AUT Journal of Electrical Engineering

AUT J. Elec. Eng., 52(2) (2020) 159-168
DOI: 10.22060/eej.2020.18037.5341

A New Method for Detecting Ships in Low Size and Low Contrast Marine Images: Using Deep Stacked Extreme Learning Machines

S. V. Shojaedini[1,*], M.R. Abedi[2], M. Moshtaghi[3]

[1]Associate Professor, Department of Electrical Engineering, Iranian Research Organization for Science and Technology, Tehran, Iran
[2]MSC in Electrical Engineering, Faculty of Electrical, Biomedical and Mechatronics Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
[3]PhD Candidate in Electrical Engineering, Faculty of Electrical, Biomedical and Mechatronics Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

ABSTRACT: Detecting ships in marine images is an essential problem in maritime surveillance systems. In recent years deep neural networks have been utilized as a tool having high potential to overcome the challenges of this application. Unfortunately the performance of such networks greatly drops when they are exposed to low size and low contrast optical images which have been captured by ground, aerial and satellite based systems. On the other hand, image clutters (e.g. sea waves, cloud and wave sequences caused by the floats) may exacerbate this problem. In this paper a new method is proposed to improve the performance of deep neural networks in detecting ships in low size and low contrast marine images which has been based on the concept of deep stacked extreme learning machines. In proposed method the extracted features have more generality in modeling of marine images based on superposition of dedicated mapping functions of extreme learning machines. Furthermore they have the minimal overlap thanks to performing decorrelation process on features which are propagated between network layers. The performance of the proposed method is evaluated on several marine images which have been captured in sunny, rainy and hazy conditions. The obtained results are compared with some other state-of-the-art detection methods by using standard parameters. Increased F-measure of the proposed method (i.e. 3.5 percent compared to its closest alternative) in parallel with its better accuracy, recall and precision shows its effectiveness in detecting ships in low size and low contrast marine images.

Review History:

Received: 2020-03-03
Revised: 2020-08-10
Accepted: 2020-08-11
Available Online: 2020-12-01

Keywords:

Ship Detection
Marine Images
Deep Neural Network
Deep Stacked Extreme Learning Machine
Decorrelation

1. Introduction

Identification of marine floats in the images is one of the most important issues in passive marine monitoring [1]. The aim of this procedure is determining the presence of the floats based on images taken from various marine scenes which subsequently leads to estimate the location and other desirable characteristics of the detected floats [1].

Generally, such monitoring systems are divided into three main categories including ground-based cameras [2, 3], aerial-based cameras [4, 5] and satellite based solutions [6, 7]. The first two types are both older and simpler, but have serious limitations, the most important of which are: poor concealment, limited space coverage, and the requiring to sensor installation and maintenance which all of them may be addressed by using satellite-based monitoring. This method may itself be divided into SAR images as well as optical imaging. Optical satellite images have higher spatial resolution than SAR images that are more suitable for the purpose of ship monitoring [8].

For several years human interpretation has been the most traditional method for interpretation of marine images in which the captured images were analyzed by an expert human [9]. Although this method has considerable accuracy but it is so time consuming, therefore human analyzing is not applicable approach especially when it is utilized in a wide area which includes multiple cameras. To address this limitation the automated methods have been substituted in parallel with the expansion of the use of images in the analysis of marine scenes [9]. The most important step in automated techniques is ship detection in which the presence of a ship or marine float in captured images is indicated [10]. A serious challenge in ship detection occurs when there is low difference between ship and background intensities which leads to either missing some floats or false alarms. Furthermore small dimensions of floats and overlap of various image components are other factors which may decrease the performance of automated methods. Finally, optical images are usually disturbed by weather conditions, such as clouds or sea waves [8]. These limitations caused that automated ship detection still remained as an open problem in passive marine monitoring domain [11].

Several methods have been introduced to address automated ship detection problem in optical images, which

*Corresponding author's email: shojaeddini_va@yahoo.com

the simplest one is making use of static or dynamic thresholds [12] which are calculated from the intensity of the pixels. Unfortunately, the above approach often leads to detecting considerable false objects. The reason for this problem is that non-ship objects have the similar intensity distribution as the ships, therefore the resultant histograms are not acceptably bimodal. In some researches the fuzzy logic is incorporated in detecting ships based on this fact that the algorithms in this paradigm are able to make better decisions than their alternatives by using uncertain data [13].

A number of ship detection methods have been proposed based on the adoption of the coarse-to-fine strategy, which may be illustrated as sequential applying of ship candidate extraction and false alarm elimination steps [14].

Multiscale methods have also been widely used for ship detection [15, 16]. For instance in wavelet based schemes, the images are firstly divided into several sub-sections. In next step each section is subjected to multi-resolution transform and finally dependence of each section to ship or background is determined. Despite of superiority of this scheme against usual thresholding, but the accuracy of multi-resolution methods drops dramatically in parallel with decrease in image contrast. The Gaussian mixture model is another paradigm which has been examined to address ship detection problem [17]. High computational cost, the unknown number of the mixture models and the high sensitivity of this method to model parameters are main factors which hamper the use of this idea in real marine scenes.

In some studies a priori coastline data is utilized to detect sea region and consequently to detect ships [18]. The high sensitivity of the performances of these type of algorithms to accurate detection of coastal line is the main parameter which hampers their vast application in ship detection.

In last decade some researches has been focused on ship detection by using Artificial Neural Networks (ANNs) [19]. Unfortunately, the accuracy of classic ANNs are strongly dependent on the extracted features from the image under test. The above factors impress the performance of traditional neural networks in distinguishing ships from other parts of marine image in real world applications. To address the limitations of traditional neural networks, Deep Neural Networks (DNNs) have been used which led to considerable improvement in ship detection thanks to their deep structure and ability in multiple level data representation [20]. During recent years, several versions of deep learning schemes, has been utilized to detect marine objects in different types of optical images [21, 22]. Despite of their great potential in detecting ships and their valuable specifications such as the position and direction [23, 24], but unfortunately deep networks mostly require significant amount of training data depending on their size. However, in the case of marine ships, the amount of training data is small which yields poor performance due to overfitting phenomenon. Recently **E**xtreme **L**earning **M**achines (i.e. ELMs) have been proposed to overcome the mentioned problem [25, 26]. This type of learning machines randomly choose hidden nodes and analytically determine the output weights. In theory, this algorithm tends to provide good generalization performance at fast learning speed. Despite the above impressive advantages but a number of redundant nodes may be generated in ELMs, which have a minor effect on the outputs of the network. However, the existence of redundant nodes may eventually increase the complexity of the network.

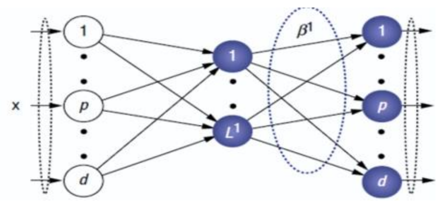

Fig. 1. Description of ELM

In this paper, a new structure is introduced to improve ship detection in low size and low contrast marine images. The proposed structure is composed of successive layers; each of them is composed of some different ELMs. Each ELM extracts a set of features based on its dedicated mapping function. Propagating these features trough next layers leads to higher level features which are extracted by their own ELMs. Since each ELM has its own mapping function, therefore, the resultant features have more generality in modeling of input images. Additionally the Principal Component Analysis (PCA) is applied on features which are transferred between layers which performs the final features with the least amount of overlap. The paper is organized as follows: section 2 includes description of the proposed method for ship detection. In Section 3, the results of the applying the proposed structure for ship detection are demonstrated. In Section 4, the obtained results are compared to some state-of-the-art structures by using their effective parameters. The conclusion is presented in the last section of the paper.

2. Materials and Methods

In this section, firstly ELM networks are briefly reviewed. Then the performance of ELM is promoted by applying Deep Restricted Boltzmann *Machines as a more sophisticated structure called as* DRBM-ELM. Finally, deep stacked ELM is discussed as our proposed scheme for improving discrimination capability of features thanks to its deep hierarchical mapping in parallel with performing decorrelation process.

2-1- ELM Networks

Although Single-Layer Feed-Forward Neural Networks (SLFNN) are considered as basic networks among others, but they provide the basis for more complex structures. One of these structures is Extreme Learning Machine (ELM) which is demonstrated in Fig. (1).

The output function of ELM is defined as follows [27]:

$$F(x) = h(x)\beta = \sum_{l=1}^{L} \beta_l h_l(x) \tag{1}$$

In which function h(x) maps the d-dimensional space of the input to a next L-dimensional space. Also β is weight vector between hidden and output layers. This model has the potential of estimating many complex functions providing that proper mapping is selected in the hidden layer. Unlike the usual learning methods, ELM not only tries to minimize the error of the training data, but also tries to minimize the norm of weights belonging to the output. According to Bartlett's Theory, jointly decrease in above parameters may lead to more generalization in network. The minimization is described as:

$$\beta_{\text{opt}} = \arg\min\left[\left\|H\beta - T\right\|^2 \ \ and \ \ \left\|\beta\right\|\ \right] \tag{2}$$

In which T and H represent the target vector and hidden layer as follows:

$$\text{H}=\begin{bmatrix} h(x_1) \\ \vdots \\ h(x_n) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \vdots & \vdots \\ h_1(x_N) & \cdots & h_L(x_N) \end{bmatrix} \tag{3}$$

2-2- DRBM-ELM Networks

The performance of ELM model may be modified by using the sophisticated combination with the Deep Restricted *Boltzmann Machines* (which is called DRBM-ELM for brevity in this article) as demonstrated in Fig. (2).

The DRBM-ELM Structure includes two parts: i) A non-monitored deep network which is used only to reduce the dimension; ii) The ELM model which takes its input from the output of the deep network. The former model is completely unstructured and layer-by-layer, furthermore, the reconstruction error occurs throughout the network (fine-tuning). The data labels are not used in this stage, and eventually one ELM is independently trained to predict the label.

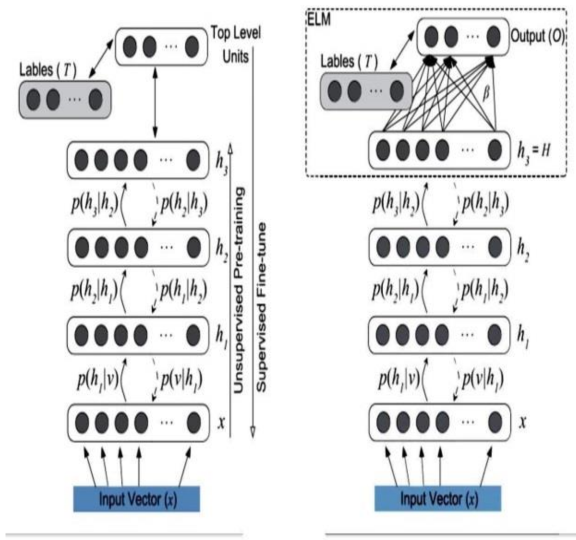

Fig. 2. Structure of DRBM-ELM

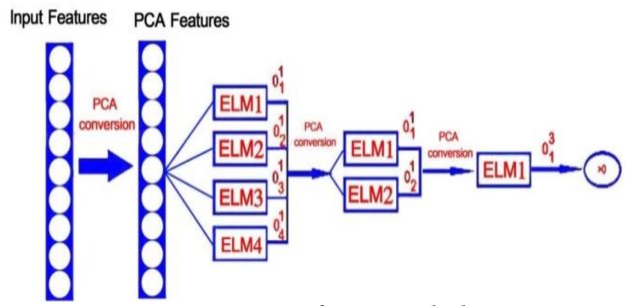

Fig. 3. Description of Deep-Stacked-ELM

2-3- Deep Stacked ELM

The proposed model in this study is Deep Stacked ELM. In proposed structure each of successive layers is composed of some different ELMs which are trained independently, then the obtained outputs are used as the input of the next layer after performing decorrelation procedure. The structure of Deep Stacked ELM is shown in Fig. (3).The idea behind this method is that each of ELMs has its own mapping function, therefore each one may obtain better accuracy on a specific part of data set. As result, feeding the output of these networks to next layer (i.e. extracted features) may lead to more generality in modeling of data set. The necessary condition for such improvement is that the features which are transferred to the next layer have the minimum amount of overlap.

In order to eliminate the correlation between these features the Principal Component Analysis (PCA) is performed. Consequently, existing ELMs in the next layer are trained with features which have the lowest degree of dependency and each of them is best-fitted for a specific portion of data. This procedure may be performed in several consecutive layers which leads to extracting higher level and as far as possible independent features. Finally, an ELM which is used in last layer of deep stacked network plays the role of a decision maker to recognize type of input data (i.e. ship or non-ship).

The pseudo code of proposed algorithm is presented in Fig.s (4-a) and (4-b). Firstly Fig. (4-a) illustrates Inputs of the algorithm and subsequently (4-b) describes essential training steps of Deep-Stacked-ELM.

3. Results

In order to evaluate the performance of the proposed algorithm it was applied on a set of images containing several scenes which either included or didn't include ships. The examined dataset contained totally 1507 maritime images and included 544 ship images and 963 non-ship images. Furthermore the images may contained several phenomena such as sea wave, cloud and wave sequence caused by the ship. These effects are called as clutter in the rest of this article. Fig. (5) shows some representative frames which contains ships and Fig. (6) demonstrates some other frames which contain only clutters. These two categories of frames are called ship and non-ship images respectively. Table (1) shows the main characteristics of the images that are subjected to the methods

1- Vectors of the train data features $\in R^{d*N}$
2-Vectors of the test data features $\in R^{d*M}$
3- $trainLabel \in \{+1,-1\}^{1*N}$ *(ship or non-ship).*
4- $TestLabel \in \{+1,-1\}^{1*M}$ *(ship or non-ship).*
5- The number of layers in network.
6- T_l *: The number of ELM units in Lth layer.*
7- NHNi: The number of neurons in each ELM network.
8-$ActFunction$*: The activity functions of the neurons in the deep network.*

(a)

Starting the **main loop**

Inner loop: teach the ELM models the L Layer from t = 1 to t = T_l

-Starting the inner loop

Teaching $\mathrm{ELM}^{\mathrm{t}}$ Model

$[\mathrm{EL}M_t^l]$ = $\boldsymbol{ELM\_Training}$ $(trainMap^{l-1}, trainLabel)$.

- Calculating output t-th unit

$[trainMap_t^l]$ = $\boldsymbol{ELM\_Output}$ $(ELM_t^l$, $trainMap^{l-1})$.

$[\mathrm{test}.Map_t^l]$ = $\boldsymbol{ELM\_Output}$ $(ELM_t^l$, $\mathrm{test}.Map^{l-1})$.

-End of inner loop

-Calculating the output of the l layer

$[trainMap^l\ ]$ =[$trainMap_1^l, \dots ,$ $trainMap_1^l]'$;

- Applying PCA conversion on the output ELMs

$A^l = PCA(trainMap^l\ )$.

$train\ Map^l \leftarrow (A^l)' * trainMap^l$.

$\mathrm{test}.\ Map^l \leftarrow (A^l)\ ' * \mathrm{test}.Map^l$.

-The end of the **main loop**

-Calculate the final output of the network (tagging)

$trainLabel \leftarrow trainMap^{\mathrm{numlayers}}$ > *Thr.*

$testLabel \leftarrow testMap^{\mathrm{numlayers}}$ > *Thr.*

**Note: Thr* is the threshold of the making decision that is zero in the default state.
**Constraint: There is an ELM in the last layer in another word* $T^{l=numlayers} = 1$

(b)

Fig. 4. Pseudocode of proposed scheme, (a) Inputs of algorithm, (b) training steps

of this paper.

In this study, in order to assessing the effectiveness of the proposed method, three alternative methods were implemented including basic Extreme Learning Machine (i.e. ELM) [27], Deep Restricted *Boltzmann Machine combined with ELM* [28, 29] *which is called as DRBM-ELM for brevity in this article,* Deep Restricted Boltzmann *Machine* with Discriminative layer [30] *which is called as DRBM-Disc for*

Fig. 5. Representative frames from set of examined Images which include ship

Fig. 6. Representative frames from set of examined Images which only include clutter

brevity in this article. The most important common point of the above alternative methods is that all of them are based on the various combinations of Deep Restricted Boltzmann *Machine* (DRBM) and Extreme Learning Machine (ELM) concepts therefore may be considered as members of same family with the proposed method. The proposed and alternative methods were examined on both sets of ship and non-ship images. Fig.s (7)-(10) show the results obtained from applying the above methods on frames which have been shown in Fig.s (5)-(6). Note the label above each image shows diagnosis of that algorithm in such way that the blue label means the diagnosis of the algorithm has been correct and the red label means the diagnosis of the algorithm has been wrong. Fig.s (7)_(10) illustrate that the frames a, d, e, j, k, have been correctly identified by using either the proposed method or its alternatives. The common feature of all these frames is the sharp difference between the main object and backgrounds (i.e. maximally 65% and minimally 55%) which caused they have been interpreted correctly by all methods. Another considerable sample is the low quality frame c (i.e. contrast equal 17%) which led to false recognitions when alternative algorithms were used while it was correctly identified by using proposed approach. This result may be interpreted as an example for superiority of the proposed method against its alternatives in recognizing low quality images. For some frames, the recognition was correct by utilizing the proposed method along with one or two alternatives methods. For example for frame h, the proposed method led to correct detection in parallel with ELM, However other methods have resulted in false alarms. There was a similar situation for the frame f, which has been recognized correctly by proposed method along with DRBM-ELM, while it has been mistakenly recognized by other methods. It may be noted the sharpness of this category of images is significantly lower than a, d, e, j, k, therefore they have been miss interpreted by some algorithms. For instance the contrast of frame h was in 34% which was at least 21% lower than mentioned high contrast frames. An exceptional case was the frame i, which was misdiagnosed by using the proposed method and DRBM-ELM while this frame was accurately interpreted by using DRBM-Disc and basic ELM. The remarkable fact about this frame is its moderate contrast (i.e. 38%) which, as a rule, should lead to an acceptable result. As an interesting item among the examined frames, we can name the frame b, which led to miss recognition in either proposed or alternative schemes. Investigating the contrast of this frame (i.e. 11%) showed its minimum sharpness compared to all examined frames. The results indicated that the superiority of the proposed method against its alternatives was generally related to the quality (i.e. sharpness) of the images. This relation was in such way that in parallel to the sharpness increase in the frame, the chances of correctly recognizing the alternative methods were reduced, while the correctness of the diagnosis of the proposed method may remain acceptable until lower contrasts.

4.Discussion

The proposed algorithm, ELM, *DRBM-Disc and* DRBM-ELM were applied on all of images belonging to data set which was described in section 3. Then four basic parameters were measured to evaluate the performance of each method. The measured parameters consisted of True Positive (TP) which shows the number of correctly identified ships, True Negative (TN) which shows the non-ship objects which were rejected correctly, False Positive (FP) which is the number of false detections and False Negative (FN) which shows the number of missed ships. Finally accuracy, Recall, Precision and F-Measure were estimated by using bellow formulas for all examined methods to compare their effectiveness in recognizing ship and non-ship contained frames. The accuracy illustrates the rate of the correct recognitions (either ships or non-ships) as:

$$Accuracy = \frac{TN + TP}{TN + FN + FP + FN} \quad (4)$$

Recall means the probability that a ship to be identified if it exists. This parameter is defined as:

Table 1. Specifications of data set

Specification	Value	Specification	Value
Number of images	1507	Image size	40*70pixel
Ship images	544	Ship size	Averagely 50pixel
Non-ship images	963	Min and Max Contrast	11%-76%
Image content	Sea wave, Horizon	Weather condition	Sunny Rainy Hazy

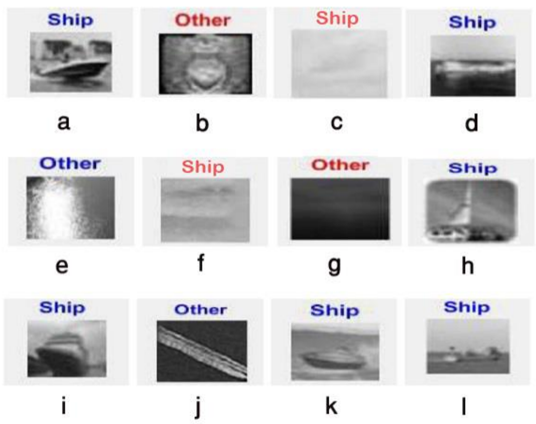

Fig. 7. Results of ELM

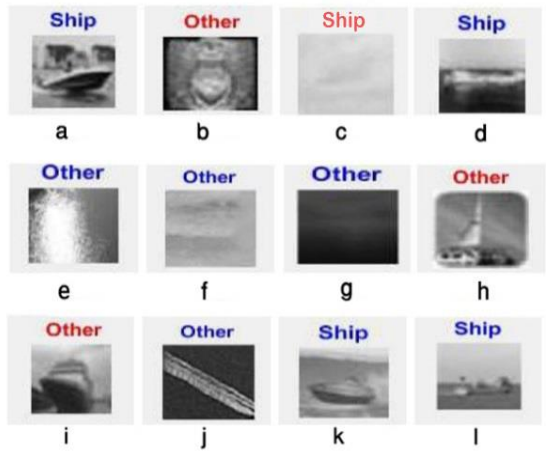

Fig. 9. Results of DRBM-ELM

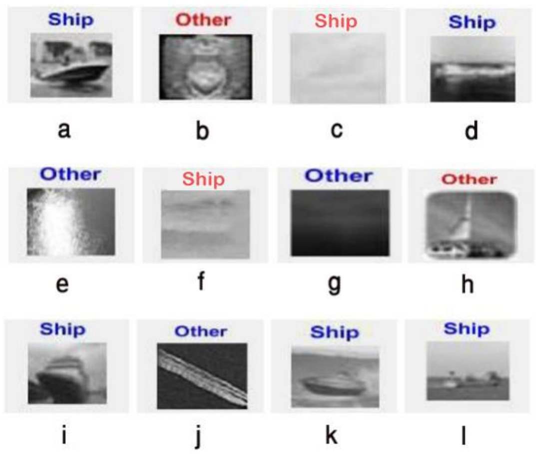

Fig. 8. Results of DRBM-Disc

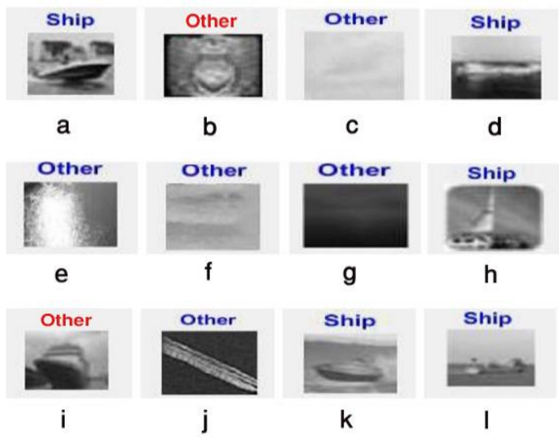

Fig. 10. Results of the proposed method

$$Recall = \frac{TP}{FN + TP} \quad (5)$$

Precision illustrates the correct percentage of ship detection, in other words, from 100 reports of the ship how many have been actually ship reports. This parameter is calculated as:

$$Precision = \frac{TP}{FP + TP} \quad (6)$$

An ideal ship recognition algorithm should have a high Recall and Precision, which seldom happens. These two criteria are inversely related to the technical point of view. The F-measure criteria may be used as an appropriate combination of these two concepts as a standard scale for choosing the efficient paragon as:

$$F\text{–}measure = 2\,\frac{Precison * Recall}{Precision + Recall} \quad (7)$$

Table 2. Comparison of the performances of proposed and alternative algorithms

Method name	Accuracy	F-Measure	Precision	Recall
ELM	91.30	88.29	90.86	85.99
DRBM-Disc	92.19	88.65	89.61	88.03
DRBM-ELM	91.30	88.45	89.39	87.61
Deep-Stacked ELMs	94.11	92.15	92.13	92.34

Table 3. Comparison of the performances of proposed and alternative algorithms based on different weather conditions

Method	Condition	Accuracy (percent)	F- Measure (percent)	Precession (percent)	Recall (percent)
ELM	Sunny	94.15	90.2	93.24	89.21
	Rainy	92.3	89.1	90.16	86.27
	Hazy	87.45	85.57	89.18	82.49
DRBM- Disc	Sunny	95.22	94.21	93.02	93.14
	Rainy	91.12	87.3	88.12	87.02
	Hazy	90.23	87.44	87.69	83.93
DRBM- ELM	Sunny	94.25	93.21	94.71	92.12
	Rainy	90.11	87.02	87.12	86.31
	Hazy	89.54	86.12	86.34	84.40
Deep -Stacked-ELM	Sunny	97.31	95.01	94.11	96.28
	Rainy	93.16	91.12	92.02	91.20
	Hazy	91.86	90.32	90.26	89.54

Table (2) shows the comparison of the performances of the proposed and alternative schemes in terms of four mentioned parameters.

As shown in Table (2), the proposed method outperformed all of the examined parameters against its alternatives as described below. The obtained Accuracies revealed that the best value was gained by using the proposed method which has been 2.81, 1.92, and 2.81 percent better than those values which had been obtained by applying ELM, *DRBM-Disc and* DRBM-ELM methods respectively. According to Precision the proposed scheme achieved the best value (i.e. 92.13%) which has been 1.27, 2.52 and 2.81 percent better than those values which had been obtained by applying ELM, *DRBM-Disc and* DRBM-ELM methods respectively. Exploring Recall still showed the superiority of the proposed algorithm against alternatives in such way that it's obtained value was better than those which had been obtained by other methods by extents of 6.35, 4.31, and 4.73 percent for ELM, *DRBM-Disc and* DRBM-ELM methods respectively. Eventually, the F-Measure of the proposed structure confirmed its better performance in such way it was 3.86, 3.5 and 3.7 percent better than those values which had been obtained by applying ELM, *DRBM-Disc and* DRBM-ELM methods respectively. As described in section 3, the images were captured in three different weather conditions including sunny, rainy and hazy. Table (3) demonstrates the performances of the proposed and alternative algorithms in terms of above atmospheric conditions. The results which have been described in this table indicated that the proposed method in all three types of atmospheric conditions has shown to be more capable than its alternatives in detecting ships.

The results described in this table reflect this important fact that the image contrast is the most effective parameter in the behavior of the proposed method. The values reported in the above table demonstrate a tight relationship between performance losses of the proposed method with the decrease in contrasts of images under test. Furthermore the above behavioral logic is relatively similar for all four evaluation parameters (i.e. Accuracy, F-Measure, Precision and Recall).

Exploring the trend of changes in the values reported in Table 3 shows that the performance parameters of the proposed method became weaker in rainy condition than in sunny condition. In a same manner the above table clearly indicates evaluation parameters reach their lowest values in hazy conditions. To make a meaningful numerical comparison, let to assume the sunny condition as a benchmark, then the parameters which have been obtained in other states may be compared with results obtained in sunny conditions as reference values. Table 3 shows that as the contrast of the images decreases compared to the benchmark (comparison of rainy and sunny conditions), the evaluation parameters also decrease.

Investigation of the Accuracy, F-Measure, precision and Recall which have been obtained for rainy conditions shows they dropped almost 2.1 to 5.1 percent compared to their base values (i.e. by extents of 4.1%, 3.8%, 2.09% and 5.08% respectively). In the lowest contrast case (i.e. hazy conditions), it was observed that the performance of the proposed method in detecting ships were 3.8 to 6.7 percent lower than its performance in benchmark (i.e. sunny) conditions (e.g. 5.45%, 4.7%, 3.85% and 6.74% loss in terms of Accuracy, F-Measure, precision and Recall respectively).

The proposed method achieves more acceptable detection parameters than its alternatives even in weaker contrasts, therefore it may be considered as a high potential scheme for ship detection in marine images without exception of specific atmospheric conditions. However, it should be noted that the severe decrease in contrast of captured images (that usually occurs in some conditions such as hazy scenes) may also be a challenge for this method.

5. Conclusion

In this paper a new method was introduced for recognizing ships in low size and low contrast images which have been captured from marine scenes. The proposed algorithm utilized the concept of deep stacked extreme learning machines in order to overcome two above main challenges in detecting ships in scenes contained several marine clutters (e.g. sea wave, cloud and wave sequence caused by the ship). To evaluate the performance of the proposed algorithm, it was examined on a data set including ship and non-ship images in several atmospheric conditions. Then the obtained results were compared with three existing methods (e.g. ELM, *DRBM-Disc and* DRBM-ELM).

The obtained results were compared by using standard parameters consist of accuracy, precision, recall and F-measure which showed superiority of the proposed method against its alternatives. Results showed that based on F-measure as the most effective parameter the proposed algorithm has recognized ships at least 3.5% better than its closest alternative (i.e. *DRBM-Disc)* while its gain compared to other alternatives is a bit more than this value. Furthermore it has been shown that the performance of the proposed algorithm has been at least 1.92%, 1.27% and 4.31% better than its closest alternatives based on obtained accuracy, precision and recall. Comparing the performance of the proposed method with its alternatives in terms of three atmospheric conditions (sunny, rainy and hazy) has also shown such superiorities. Based on the above results it may be concluded that the concept of deep stacked extreme learning machines may be considered as a suitable choice for recognizing ships in presence of several clutters in low size and low contrast images which were captured from different sunny, rainy and hazy marine scenes.

References

[1] J. Tang, C. Deng, G.-B. Huang, B. Zhao, Compressed-domain ship detection on spaceborne optical image using deep neural network and extreme learning machine, IEEE Transactions on Geoscience and Remote Sensing, 53(3) (2014) 1174-1185.

[2] S. Zhang, Z. Qi, D. Zhang, Ship tracking using background subtraction and inter-frame correlation, in: 2009 2nd International Congress on Image and Signal Processing, IEEE, 2009, pp. 1-4.

[3] S. Fefilatyev, D. Goldgof, C. Lembke, Tracking ships from fast moving camera through image registration, in: 2010 20th international conference on pattern recognition, IEEE, 2010, pp. 3500-3503.

[4] J. Wu, S. Mao, X. Wang, T. Zhang, Ship target detection and tracking in cluttered infrared imagery, Optical Engineering, 50(5) (2011) 057207.

[5] S. Qi, J. Wu, Q. Zhou, M. Kang, Low-resolution ship detection from high-altitude aerial images, in: MIPPR 2017: Automatic Target Recognition and Navigation, International Society for Optics and Photonics, 2018, pp. 1060805.

[6] X. Wei, X. Wang, J. Chong, Local region power spectrum-based unfocused ship detection method in synthetic aperture radar images, Journal of Applied Remote Sensing, 12(1) (2018) 016026.

[7] C. Deng, Z. Cao, Z. Fang, Z. Yu, Ship detection from optical satellite image using optical flow and saliency, in: MIPPR 2013: Remote Sensing Image Processing, Geographic Information Systems, and Other Applications, International Society for Optics and Photonics, 2013, pp. 89210F.

[8] F. Yang, Q. Xu, B. Li, Ship detection from optical satellite images based on saliency segmentation and structure-LBP feature, IEEE Geoscience and Remote Sensing Letters, 14(5) (2017) 602-606.

[9] C. Corbane, L. Najman, E. Pecoul, L. Demagistri, M. Petit, A complete processing chain for ship detection using optical satellite imagery, International Journal of Remote Sensing, 31(22) (2010) 5837-5854.

[10] X. Leng, K. Ji, S. Zhou, X. Xing, H. Zou, An adaptive ship detection scheme for spaceborne SAR imagery, Sensors, 16(9) (2016) 1345.

[11] U. Kanjir, H. Greidanus, K. Oštir, Vessel detection and classification from spaceborne optical images: A literature survey, Remote sensing of environment, 207 (2018) 1-26.

[12] H. Li, L. Chen, F. Li, M. Huang, Ship detection and tracking method for satellite video based on multiscale saliency and surrounding contrast analysis, Journal of Applied Remote Sensing, 13(2) (2019) 026511.

[13] G. Margarit, A. Tabasco, Ship classification in single-pol SAR images based on fuzzy logic, IEEE Transactions on Geoscience and Remote Sensing, 49(8) (2011) 3129-3138.

[14] G. Yang, B. Li, S. Ji, F. Gao, Q. Xu, Ship detection from optical satellite images based on sea surface analysis, IEEE Geoscience and Remote Sensing Letters, 11(3) (2013) 641-645.

[15] X. Wang, C. Chen, Ship detection for complex background SAR images based on a multiscale variance weighted image entropy method, IEEE Geoscience and Remote Sensing Letters, 14(2) (2016) 184-187.

[16] F. Xu, J. Liu, C. Dong, X. Wang, Ship detection in optical remote sensing images based on wavelet transform and multi-level false alarm identification, Remote Sensing, 9(10) (2017) 985.

[17] J. Yu, Q. Wan, Q. Liu, X. Chen, Z. Li, A Novel Ship Detector Based on Gaussian Mixture Model and K-Means Algorithm, in: International Conference on Applications and Techniques in Cyber Security and Intelligence, Springer, 2018, pp. 639-646.

[18] N. Proia, V. Pagé, Characterization of a Bayesian ship detection method in optical satellite images, IEEE Geoscience and Remote Sensing Letters, 7(2) (2009) 226-230.

[19] E. Khesali, H. Enayati, M. Modiri, M.M. Aref, Automatic ship detection in Single-Pol SAR Images using texture features in artificial neural networks, The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 40(1) (2015) 395.

[20] X. Yang, H. Sun, K. Fu, J. Yang, X. Sun, M. Yan, Z. Guo, Automatic ship detection in remote sensing images from google earth of complex scenes based on multiscale rotation dense feature pyramid networks, Remote Sensing, 10(1) (2018) 132.

[21] R. Zhang, J. Yao, K. Zhang, C. Feng, J. Zhang, S-CNN-based ship detection from high-resolution remote sensing images, International Archives of the Photogrammetry, Remote Sensing & Spatial Information

Sciences, 41 (2016).

[22] Q. Li, L. Mou, Q. Liu, Y. Wang, X.X. Zhu, HSF-Net: Multiscale deep feature embedding for ship detection in optical remote sensing imagery, IEEE Transactions on Geoscience and Remote Sensing, 56(12) (2018) 7147-7161

[23] X. Yang, H. Sun, X. Sun, M. Yan, Z. Guo, K. Fu, Position detection and direction prediction for arbitrary-oriented ships via multitask rotation region convolutional neural network, IEEE Access, 6 (2018) 50839-50849

[24] Y. Yao, Z. Jiang, H. Zhang, D. Zhao, B. Cai, Ship detection in optical remote sensing images based on deep convolutional neural networks, Journal of Applied Remote Sensing, 11(4) (2017) 042611.

[25] W.-b. Huang, F.-c. Sun, A deep and stable extreme learning approach for classification and regression, in: Proceedings of ELM-2014 Volume 1, Springer, 2015, pp. 141-150.

[26] M.A.A. Albadra, S. Tiuna, Extreme learning machine: a review, International Journal of Applied Engineering Research, 12(14) (2017) 4610-4623.

[27] A. Khellal, H. Ma, Q. Fei, Convolutional neural network based on extreme learning machine for maritime ships recognition in infrared images, Sensors, 18(5) (2018) 1490.

[28] R. Mittelman, H. Lee, B. Kuipers, S. Savarese, Weakly supervised learning of mid-level features with beta-bernoulli process restricted boltzmann machines, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2013, pp. 476-483.

[29] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, B.A. Johnson, Deep learning in remote sensing applications: A meta-analysis and review, ISPRS journal of photogrammetry and remote sensing, 152 (2019) 166-177.

[30] N. Srivastava, R. Salakhutdinov, Multimodal learning with deep Boltzmann machines, Journal of Machine Learning Researches, 15(1) (2014) 2949-2980

HOW TO CITE THIS ARTICLE

S.V. Shojaedini, M.R. Abedi, M. Moshtaghi, A New Method for Detecting Ships in Low Size and Low Contrast Marine Images: Using Deep Stacked Extreme Learning Machines, AUT J. Elec. Eng., 52(2) (2020) 159-168.

DOI: 10.22060/eej.2020.18037.5341