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ORIGINAL ARTICLE

Classification of sonar echo signals in their reduced sparse forms using complex-valued wavelet neural network

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Abstract
This study aims to identify a method for classifying signals using their reduced sparse forms with a higher degree of accuracy. Many signals, such as sonar, radar, or seismic signals, are either sparse or can be made sparse in the sense that they have sparse or compressible representations when expressed in the appropriate basis. They have a convenient transform domain in which a small number of sparse coefficients express them as linear sums of sinusoidals, wavelets, or other bases. Although real-valued artificial neural networks (ANNs) have been frequently used in the classification of sonar signals for a long time, complex-valued wavelet neural network (CVWANN) is used for these complex reduced sparse forms of sonar signals in this study. Before the classification, the number of inputs was reduced to *1/3* dimension. Complex-valued sparse coefficients (CVSCs) obtained from the reduced form were classified by CVWANN. The performance of the proposed method is presented and compared to other classification methods. Our method, CVSCs + CVWANN, is very successful as 94.23% by tenfold cross-validation data selection and 95.19% by 50–50% training–testing data selection.

Keywords Sonar detection · Sonar measurements · Target recognition · Neural networks · Neurons · Compressed sensing

1 Introduction

Sonar (sound navigation and ranging) is a technology using sound propagation to detect the target information in underwater navigation and communication. Various classification algorithms are useful to recognize the type of surface from which the sonar waves are reflected. Artificial neural networks (ANNs) have been employed and become popular for the automatic identification of sonar targets. [1, 2] are the first known papers studied by Gorman and Sejnowski where neural networks (NN) were applied to the sonar target dataset in [3]. Afterward, multi-layer perceptron (MLP) [1, 2, 4, 5], general regression neural networks (GRNN) [6], radial basis function networks (RBFN) [7, 8], probabilistic neural networks (PNN) [7], and conic section function neural networks (CSFNN) [9] have also been used for the classification of sonar signals. Besides, various classification methods are available in [10–12].

A signal, which is not sparse in a given domain, can be sparse in other domains. For example, a chirp signal is not sparse in both time and Fourier domains. However, it can be made sparse in the appropriate fractional Fourier domain. A new approach is developed in this paper for sparsity that regulates the input signals in reduced sparse forms. All data signals [3] which seem complicated in time domain are transformed into Fourier domain in order to obtain more rare structures. When examining the first few transformed signals in the data files, it is seen that the *N*/3 part of the signals is different from zero and the remaining part is very close to zero. This *N*/3 part of transformed signal is chosen to be an input to the classifier. This method can be seen as a feature selection. The feature vector in this study is the reduced form of the transformed signal so that the signal can be sparsely expressed. In summary, sonar target signals are decomposed by discrete Fourier

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transform (DFT) matrix to get complex-valued sparse coefficients (CVSCs), and then complex-valued neural network (CVANN) is applied to these CVSCs.

CVANN is a machine learning algorithm in which all parameters are complex numbers. Having complex values for CVANN's parameters of input, output, weight, threshold values, and activation functions provides many advantages. These advantages can be listed as an increase in the functionalities of both the single neuron and the neural network (which is the combination of neurons), and hence an increase in performance and decrease in training time. CVANN's advantages are not limited to these. High-level functionality, better plasticity and more elasticity are its other significant advantages. CVANNs learn faster and generalize better [13]. Better plasticity and flexibility mean faster learning, and a better generalization ability of the network. The high functionality is related to the impact of the neuron. Carrying out a job by a neuron that can be done by more than one neuron indicates high functionality. Nitta has solved XOR problem in two layers by using complex-valued neural network with orthogonal decision boundaries in [14]. As is well known, XOR problem cannot be solved using two-layer real-valued neural networks (RVANN). When classical neural networks are preferred, more layers are needed for the solution of a linearly inseparable XOR problem in the real plane. This study proves the high functionality of the complex classifier. In the literature, there are many studies that emphasize the advantages of CVANN over real-valued neural networks (RVANN) [14–18].

This paper is organized as follows: Sect. 2 gives information about the dataset and reduced sparsity method. Section 3 describes the complex-valued wavelet neural network (CVWANN) structure. In Sect. 4, the experimental results are given and the comparative analysis of these results is presented. Finally, Sect. 5 outlines the conclusions.

2 Materials and methods

2.1 Dataset

The sonar data used in this study are available at UCI Machine Learning Repository [3]. There are two files which are labeled as "sonar.mines" and "sonar.rocks." The file "sonar.mines" contains 111 patterns obtained by bouncing sonar signals off a metal cylinder at various angles and under various conditions. The file "sonar.rocks" contains 97 patterns obtained from rocks under similar conditions. There are 208 patterns in total. Each pattern contains 60 features with the values ranging from 0.0 to 1.0. These values represent the energy level at a particular frequency range.

2.2 Reduced Sparse Forms of the Signals

A signal, which is not sparse in a given domain, can be sparse in other domains. N-dimensional x signal can be represented in terms of basis vectors. Using the NxN basis matrix $\Psi = \{\Psi 1|\Psi 2|\ldots|\Psi N\}$ with the vectors $\{\Psi_i\}$ as columns, x can be expressed as:

$$\boldsymbol{x} = \sum_{i=1}^{n} s_i \Psi_i. \tag{1}$$

where s is the $Nx1$ column vector of weighting coefficients:

$$s_i = \boldsymbol{x}|\Psi_i. \tag{2}$$

Clearly, s and x are equivalent mathematical representations of the signal, with x in the time or space domain and s in the Ψ domain.

In this study, DFT matrix is used to decompose the signal. After the Fourier coefficients of each signal are extracted, it is seen that the $N/3$ part of the signals is different from zero and the remaining part is very close to zero. Since this part characterizes the signal mostly and information reduction is in a very small amount, the rest is discarded for reduced sparsity form. Meanwhile, this N/3 part of the signal, which is selected for input, consists of low-frequency components. As a result of CVSCs from the frequency domain, CVANN is employed for the classification.

CR036 in Fig. 1 is the first element of "sonar.rocks" training set. CM078 in Fig. 2 is the first element of "sonar.mines" training set. Preprocessing of input data returned from the rock and mine is detailed in Figs. 1 and 2, respectively.

3 Complex-valued wavelet neural networks (CVWANN)

CVANN is a machine learning algorithm in which all parameters are complex numbers. Having complex values for CVANN's parameters of input, output, weight, threshold values, and activation functions provides many advantages. These advantages can be listed as an increase in the functionalities of both the single neuron and the neural network (which is the combination of neurons), and hence an increase in performance and decrease in training time. CVANN's advantages are not limited to these. High-level functionality, better plasticity and more flexibility are its other significant advantages [13]. Better plasticity and flexibility mean faster learning, and a better generalization

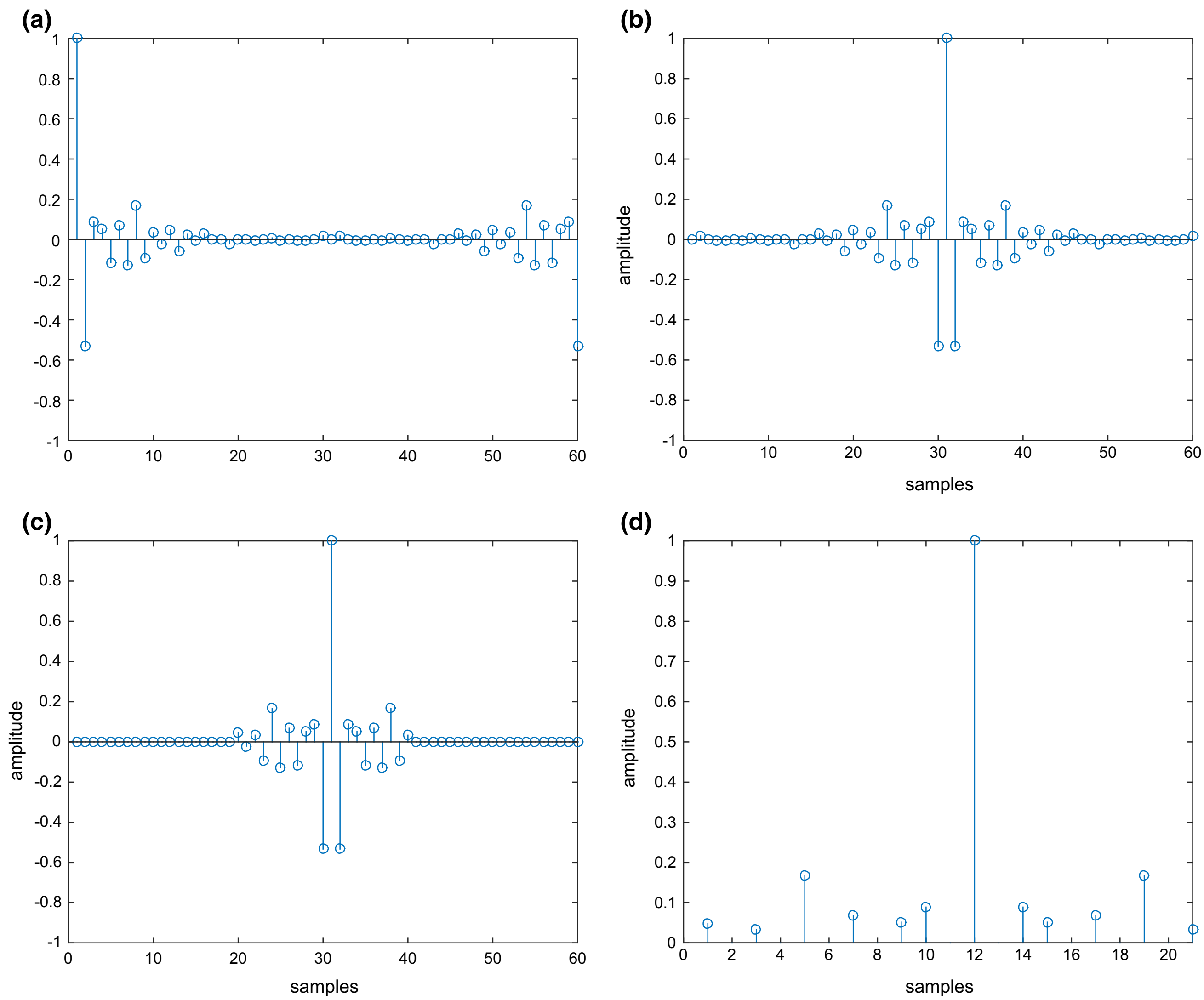

Fig. 1 **a** Compressible Fourier coefficients of a sonar signal marked as CR036, **b** shifted form of **a**, **c** compressed form of **b**, **d** reduced sparse form of **c**

ability of the network. The high functionality is related to the impact of the neuron. Carrying out a job by a neuron that can be done by more than one neuron indicates high functionality. Nitta has solved XOR problem in two layers by using complex-valued neural network with orthogonal decision boundaries in [14]. As is well known, XOR problem cannot be solved using two-layer RVANN. It can be seen that XOR problem is solved using two-layer CVANN in [14]. When classical neural networks are preferred, more layers are needed for the solution of a linearly inseparable XOR problem in the real plane. This study proves the high functionality of the complex classifier.

The number of input values is significantly reduced through the sparse form structure proposed in this study; since these input values are complex-valued, the idea of using CVANN emerged. To extract features, the complex-valued sparse form of the signal was obtained through a simple and short transformation operation without the need for parameters, and classification operation was performed. The CVWANN whose activation functions are wavelet functions was used as CVANN since it gives better results in experiments [19–21]. Complex back propagation (CBP) algorithm was preferred for training CVWANN [22]. The architecture of a neuron used in CBP is given in Fig. 3.

Y_n is the active value of the neuron n and can be calculated as:

$$Y_n = \sum_m W_{nm} X_m + V_n \tag{3}$$

Here, W_{nm} is the complex-valued connection weight, X_m presents the complex-valued input signal, and V_n presents the complex-valued threshold of n neuron. In the next

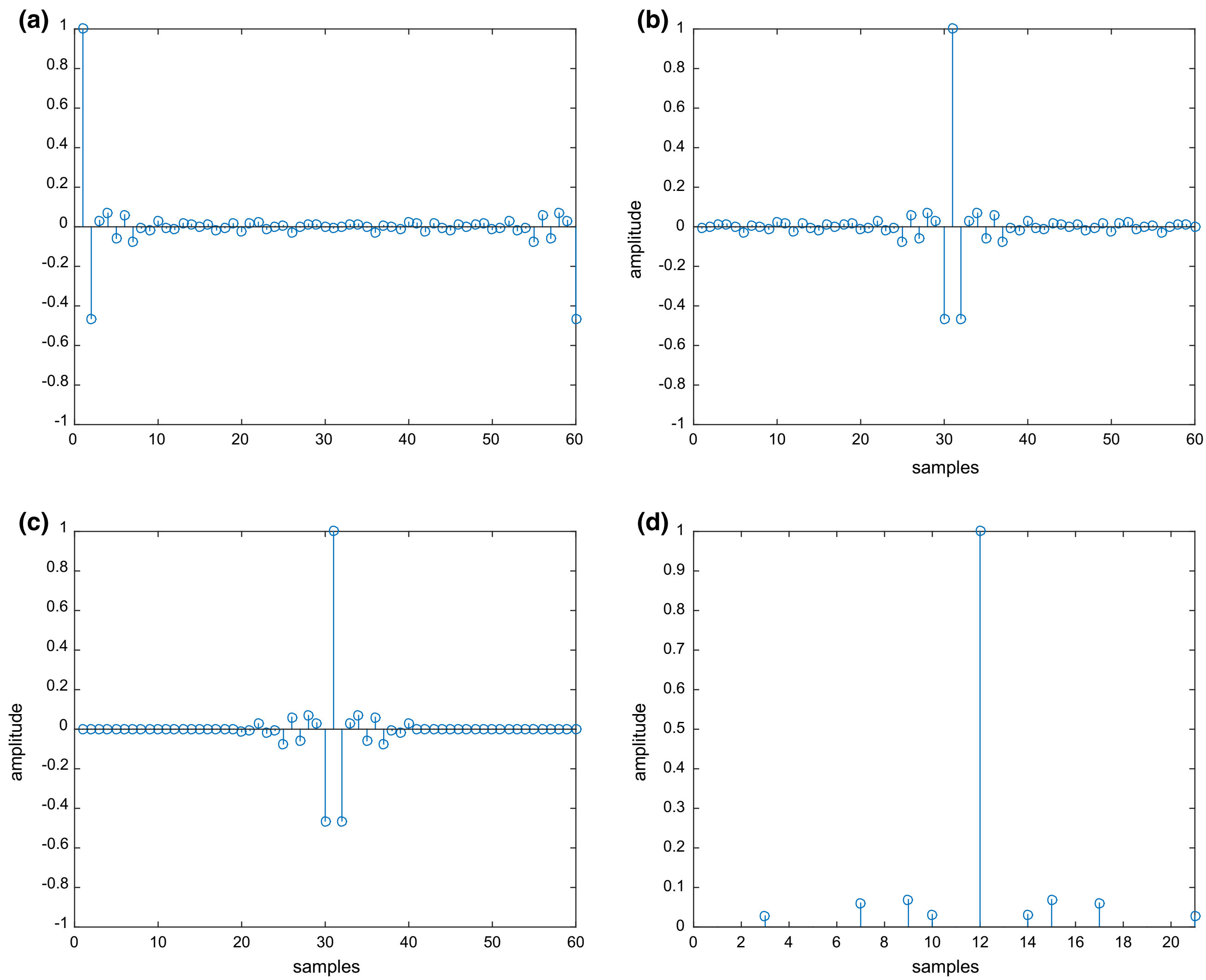

Fig. 2 **a** Compressible Fourier coefficients of a sonar signal marked as CM078, **b** shifted form of **a**, **c** compressed form of **b**, **d** reduced sparse form of **c**

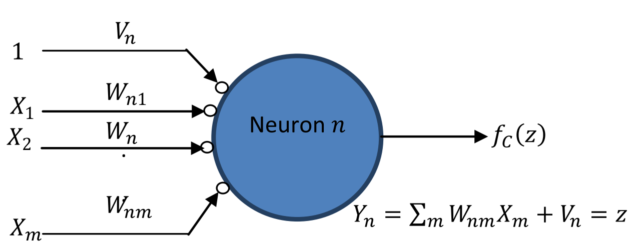

Fig. 3 A simple neuron model used in CBP

stage, Y_n value is transformed into two components that are the imaginary and real parts.

$$Y_n = x + iy = z \tag{4}$$

Here, i represents the value $\sqrt{-1}$. The output function is calculated as shown in Eq. (5).

$$f_c(z) = f_R(x) + i \cdot f_R(y) \tag{5}$$

Here, $f_R(u)$ is the activation function of the neural network. In the literature, there are different activation functions proposed for CVWANN. In this study, complex-valued Haar wavelet and complex-valued Mexican hat wavelet functions were used as activation functions. The real and imaginary parts of an output of a neuron mean the complex-valued Haar and complex-valued Mexican functions of the real part x and imaginary part y of the net input z to the neuron, respectively. These functions can be defined as in Eqs. (6) and (7).

$$\begin{aligned} f(z) &= \psi_{\mathrm{Haar}} \\ &= (1 - Re[z])e^{-(Re[z]/2)} + i(1 - \mathrm{Im}[z])e^{-(\mathrm{Im}[z]/2)} \end{aligned} \tag{6}$$

$$\begin{aligned} f(z) &= \psi_{\mathrm{Mexhat}} \\ &= \left(1 - a\,Re[z^2]\right)e^{-bRe[z^2]} + i\left(1 - a\,Re[z^2]\right)e^{-bRe[z^2]} \end{aligned} \tag{7}$$

Here, Re$[z]$ and Im$[z]$ are the real and imaginary parts, respectively. These wavelet functions are complex-valued versions of the real-valued wavelet functions and most widely used in the literature. As the complex-valued versions of these functions are available, it provides a great convenience while performing our analysis.

In this study, a CVWANN with two layers as shown in Fig. 4 was used.

Here, W_{lm} denotes the weight value between the hidden layer and the input layer neurons, V_{mn} denotes the weight value between the output layer neuron and the hidden layer neuron, θ_m denotes the threshold value for the neuron m, and γ_n denotes the threshold value for the neuron n. H_m, I_l, O_n denote the hidden layer neuron m, the input layer neuron l, the output layer neuron n, respectively. S_n and U_m are the active values of the output layer neuron m and the input layer neuron n, respectively. The mathematical model of CVWANNs is given below [18, 22].

$$U_m = \sum_l W_{ml} I_l + \theta_m \tag{8}$$

$$S_n = \sum_m V_{nm} H_m + \gamma_n \tag{9}$$

$$H_m = f_c(U_m) \tag{10}$$

$$O_n = f_c(S_n) \tag{11}$$

During the evaluation and comparison stage of the current study, square error function was used as the error function. Square error for pattern p is calculated using Eq. (12). CVWANN calculates the error using Eq. (12) based on the obtained output O_n and the target output values T_n.

$$E_p = \left(1/2\right) \sum_{n=1}^{N} |T_n - O_n|^2 = \left(1/2\right) \sum_{n=1}^{N} |\delta^n|^2 \tag{12}$$

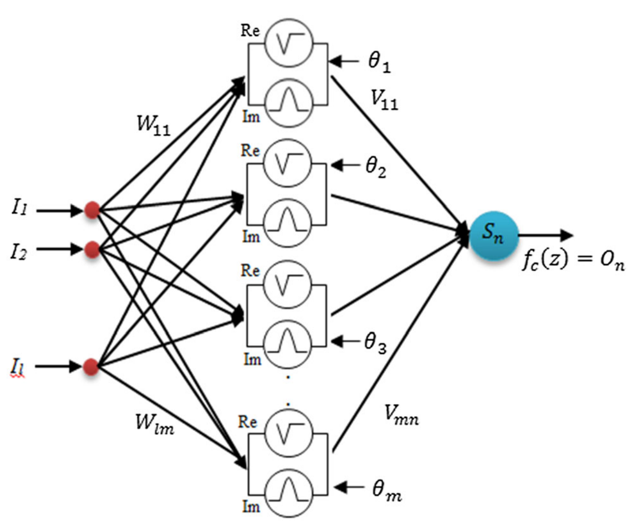

Fig. 4 A two-layer complex-valued wavelet neural network

Here, N is the number or neurons in the output layer. $(\delta^n = T_n - O_n)$ is the error between the O_n and T_n. The learning rule for CBP model is defined to minimize the square error E_p in the following equations [22]. The arrangement of weights and threshold values is adjusted according to Eqs. 13–16 (where $\eta > 0$, η is a small learning constant):

$$\Delta V_{nm} = -\eta \cdot \frac{\partial E_p}{\partial Re[V_{nm}]} - i \cdot \eta \frac{\partial E_p}{\partial Im[V_{nm}]} \tag{13}$$

$$\Delta \gamma_n = -\eta \cdot \frac{\partial E_p}{\partial Re[\gamma_n]} - i \cdot \eta \frac{\partial E_p}{\partial Im[\gamma_n]} \tag{14}$$

$$\Delta W_{ml} = -\eta \cdot \frac{\partial E_p}{\partial Re[W_{ml}]} - i \cdot \eta \frac{\partial E_p}{\partial Im[W_{ml}]} \tag{15}$$

$$\Delta \theta_m = -\eta \cdot \frac{\partial E_p}{\partial Re[\theta_m]} - i \cdot \eta \frac{\partial E_p}{\partial Im[\theta_m]} \tag{16}$$

Expressions given in Eqs. (13) to (16) can be rewritten as follows:

$$\Delta V_{nm} = \overline{H_m} \Delta \lambda_n \tag{17}$$

$$\begin{aligned} \Delta \lambda_n = \eta (&Re[\delta^n](1 - Re[O_n]) Re[O_n] \\ &+ i.Im[\delta^n](1 - Im[O_n]) Im[O_n]) \end{aligned} \tag{18}$$

$$\Delta W_{ml} = \overline{I_l} \Delta \theta_m \tag{19}$$

$$\begin{aligned} \Delta \theta_m = \eta &\left[\begin{matrix} (1 - Re[H_m]) Re[H_m] \\ x \sum_n \begin{pmatrix} Re[\delta^n](1 - Re[O_n]) \\ Re[O_n] Re[V_{nm}] \\ + Im[\delta^n](1 - Im[O_n]) \\ Im[O_n] Im[V_{nm}] \end{pmatrix} \end{matrix} \right] \\ - i\eta &\left[\begin{matrix} (1 - Im[H_m]) Im[H_m] \\ x \sum_n \begin{pmatrix} Re[\delta^n](1 - Re[O_n]) \\ Re[O_n] Im[V_{nm}] \\ - Im[\delta^n](1 - Im[O_n]) \\ Im[O_n] Re[V_{nm}] \end{pmatrix} \end{matrix} \right] \end{aligned} \tag{20}$$

CVWANN is updating weights and thresholds by using the formulas in Eqs. (17)–(20) until the minimum error.

3.1 The proposed hybrid method: CVSCs + CVWANN

This study proposes a novel approach for automatic recognition of sonar targets. The block schema of the proposed method is presented in Fig. 5. Initially, Min–Max method, which provides normalization of the data between 0 and 1, was applied. Equation (21) was used to reduce the data to 0–1 range with this method.

$$y' = \frac{y_i - y_{min}}{y_{max} - y_{min}} \tag{21}$$

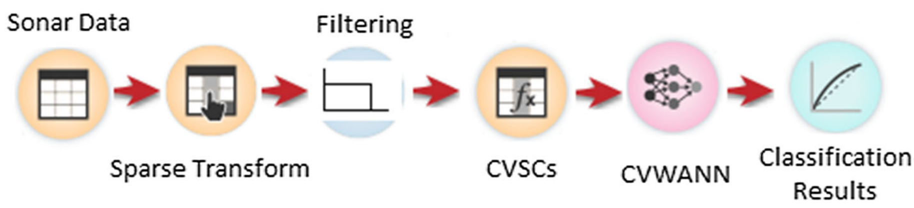

Fig. 5 The method applied for automatic recognition of sonar targets: Sonar echo signals are made complex by decomposing them into the Fourier domain. In the next step, the few complex-valued input values are classified by CVWANN

In this equation, y' denotes the normalized data. y_i denotes the input value, $y_{\min}$ denotes the minimum number in the input set, and $y_{\max}$ denotes the maximum number in the input set. In the next step, complex-valued features were extracted from the dataset. Sonar echo signals are made complex by transferring them to the Fourier domain, and the dense part is taken by taking advantage of the sparsity property. In the next step, these complex-valued input values are classified by CVWANN.

4 Experimental results and discussion

In this study, a hybrid method for classification of sonar echo signals in their sparse forms is proposed. In the experiments, data distribution was made according to 50–50% training–testing data selection and tenfold cross-validation (CV) methods. For fairness of the comparisons made with studies in the literature, experiments were performed with both of these methods because tenfold CV method was used in some studies in the literature, while 50–50% training–testing data selection method was used in some other studies. Experiments were repeated 10 times for reliability of the results and to determine their stability. Because the tenfold cross-validation method was used, a total of 100 experiments (10 repeat × tenfold) were performed, and averages of the obtained values were calculated.

Parameter values were determined through experiments made on training data, and these parameter values were used during the test stage. Multiple combinations have been tested in parameters detection, and parameter values that give best results were determined. Accordingly, detection of the parameters with following ranges has been targeted: for hidden layer neuron number 5, 10, 15,…, 100, for learning coefficient, 0.1, 0.2,…, 0.9, for the number of iterations, 100, 200,…, 1000. A total of 100 experiments have been carried out with different combinations of these parameters, and the combination with the best result has been determined with these experiments. Optimal network structure (input-hidden-output) was found to be (21–15–2) according to the tenfold CV method. Learning ratio was determined as 0.5, and Eq. (12) was used as the stopping criterion. Optimal network structure (input-hidden-output) was found to be (21–20–2) according to 50–50% training–testing data selection. Learning ratio was determined as 0.5, and Eq. (12) was used as the stopping criterion. Complex-valued Mexican hat wavelet was used as activation function for the hidden layer according to both data selection methods because it gave good results in the experiments performed. Complex sigmoid function was used as an activation function for the output layer. The success performance of the proposed system was tested according to the performance of the evaluation metrics below.

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN}} \times 100\% \tag{22}$$

$$\mathrm{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \times 100\% \tag{23}$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{FP}+\mathrm{TN}} \times 100\% \tag{24}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{25}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{26}$$

$$f\text{-measure} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{27}$$

Here, TN, TP, FN and FP are the true negative, true positive, false negative, and false positive, respectively. Precision and Recall values are not sufficient by themselves for us to obtain a meaningful comparison result. Evaluating both metrics together yields better results. For this, f-measure was defined. The f-measure is the harmonic mean of Recall and Precision. This metric assumes values in the 0–1 range. In a classification with a high performance, f-measure is expected to assume a value close to one. Kappa statistic value (KV) is another metric frequently used as a performance evaluation criterion. KV is a significant method used in calculating the agreement between the evaluations made by two or more evaluators. This value is computed as seen in Eq. (28).

$$\mathrm{KV} = \frac{X_0 - X_c}{1 - X_c} \tag{28}$$

where X_0 is the classification accuracy and X_c is the classification accuracy value obtained through random prediction on the dataset. The kappa value takes values between − 1 and 1. A value of − 1 indicates that a completely false classification was made. A value of 1, on the other hand, shows that a completely true classification was made.

In this study, receiver operation characteristic (ROC) curves were also used to measure the success of the proposed method. A ROC curve is a technique used for selecting classifiers based on their performances and organizing and visualizing them. ROC curves are usually used at decision making stage; recently, they are being used increasingly more in machine learning and data mining research. A ROC curve explains the visual relationship between true positives and false positives. The area that remains under the ROC for a detection test is called area under curve (AUC). AUC assumes values between 0.50 and 1.00. Bigger the AUC, better the performance of the classifier.

Results obtained with the proposed system are given in Table 1. Results obtained with real-valued ANN are also shared in the table. The results are shown as $a \pm b$. Herein, a is the accuracy ratio and b is the standard deviation. Accordingly, 94.23% classification accuracy was achieved by CVSCs + CVWANN method according to the tenfold CV method. 93.26% accuracy was obtained by applying CVSCs + CVANN method. Accuracy obtained by applying ANN method to the original dataset is 81.25%. For 50–50% distribution, while 95.19% accuracy was achieved by CVSCs + CVWANN method, 93.75% classification accuracy was achieved by CVSCs + CVANN method. Accuracy obtained by applying ANN method to the original dataset is 86.53%. CVSCs + CVWANN method is observed to yield good results in kappa statistic and f-measure values, as well. As the results demonstrate, performance achieved by complex-valued neural networks was higher than that achieved by the real-valued neural network. It is also observed that CVWANN method yields better results for this problem than CVANN. Standard deviation of CVSCs + CVWANN method was smaller. This shows that the proposed method is more robust and reliable.

In the ROC curves used for success performance of the proposed system, a comparison of CVSCs + CVWANN, CVSCs + CVANN and original dataset + real-valued ANN methods according to tenfold CV and 50–50% training–testing data selection methods is presented. ROC curve obtained according to tenfold CV is presented in Fig. 6. As can be seen in the ROC graphic, there is an important difference between the areas computed for complex-valued classifiers and the real-valued classifier (AUC = 0.968 for CVSCs + CVWANN, AUC = 0.965 for CVSCs + CVWANN and AUC = 0.88 for original features + ANN). ROC curve obtained according to 50–50% training–testing data selection method is presented in Fig. 7. As can be seen in the ROC graphic, there is an important difference between the areas computed for complex-valued classifiers and the real-valued classifier (AUC = 0.981 for CVSCs + CVWANN, AUC = 0.969 for CVSCs + CVWANN and AUC = 0.929 for original features + ANN).

To evaluate the performance of the proposed method during the analysis stage, experiments were performed with different classification algorithms, as well. SVM, naive Bayes, Random Forest, C4.5 Decision Tree and Radial Basis Function (RBF) network, which are often preferred

Table 1 The results obtained from performance evaluation criteria

Method	Statistical measures	Tenfold CV	50–50% training–testing
Original features + ANN	Accuracy	81.25 ± 5.96	86.53 ± 4.45
	Sensitivity	79.40 ± 6.05	87.23 ± 3.88
	Specificity	82.91 ± 5.12	86.47 ± 3.52
	f-measure	0.812	0.866
	Kappa	0.623	0.729
CVSCs + CVANN	Accuracy	93.26 ± 3.85	93.75 ± 3.26
	Sensitivity	89.60 ± 4.05	91.50 ± 4.10
	Specificity	97.10 ± 3.12	96.10 ± 2.95
	f-measure	0.933	0.937
	Kappa	0.865	0.875
CVSCs + CVWANN	Accuracy	94.23 ± 3.05	95.19 ± 2.25
	Sensitivity	91.50 ± 3.56	92.50 ± 3.18
	Specificity	97.10 ± 2.95	98.00 ± 1.93
	f-measure	0.942	0.952
	Kappa	0.884	0.903

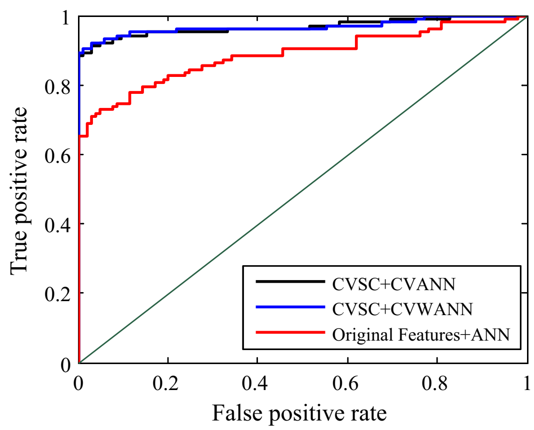

Fig. 6 ROC graph according to the tenfold CV

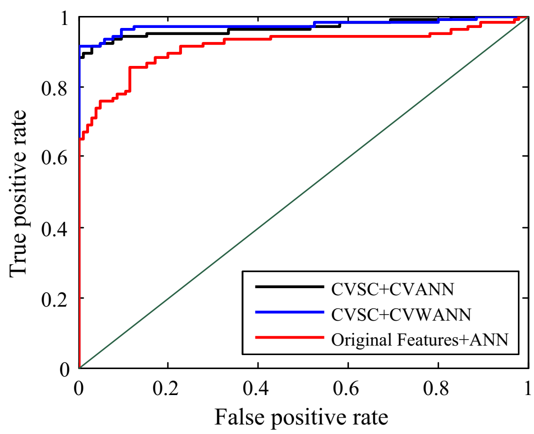

Fig. 7 ROC graph according to 50–50 training–testing

in the literature, were chosen as a classification algorithm. Parameter values of SVM algorithm have been determined as follows. RBF kernel function which is commonly used in the SVM applications was preferred as the kernel function. Parameter values of algorithm have been found by using tenfold cross-validation on grid search mechanism and training dataset. Grid search mechanism is one of the most widely used methods for determining kernel parameter γ and regularization parameter C. In the grid search, the regularization parameter C was explored on $C = 2^{-5}, 2^{-4}, \ldots, 2^{15}$. The kernel parameter γ was explored on $\gamma = 2^{-15}, 2^{-14}, \ldots, 2^{3}$. Effective parameter values for other algorithms have been tested with multiple combinations, and determination of parameters with good results has been provided. C4.5 algorithm was used as Decision Tree. Number of trees was determined as 100 in Random Forest algorithm. Experiments were performed according to 50–50% training–testing data selection method. Results obtained for the same problem by using these algorithms are presented in Fig. 8.

When Fig. 8 is examined, it can be seen that the proposed CVSCs + CVWANN method yields better results. Random Forest algorithm gives the best result after this method. The lowest classification accuracy is obtained with naive Bayes algorithm. In Table 2, comparative analysis of the results obtained by the proposed method with studies previously performed on the same dataset is presented. The results obtained in previous studies are the results that the authors reported in their work. For a fair comparison, all methods must be performed on the same computer and with the same parameter values. However, in many studies on the table, no information is given about the parameter values used. As can be seen in the table, the proposed method yielded better results than the methods proposed in previous studies. While accuracy values varying in the range 70%-93% are generally obtained in the literature, a classification accuracy of 95.19% was reached with the proposed method. Therefore, it is apparent that the proposed study will have a significant contribution to this field.

In Fig. 9, the accuracy level can be observed according to the sparsity in other words according to the N, the number of inputs. In the figure, the AWGN is additive white Gaussian noise. In general, good results are obtained with the help of the proposed method.

In previous studies, we have observed that CVANN gives higher-accuracy dataset compared to traditional real-valued ANN applied to the same problem and the same dataset [34]. In particular for the systems which naturally work with complex values, CVANN provides significantly better prediction results [15, 35]. There are a number of possible reasons behind the success of CVANN, such as the following:

- Mapping capability of CVANN: A neuron has two main functions to perform: an aggregation function and an activation function. The aggregation function maps a multidimensional input space into the neuron's net input space, which is one dimensional for a real-valued network and two dimensional for a complex-valued network [36]. The activation function allocates net input space into discrete clusters which represent different classes using a threshold operation on the output provided by the activation function collector. In the mapping by the aggregator, each input is multiplied by a connection weight, and then the resulted weighted inputs are added. If we consider $\Im_R$ as the set of all possible mappings for a real-valued network and $\Im_C$ as the set of all possible mappings for a complex-valued networks, it can be seen that $\Im_R \subset \Im_C$. This is because a complex multiplication scales and rotates an input with any optional amount, whereas a real multiplication does a scaling with an optional amount but a rotation of only 0 or π [36]. In other words, the mapping

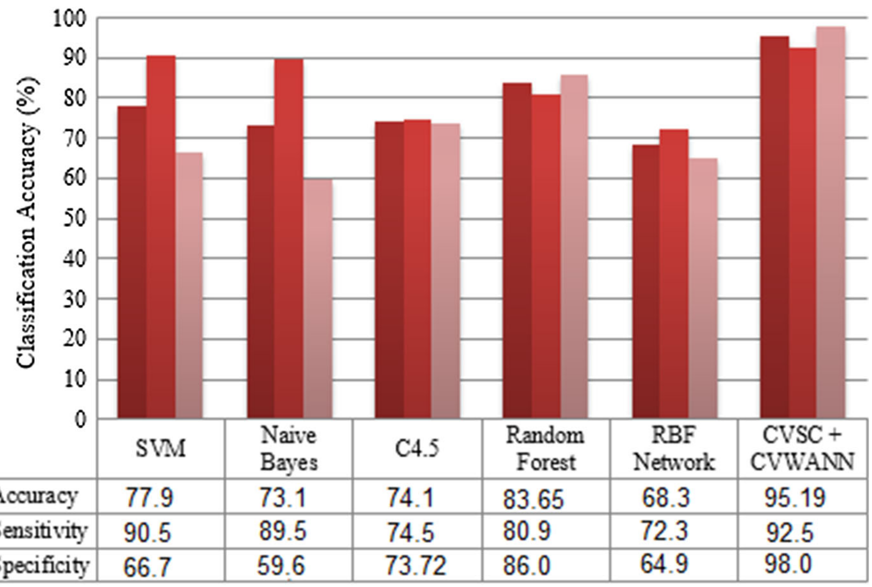

Fig. 8 Comparison with different classification algorithms

Table 2 Comparative analysis with studies previously carried out on the same dataset

Study	Method	Data selection method	Accuracy (%)
Chen et al. [23]	Robust support vector data description (εNR-SVDD)	Training: 90% of the normal data and 10% of the outliers Testing: 10% of the normal data + 90% of the outliers	81.37
Chatterjee and Raghavan [24]	Similarity graph neighborhoods + support vector machine (SGN + SVM)	(60–40% training–testing)	86.27
Jiang et al. [25]	Randomly selected naive Bayes	Fivefold CV	83.64
Kheradpisheh et al. [26]	Mixture of feature-specified experts	Fivefold CV	72.34
Jiang [27]	Random one-dependence estimators	Tenfold CV	82.19
Koshiyama et al. [28]	GPFIS-CLASS: A genetic fuzzy system based on genetic programming	Tenfold CV	74.29
Li and Wang [29]	A hybrid coevolutionary genetic algorithm (HCGA)	Tenfold CV	74.43
Tahir and Smith [30]	Ensemble 1NN classifier (DF-TS-1NN)	Tenfold CV	90.7
Sreeja and Sankar [31]	Pattern matching-based classification (PMC)	Tenfold CV	90.87
Erkmen and Yildirim [32]	General regression neural network + PCA	50–50% training–testing	93.26
Our study	CVSCs + CVWANN	Tenfold CV	94.23
Our study	CVSCs + CVWANN	50–50% training–testing	95.19

capabilities of a complex-valued network are superior to a real-valued network, and this may be one of the main reasons for its superior performance.

- High functionality is the ability of a single neuron to learn linearly inseparable input/output mappings. Therefore, a neuron has the ability to learn these mappings in the initial stage before producing a higher level of input, and transforming to a higher dimensional space, respectively. Studies showed that a single neuron with complex-valued weights can solve linearly inseparable problems such as the exclusive or (XOR) classification problem. This ability suggests that a single CVANN has a higher functionality than a single ANN [13].
- In ANNs, input variables are single values (i.e., real numbers), while in CVANNs, input variables are complex values (complex numbers consisting of real and imaginary parts). Therefore, in CVANN, two-

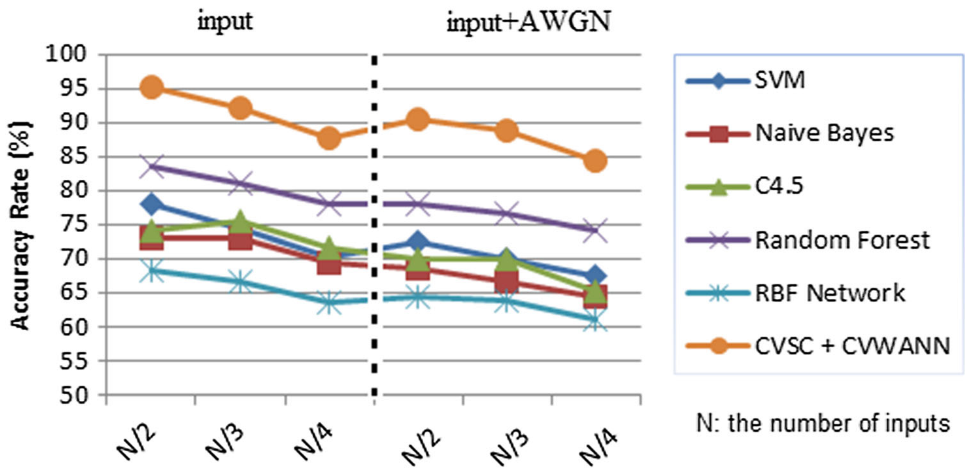

Fig. 9 Comparison with different classification algorithms

dimensional data inputs are possible. As described in Sect. 2.2, this multidimensional data representation and complex multiplication operations may be among the main factors that improve the accuracy and thus increasing the popularity of CVANN.

In summary, the main reason for CVANN to achieve better diagnosis performance than its traditional counterparts is its superior mapping capabilities coupled with efficacy in high functionality.

5 Conclusion

In this study, a novel method for classification of sonar echo signals in their sparse forms is proposed and its stages are presented in detail. To determine the performance of the proposed method, a well-known and frequently preferred dataset was used. Therefore, it was possible to make comparisons with studies in the literature performed on the same dataset. Sonar echo signals were made complex-valued by transferring them to the DFT domain, and the dense parts were utilized by taking advantage of the sparsity property [33]. Therefore, the number of inputs was reduced. During the classification stage, CVWANN algorithm, which has high functionality and good classification ability, was preferred. CVSCs obtained from the sparse form were classified by CVWANN [27]. Our method, CVSCs + CVWANN, is very successful as 94.23% by tenfold CV data selection and 95.19% by 50–50% training–testing data selection.

Compliance with ethical standards

Conflict of interest There are no conflicts of interests.

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