasingly, autonomously following a pre-programmed mission. Due to their advantages, UAVs are used in many civil and military applications such as aerial surveillance, remote sensing, cargo delivery, etc. Unlike the large aircrafts and satellites, the UAV systems are the low cost systems for remote sensing applications. The images obtained from UAVs are used especially in areas such as environmental monitoring, wildfire monitoring, wildlife population tracking, border patrol, and search and rescue.

One of the methods used in remote sensing is hyperspectral imaging (HSI) technique. Hyperspectral remote sensing, also known as imaging spectroscopy, is a relatively new technology that is currently being investigated by researchers and scientists with regard to the detection and identification of minerals, terrestrial vegetation, man-made materials, anomalies, military or civil targets and backgrounds. Due to its spectral resolution across a wide range of the electromagnetic spectrum, HSI can be used as the most attractive method for detection applications.

G. Lokman is lecturer at Gerze Vocational School, Sinop University, Gerze 57600, Sinop, Turkey. G. Lokman is also with Department of Computer Engineering, Turkish Air Force Academy, Aeronautics and Space Technologies Institute, Yesilyurt, 34149, Istanbul, Turkey. glokman@sinop.edu.tr

G. Yilmaz is with Department of Computer Engineering, Turkish Air Force Academy, Aeronautics and Space Technologies Institute, Yesilyurt, 34149, Istanbul, Turkey. gyilmaz@hho.edu.tr

In spectral anomaly detection algorithms, pixels that have a significantly different spectral from neighboring pixels are identified as spectral anomalies. These algorithms do not require knowledge of the reference spectrum of the targets of interest. The best known algorithm in the literature for spectral anomaly detection is Reed–Xiaoli (RX) algorithm [1]. This algorithm was developed for detecting targets of unknown spectral characteristics against a background clutter with unknown spectral covariance. In the literature, there are also other algorithms that were developed using RX algorithm to detect anomalies [2], [3].

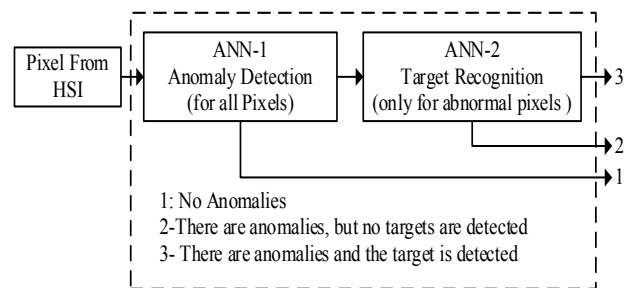


Fig. 1. General Structure of Proposed Model

Spectral target detection algorithms are among the topics which are done a lot of studies on. One of the most well-known target detection algorithms in the literature is Orthogonal Subspace Projection (OSP) algorithm [4]. This algorithm is based on maximizing the signal-to-noise ratio (SNR) of the target data in the subspace orthogonal to the background subspace. Additionally, a large number of spectral detection algorithms have been reported in the literature [5] - [13].

The image processing starting to receive HSI from the UAVs, pass through the pre-processing and be followed to decision-making process can be quite costly in terms of time. Methods that can lower the cost of time should not reduce the accuracy of the results. Especially in the military applications, the accuracy and speed of the discovery and observation is important to perform the procedures and to take precautions. Taking into considerations these requirements, designing an algorithm that allows for the fastest and most reliable way to detection anomalies and recognition targets process are located in this study.

A new method that performs anomaly detection and target recognition process using two stages Artificial Neural Networks (ANN) is proposed. The detection process will be carried out quickly and reliably by using a combination of HSI’s capabilities and high generalization and classification ability of ANNs in this method.

The general structure of proposed method is as shown in Figure 1. The first stage of the method is a Multi-Layered Neural Network (ML-NN) called as ANN-1. This network is trained to detect anomalies in HSI. The second stage of method is also is a ML-NN called as ANN-2, and this network determines whether these anomalies are belonging to any pre-defined targets. Pixels in HIS are applied to our method as inputs. Output of the method can have three different values. Outputs can be “1-No Anomalies”, “2- There are Anomalies, but no targets are detected” or “3- There are Anomalies and the target is detected”.

The ongoing sections of the paper are organized as follows: the Hyperspectral Images and Artificial Neural Networks are briefly summarized in Section II. Proposed method is described in detail in Section III. Section IV contains experimental study and its results. Finally, Section V includes conclusion.

II. BACKGROUND

A. Hyperspectral Imaging

The hyperspectral era began in the late 1970s and early 1980s [14]. Hyperspectral remote sensing is concerned with the extraction of information from objects or scenes lying on the Earth surface, based on their radiance acquired by airborne or space-borne sensors. Hyperspectral imaging can be visualized as shown in Figure 2. The spectral sensors are instruments called imaging spectrometers. The most popular spectrometer in the literature is the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) that was proposed by NASA in 1983. AVIRIS is a unique optical sensor that delivers calibrated images of the upwelling spectral radiance in 224 contiguous spectral dimensions (also called bands) with wavelengths from 400 to 2500 nanometers [15].

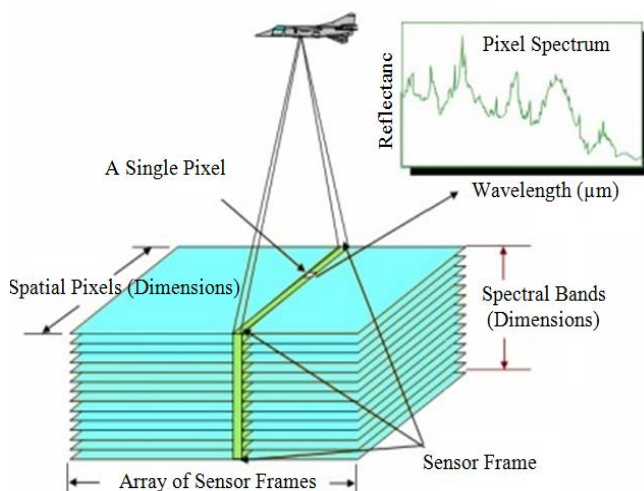


Fig.2. Pixels, Spectral bands and Acquisition of Hyperspectral Images. A plot of the reflectance values versus wavelength shows the continuous spectrum for the pixels. Reflectance is a unitless quantity; it can be also expressed as a percentage.

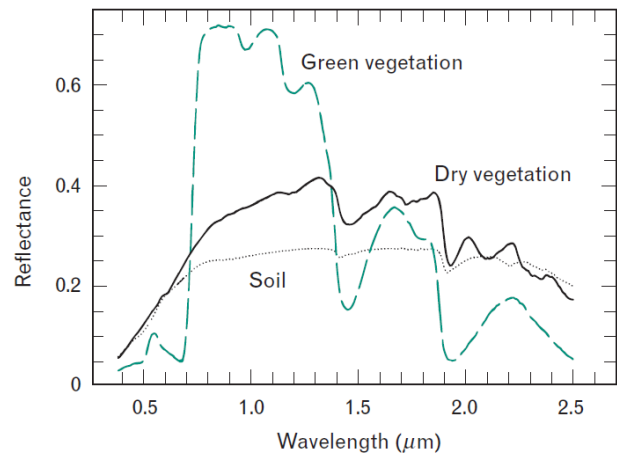


Fig.3. Different materials produce different electromagnetic radiation spectra. The spectral information contained in a hyperspectral image pixel can therefore indicate the various materials present in a scene [13].

Certain objects leave unique spectral signatures across the electromagnetic spectrum and shown as in Figure 3. These signatures enable identification of the materials that make up a scanned object. Size of the ground area represented by a single set of spectral measurements defines the spatial resolution. When the size of the ground resolution cell is large, it is more likely that more than one material contributes to an individual spectrum. The result is composite or mixed spectrums that contribute to the mixture are called end-member spectra [16]. Example of such a phenomenon is shown in the Figure 4. To overcome such these problems, various algorithms have been proposed in the literature [17]-[21].

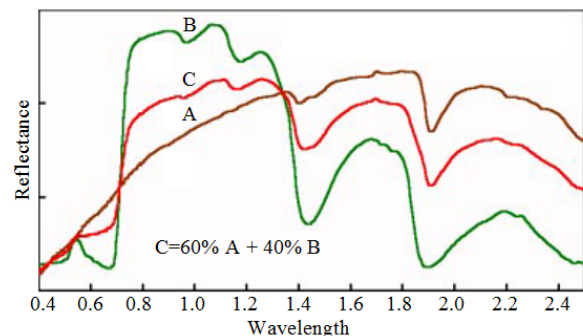


Fig.4. Example of a composite spectrum. (A) and (B) are dry soil and green vegetation spectra respectively, (C) that is a linear mixture of these two spectra [16].

B. Artificial Neural Networks

Artificial Neural Network (ANN), as the hot topic for classifying hyperspectral image, is likely to be used to detect anomalies and to recognize targets effectively. For high-dimensional information, ANN has advantages over traditional methods. Therefore, many works in the literature uses ANNs on HSI analysis [22]-[24]. There are two widely used ANN algorithms used for HIS: Back Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN).

BPNN is the most popular network owing to its simplicity, strong capacities and easy to use. The network consists of three layers: input layer, hidden layer and output layer. Neurons in adjacent layers are connected by a specific weight [25]. The basic structure of this network is as shown in the Figure 5. It should be noted that BPNN can have more than one hidden layer.

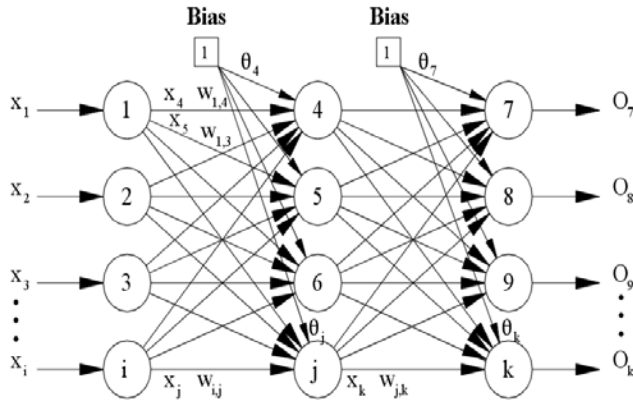


Fig.5. Back propagation Neural Network with one hidden layer. [25]

RBFNN is also a type of three layer networks. Radial basis Functions are embedded into a two-layer feed-forward neural network. The hidden units between the inputs and outputs implement a radial basis function [26]. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually can be trained much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the RBF hidden units. There are also many ANN approaches used for HSI analyses in the literature, some of them are investigated [27]-[30].

III. PROPOSED METHOD

Compared with black-and-white and RGB images, working with Hyperspectral images requires more time. Because the traditional images have less spectrum data and it is carried out using a limited number of framework. In other words, the number of bands is quite more and the operations are performed for all pixels in the HSI. Despite the time cost, methods that use hyperspectral images can produce more accurate results in target recognition compared to other images. Especially considering the small size targets that are represented by one or little more pixels, HSI is clearly more advantageous technique. Thus, this technique is preferred for anomaly detection and target recognition process in proposed method.

In this study, a new anomaly detection and targets recognition method is introduced, that is designed as two-stage Multi-Layered Neural Networks and it can be used in unmanned aerial vehicles applications. Considering the characteristics of Hyperspectral images, a pixel-based (spectral matching) approach is located to this method.

In network called ANN-1 in the method, the input layer has inputs as the number of available bands in HSI data set, the hidden layer has ten neurons and the output layer has just an output. This network is trained just to identify pixels that contain anomalies. Thus the anomalies can be sensed by using spectral signatures in these pixels. The unknown anomalies also can be determined in this way with the generalization feature of ANNs.

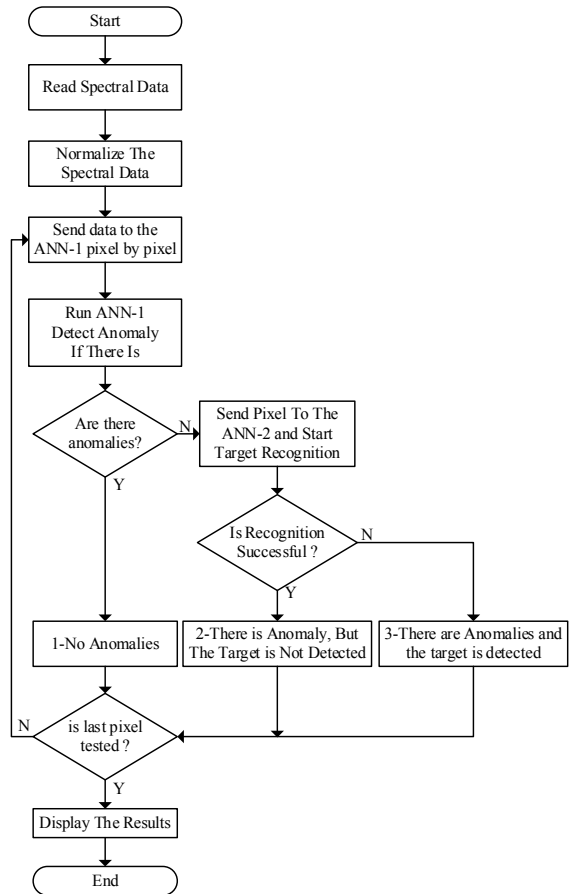


Fig.6. Flow Chart of the Proposed Method

Output of the ANN-1 can be “0” or “1”. If the output is “0”, the corresponding pixel is evaluated as a background data, but if the output is “1”, the pixel is considered to have an anomaly. Unlike the ANN-1, the network called ANN-2 in the method is trained to recognize specific targets. If output of ANN-2 is 0, it means there is an anomaly but there is not any defined target. If the target is detected in pixel, the output will have a value that represents the corresponding target. In order to reduce time delay, ANN-2 is just run for the pixels having anomaly.

The flow chart of the proposed method is as shown in Figure 6. Firstly, HSI data set is read from the disk. Afterwards, the bands that cannot be used due to the weather and sensor conditions and atmospheric effects are cleaned. Then the data is normalized and made ready for the ANNs. In the next step, data are sent to the ANN-1 to start anomaly detection process.

In anomaly detection process, if the pixel is detected as anomaly, corresponding coordinates in the output matrix is marked as “-1”. If any anomaly is detected in ANN-1, the same pixel is sent to the ANN-2 and target recognition process is started. If the pixel's spectrum has similar characteristics with the signature of any target used during training of ANN-2, corresponding coordinates in the output matrix will be marked with the value representing that target class. So that the pixel is determined as belonging to that target class. However, if the output is 0 as a result of ANN-2, assuming the target identification could not be made; corresponding coordinates in the output matrix will be marked as "0". After processing all these pixels in this way, gray image obtained from HSI data is combined with data in the output matrix. In this generated image, the background pixels are displayed normally, and the pixels that belong to the targets or the pixels that contain anomaly are represented by respective colors.

IV. EXPERIMENTAL STUDY

A. Data Sets

We used two different hyperspectral data set collected by the AVIRIS. The first consists of 1087x614 pixels, 224 spectral bands and it is approximately 292 MB. The second consists of 512x614 pixels, 224 spectral bands and it is approximately 137 MB. The gray scaled images formed from the data sets that used in this study are as shown in Figure 7 and Figure 8. In experiments, the 160 bands that are available in these data sets were selected.



Fig.7. Gray scaled image of an AVIRIS hyperspectral data collected by NASA. It is freely available online: http://aviris.jpl.nasa.gov/data/free_data.html



Fig.8. Gray scaled image of an AVIRIS hyperspectral data collected by NASA. It can be downloaded from http://aviris.jpl.nasa.gov/data/get_aviris_data.html

B. The creation of Neural Networks

We implemented this algorithm using a PC that has an Intel Core I7 3630QM 2.4 Ghz processor, 8 GB memory, Windows 8.1 64 bit operating system. Mathworks Matlab version R2010a has been used for implementing proposed method. Using neural network toolbox of Matlab, two networks were created. Both of these networks have 160 inputs in the input layer as the same number of selected bands. There are 10 neurons in the hidden layers of networks. Both of networks have an output there are multiple outputs values in output layer of ANN-2.

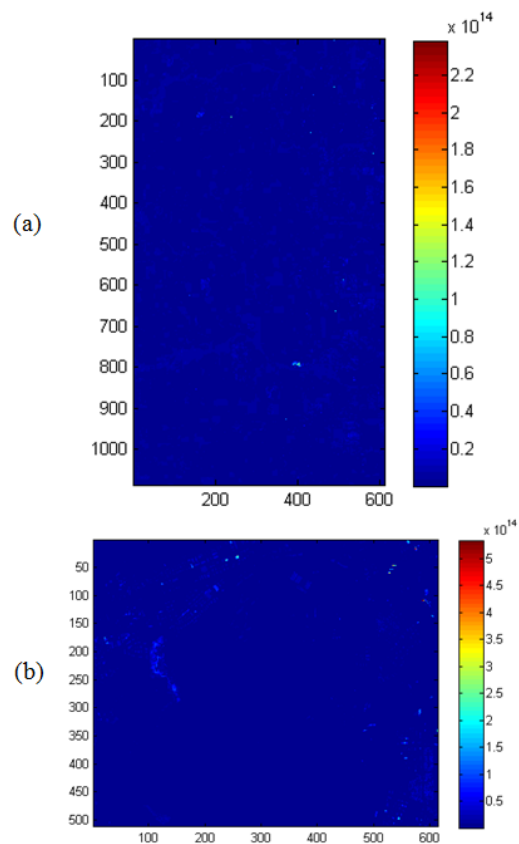


Fig.9. RX algorithm Result for (a) first spectral data set (b) second spectral data set.

C. Training of the Networks

The well-known RX algorithm [1] is used to create the data sets required for training of artificial neural networks in this study. Therefore, first RX algorithm was run for the data sets. The results obtained from RX algorithm for spectral data are as shown in Figure 9. Using the results obtained from RX algorithm, the 154 and 244 pixels with the highest level of anomaly are selected as anomalies from the data sets respectively. These pixels and others were used to generate the training sets. Data sets are divided into three sets: training 60%, validation 20% and testing 20% randomly. As a performance criterion, the mean squared/square/ error (MSE) is used. Structure of ANNs is shown in Figure 10. ANN-1 was trained by using *nntool* for 1000 epochs. The average performance value of ANN-1 is $3.14e-07$.

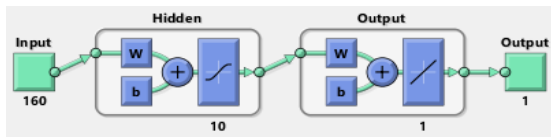


Fig.10. Structure of ANNs. The network has 160 inputs, 10 hidden neurons and an output.

The same 154 and 244 pixels were used to create the training set of ANN-2. However, these pixels were divided into classes by using *nctool*, because the ANN-2 is used to recognize targets. This tool uses a Self-Organizing Map (SOM) to classify the input data. As a result of classification, these 398 pixels were divided into 16 classes for training set of ANN-2. SOM layer that used to classification and resulting information are given in Figure 11. ANN-2 also was trained by using *nntool* for 1000 epochs. The average performance value of ANN-2 is $4.35e-07$.

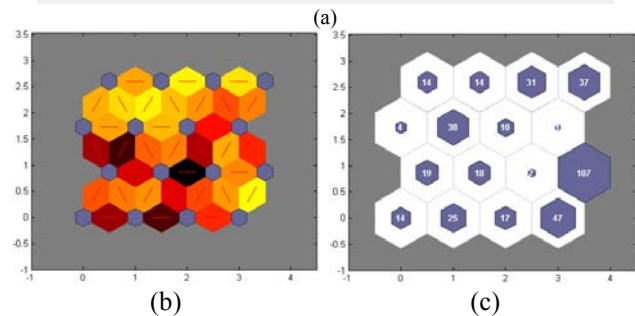
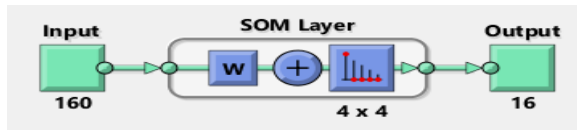


Fig.11. (a) Structure of Classification Network, (b) Weight Distance of SOM Neighbor, (c) Sample Hits of SOM.

D. Implementation of Method

A part of the first training set that does not contain any anomalies or any targets is used as test data. When the test data pattern is applied to method without any change, naturally there will not be any anomaly. Therefore, experiments are continued in different way.

Firstly, various numbers of targets were injected to data set and the model performance was measured. The injected targets and their coordinates were selected randomly in this type experiments. Results of experiments are stated in Table I. Gray scaled images that created from injected and raw test data are given in Figure 12.

TABLE I. RESULTS OF FIRST TYPE EXPERIMENTS

Number of Targets	ID	Anomaly Detection (ANN-1)		Target Recognition (ANN-2)	
		TP	FP	TP	FP
50	1	2	0	2	0
	2	3	0	3	0
	3	3	0	3	0
	4	6	0	6	0
	5	3	0	3	0
	6	3	0	3	0
	7	0	0	0	0
	8	10	0	10	0
	9	1	0	1	0
	10	5	0	5	0
	11	1	0	1	0
	12	0	0	0	0
	13	2	0	2	0
	14	2	0	2	0
	15	4	0	4	0
	16	5	0	5	0

TP (number of True Positive), FP (False Positive) and FN (False Negative), ID (Target ID)

Because similar results were obtained, the results are given for only one value.

As can be understood from these results, the performance of method is quite high. All entries were found to be correct using this method. This situation shows that the artificial neural networks used in the design is trained well. However, the behavior of the network for the different situations has to be tested. For this purpose, in the experiments of the second type, some random noises are added to input data set in positive and negative direction. Thus, the behavior of the model was tested in different values of noises. Information about experiments and results were as shown in Table 2. In these experiments, the number of target that injected to input data set is selected as 100.

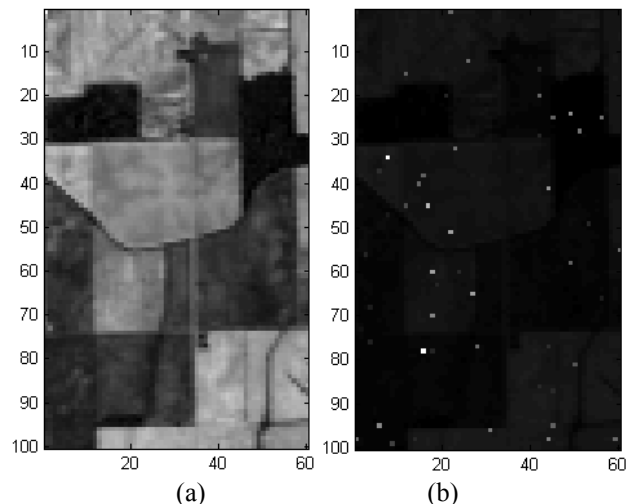


Fig.12. Spectral data set for input (a) raw data (b) injected fifty-targets

V. CONCLUSION

In this study, a new method is proposed for anomaly detection and target recognition. A pixel-based (spectral matching) approach is located to this method that used HIS technique. Proposed method has two neural networks, the first is for anomaly detection and the second is for target recognition. Since these networks are trained with their own data sets, their performances are high. The training sets of network were created using RX and SOM algorithm. To test this method, a part of spectral image obtained from training sets is used. Two type experiments are performed to evaluate this method. Firstly, various numbers of targets were injected to hyperspectral image. Secondly, some random noises are added to the input data set in positive and negative direction. In the first, all entries were found to be correct. In the second, when noise level is increased, performance of the model is decreased. The reason of the good performance is related to training phase. If the network is not trained with the right data sets, performance will decrease.

In our future studies, we will apply the method onto other hyperspectral data sets. According to the findings, we will try to improve the performance of the method. Furthermore, processes that require processing power such as artificial neural network training are also aimed to accelerate using parallel algorithms. Because it can be used in unmanned aerial vehicle, the use of the GPUs is planned as a parallel computing method.

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TABLE II. RESULTS OF SECOND TYPE EXPERIMENTS

Noise Ratio	ID	Anomaly Detection (ANN-1)		Target Recognition (ANN-2)	
		TP	FP	TP	FP
0.1%		<i>similar to the first type</i>			
1%		<i>similar to the first type</i>			
5%	1	4	0	4	0
	2	6	0	6	0
	3	4	0	4	0
	4	9	1	9	0
	5	5	0	5	0
	6	5	0	5	0
	7	3	0	3	0
	8	19	2	19	0
	9	4	0	4	0
	10	13	0	13	0
	11	4	0	4	0
	12	2	0	2	0
	13	3	0	3	0
	14	5	0	5	0
	15	6	0	6	0
	16	8	1	8	0
10%	1	2	0	2	0
	2	6	0	6	0
	3	4	1	4	0
	4	9	4	9	0
	5	5	0	5	0
	6	5	1	5	0
	7	3	0	3	0
	8	19	5	19	0
	9	4	0	4	0
	10	13	4	13	0
	11	4	0	4	0
	12	2	1	2	0
	13	3	0	3	0
	14	5	0	5	0
	15	6	1	6	0
	16	8	2	8	0
15%	1	2	0	2	0
	2	6	2	6	0
	3	4	1	4	0
	4	7	4	7	1
	5	3	0	3	0
	6	6	1	5	0
	7	3	0	3	0
	8	15	8	15	1
	9	4	0	4	0
	10	7	4	7	0
	11	4	1	4	0
	12	2	1	2	0
	13	3	0	3	0
	14	5	0	5	0
	15	6	3	6	0
	16	6	2	6	0

TP (number of True Positive), FP (False Positive) and FN (False Negative). ID (Target ID)

As can be understood from these results, we have known targets and anomalies may be detected by this method. When noise level is increased, performance of the model decreases. As seen, the anomalies can be detected, even if it is not in any target class. This shows that this method can be used for similar detection applications.

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