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Evaluation of Randomized Variable Translation Wavelet Neural Networks

disusun oleh:
Khairul Anam dkk

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Azlinah Mohamed
Michael W. Berry
Bee Wah Yap (Eds.)

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Preface

We are pleased to present the proceedings of the Third International Conference on Soft Computing in Data Science 2017 (SCDS 2017). SCDS 2017 was held in the Royal Ambarrukmo Hotel in Yogyakarta, Indonesia, during November 27–28, 2017. The theme of the conference was "Science in Analytics: Harnessing Data and Simplifying Solutions." Data science can improve corporate decision-making and performance, personalize medicine and health-care services, and improve the efficiency and performance of organizations. Data science and analytics play an important role in various disciplines including business, medical and health informatics, social sciences, manufacturing, economics, accounting, and finance.

SCDS 2017 provided a platform for discussions on leading-edge methods and also addressed challenges, problems, and issues in machine learning in data science and analytics. The role of machine learning in data science and analytics is significantly increasing in every field from engineering to life sciences and with advanced computer algorithms, solutions for complex real problems can be simplified. For the advancement of society in the twenty-first century, there is a need to transfer knowledge and technology to industrial applications to solve real-world problems. Research collaborations between academia and industry can lead to the advancement of useful analytics and computing applications to facilitate real-time insights and solutions.

We were delighted this year to collaborate with Universitas Gadjah Mada, and this has increased the submissions from a diverse group of national and international researchers. We received 68 submissions, among which 26 were accepted. SCDS 2017 utilized a double-blind review procedure. All accepted submissions were assigned to at least three independent reviewers (at least one international reviewers) in order to have a rigorous and convincing evaluation process. A total of 49 international and 65 local reviewers were involved in the review process. The conference proceeding volume editors and Springer's CCIS Editorial Board made the final decisions on acceptance, with 26 of the 68 submissions (38%) being published in the conference proceedings.

We would like to thank the authors who submitted manuscripts to SCDS 2017. We thank the reviewers for voluntarily spending time to review the papers. We thank all conference committee members for their tremendous time, ideas, and efforts in ensuring the success of SCDS 2017. We also wish to thank the Springer CCIS Editorial Board, organizations, and sponsors for their continuous support.

We sincerely hope that SCDS 2017 provided a venue for knowledge sharing, publication of good research findings, and new research collaborations. Last but not least, we hope everyone benefited from the keynote, special, and parallel sessions, and had an enjoyable and memorable experience at SCDS 2017 and in Yogyakarta, Indonesia.

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Evaluation of Randomized Variable Translation Wavelet Neural Networks

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Abstract. A variable translation wavelet neural network (VT-WNN) is a type of wavelet neural network that is able to adapt to the changes in the input. Different learning algorithms have been proposed such as backpropagation and hybrid wavelet-particle swarm optimization. However, most of them are time costly. This paper proposed a new learning mechanism for VT-WNN using random weights. To validate the performance of randomized VT-WNN, several experiments using benchmark data form UCI machine learning datasets were conducted. The experimental results show that RVT-WNN can work on a broad range of applications from the small size up to the large size with comparable performance to other well-known classifiers.

Keywords: Wavelet · Neural network · Random weight

1 Introduction

A wavelet neural networks (WNNs) is a type of artificial neural networks that incorporate wavelet theory in the networks as the activation function [19]. WNN has been applied to many applications [6], such as groundwater lever forecasting [1], electricity price forecasting [13], nonlinear time-series modelling [11], monthly rainfall prediction [14], transportation control system [7], breast cancer recognition [16] and myoelectric pattern recognition [17]. Although involving wavelet theory, WNN still utilizes same learning algorithm as an ordinary WNN i.e. backpropagation [19].

To improve the performance of WNN, Ling et al. [12] proposed variable translation wavelet neural networks (VTWNNs). VTWNM is a type of WNN in which the translation parameter of the wavelet function is varied according to the variation of input. To train the weight of VTWNN, Ling et al. [12] implemented a hybrid particle swarm optimization wavelet mutation (HPSOWM). The experimental results showed that VTWNN performed better than WNN and feed-forward neural network. However, the training procedure of the VTWNN using the extension of PSO (HPSOWM) is complex and time-consuming.

To overcome time-consuming process, the idea of random weights has emerged since decades. The earlier work that considers a constant random weight in the hidden layer was proposed by [15]. They examined the performance of single layer feed-forward neural networks (SLFN) whose hidden weights were determined

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randomly and kept fixed. Meanwhile, the weights of the output layers were optimized and calculated numerically using a fisher method. The main idea in the fisher method is a numeric calculation of the invers of the hidden output multiplied by the vector of the target. They found the output weights were significantly more importance than the hidden layer weights. In other words, the fixed random hidden layer weight does not influence the performance of the system as long the output weight optimized properly.

Similar to Schmidt et al. [15], Huang et al. [9] optimized the calculation the output weight by putting constraints. This learning mechanism was called as extreme learning machine (ELM). ELM has been tested in various implementation such as classification [3], regression [10] and clustering [8]. Another algorithm for random weight is random vector functional link (RVFL) [4]. More survey on the randomized neural network can be found in [18].

Based on this fact, this paper extends the theory VTWNM using random weight. Instead of using backpropagation or HPSOWM, the VTWNM selects random hidden layer weights and calculate the output weights using least-square optimization. The efficacy of the proposed system will be tested on various benchmark data collected from UCL machine learning repository [5]. The idea to implement random weight in VTWNN was conducted by [2]. However, the model was tested on the case of myo-electric patter recognition only. The general evaluation is necessary to verify its efficacy for the random VTWNN for general application.

2 Variable Translation Wavelet Neural Networks (VTWNNs)

Figure 1 shows the reconstruction of VTWNN model proposed by [12]. The output function of the model for arbitrary samples $(\boldsymbol{x}_k, \boldsymbol{t}_k) \in \boldsymbol{R}^{\mathrm{n}}$ x $\boldsymbol{R}^{\mathrm{o}}$ with M hidden nodes is

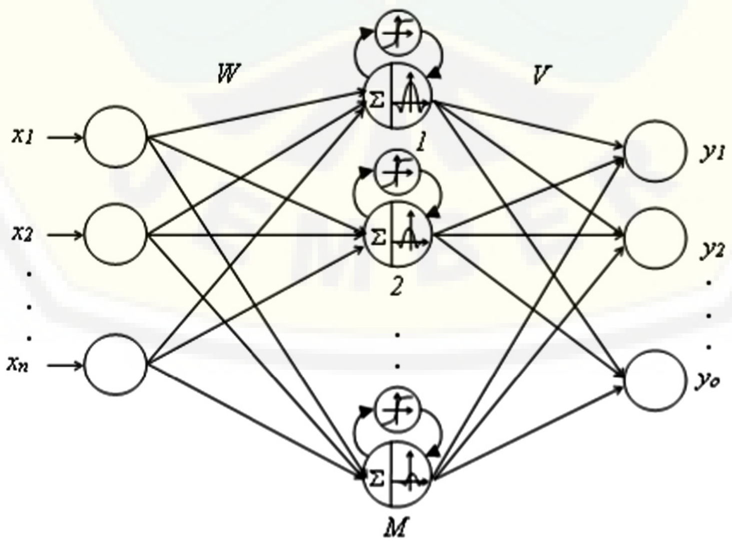

Fig. 1. The variable translation WNN (VTWNN)

$$f_i^k(\mathbf{x}) = \sum_{j=1}^{M} V_{ij}\psi_{a_jbj}(w_j, c_j, \mathbf{x}_k) \qquad i = 1, 2, \ldots, O \tag{1}$$

where

$$\psi_{a_jbj}(x) = \frac{1}{\sqrt{a_j}}\psi\left(\frac{x - b_j}{a_j}\right), \qquad j = 1, 2, \ldots.., M \tag{2}$$

In the Eq. (2), a_j and b_j are dilatation and translation parameters of the wavelet, respectively. The input of the hidden layer H_j when M is the number of hidden node and N is the number of input is given by:

$$H_j(x) = \sum_{i=1}^{N} x_i.w_{ji} + c_j \qquad j = 1, 2, \ldots, M \tag{3}$$

where x_i are the input variables and w_{ji} are the weights of the connection between ith input and jth hidden nodes. Meanwhile c_j denotes the bias of jth hidden layer. From Eq. (3), the output of the hidden node can be calculated using:

$$\psi_{a_jb_j}(H_j(x)) = \psi\left(\frac{H_j(x) - b_j}{a_j}\right), \qquad j = 1, 2, \ldots, M \tag{4}$$

In the VTWNN model proposed by Ling et al. [12], the dilatation parameter a_j is equal to j, so:

$$\psi_{a_jb_j}(H_j(x)) = \psi\left(\frac{H_j(x) - b_j}{j}\right), \qquad j = 1, 2, \ldots, M \tag{5}$$

In VTWNN or WNN in general, the mother wavelet $\psi_{a_ib_i}$ can be in different model such as Mexican Hat function [12], as described in Fig. 2.

Following Ling et al. [12], this paper selects this function as the mother wavelet $\psi_{a_ib_i}$. It is defined as

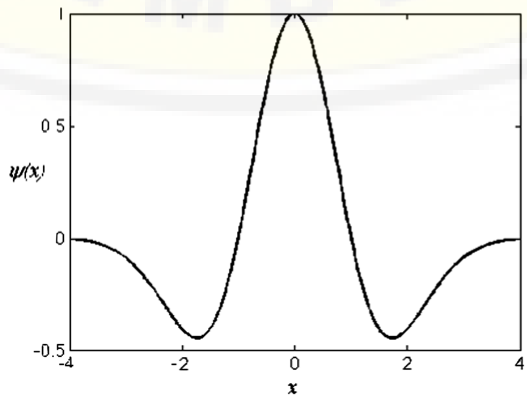

Fig. 2. The mother wavelet of the Mexican hat

$$\psi(x) = e^{-x^2/2}(1 - x^2) \tag{6}$$

Finally, the output of the activation function of VTWNN is:

$$\psi_{a_j b_j}(H_j) = e^{-0.5\left(\frac{H_j - b_j}{j}\right)^2}\left(1 - \left(\frac{H_j - b_j}{j}\right)^2\right) \tag{7}$$

According to its name, VTWNN varies the value of the translation parameters b_j according to the input information. It is driven by a nonlinear function as shown in Fig. 3 and defined by:

$$b_j = f(P_j) = \frac{2}{1 + e^{-P_j}} - 1 \tag{8}$$

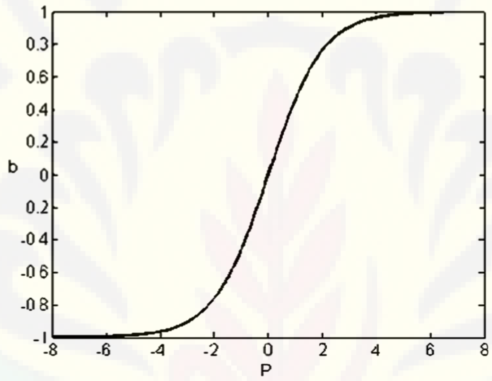

Fig. 3. A sigmoid function to calculate b_j

3 Randomized VTWNN

Different from VTWNN developed in [12], this paper applies random weight for the hidden layer and then calculates the output weight. Because the weights of the hidden layer are set random, the output of the hidden layer can be considered as a constant. Therefore Eq. (1) can be can be written as a linear system:

$$\mathbf{F}{=}\mathbf{VQ} \tag{9}$$

where V is the output weight and Q is the output if hidden layer as described below.

$$\mathbf{Q} = \begin{bmatrix} \psi_{a_1 b_1}(H_1(\mathbf{x}_1)) & \cdots & \psi_{a_M b_M}(H_M(\mathbf{x}_1)) \\ \vdots & \vdots & \vdots \\ \psi_{a_1 b_1}(H_1(\mathbf{x}_L)) & \vdots & \psi_{a_M b_M}(H_M(\mathbf{x}_L)) \end{bmatrix}_{LxM} \tag{10}$$

$$\mathrm{V} = \left(\boldsymbol{v}_1^T \quad \boldsymbol{v}_2^T \quad \cdots \quad \boldsymbol{v}_O^T\right)_{MxO}^T \tag{11}$$

Assume, desired output is defined as:

$$\mathbf{Z} = \begin{pmatrix} z_1^T & z_2^T & \ldots & z_L^T \end{pmatrix}_{LxO} \tag{12}$$

Then, the learning mechanism can be simplified by:

$$\mathbf{VQ} = \mathbf{Z} \tag{13}$$

The aim of learning is to calculate the output weight as follow:

$$\hat{\mathbf{V}} = \mathbf{Q}^{\dagger}\mathbf{Z} \tag{14}$$

where $\mathbf{Q}^{\dagger}$ is a pseudoinverse of $\mathbf{Q}$. Finally, the training algorithm of the randomized VTWNN is presented in (Fig. 4).

```
Begin
   Load input x, target z
   Randomize hidden weights w and bias c
   Calculate input hidden layer H                  // Eq. (3)
   Calculate translation parameter b               // Eq. (8)
   Calculate output hidden layer Q                 // Eq. (10)
   Calculate the output weights V                  // Eq. (14)
end
```

Fig. 4. Pseudo code for randomized VTWNN

4 Performance Evaluation

The evaluation of the randomized VTW performances was conducted by using benchmark datasets that are available online from the UCI machine learning website [5]. The selected datasets are presented in Table 1. The experiment was conducted based on the size of the data. For small and medium size data, the experiments will be performed using 5-fold cross validation for small and medium size data. Meanwhile, a 3-fold cross validation will be applied to the large size data. Special for large size data,

Table 1. Data specification for benchmarking

Dataset	Group	# data	# features	#classes
Iris	Small size	150	4	3
Glass		214	9	6
Vehicle	Medium size	846	18	4
Vowel		990	10	11
Satimage	Large size	6435	36	6
Letter		20000	16	26
Shuttle		58000	9	7

there is no randomization on the data. Instead, the data was just divided into three groups and then validated using cross-validation technique.

This experiment considered seven different classifiers: randomized WNN (RWNN), randomized VT-WNN (RVT-WNN), randomized single layer feedforward neural networks (RSLFNs), radial basis extreme learning machine (RBF-ELM), support vector machine from libsim (LIBSVM), linear discriminant analysis (LDA) and k-nearest neighbour (kNN).

Before conducting the experiment, the optimal parameters of the classifiers were found. For instance, LIBSVM with radial basis kernel relies on parameter regulation C and gamma. A grid-search method is used to select the optimum number of nodes in the node based ELM. As for C and gamma in RBF-ELM and LIBSVM, the optimal parameters were taken from [10] due to the similarity in data and classifiers. Table 2 provides all parameters used in the experiment (Table 3).

Table 2. The optimal parameters used by each classifier in the UCI dataset experiments

Dataset	# Nodes			RBF-ELM		LIBSVM		kNN
	RWNN	RVT-WNN	RSLFN	C	gamma	C	gamma	k
Iris	30	30	20	1	1	1	0.25	10
Glass	30	30	20	32	1	1	0.25	10
Vehicle	190	170	210	64	8	2^{14}	4	10
Vowel	290	350	440	32	0.5	1	1	10
Letter	970	980	920	8	0.25	2^{10}	2^{-4}	10
Satimage	740	640	770	16	0.25	1	1	10
Shuttle	900	500	970	2^{20}	2^{-10}	2^{10}	0.25	10

Table 3. The accuracy of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data

Dataset	Accuracy (%)						
	RWNN	RVT-WNN	RSLFN	RBF-ELM	LIBSVM	kNN	RBF-ELM
Iris	96.00	96.67	96.67	96.67	96.67	<u>98.00</u>	96.00
Glass	65.03	65.38	66.29	<u>69.23</u>	63.48	57.50	63.98
Vehicle	82.50	81.68	80.61	<u>84.17</u>	71.51	78.47	70.21
Vowel	94.44	93.54	93.84	<u>94.65</u>	91.21	60.81	84.75
Satimage	87.35	87.26	87.99	<u>90.57</u>	89.91	82.70	88.66
Letter	62.78	62.65	61.99	<u>69.96</u>	46.56	33.01	67.31
Shuttle	99.74	99.57	99.72	<u>99.90</u>	98.59	85.30	99.81

In addition, Table 4 shows that RVT-WNN could perform moderately across seven different datasets. The comparison of RVT-WNN and RSLFN shows that both classifiers are comparable. One-way ANOVA test shown in Table 5 explains that the accuracy gap between them is not significant ($p > 0.05$). It means that they are

Table 4. The accuracy of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data

Dataset	Accuracy (%)						
	RWNN	RVT-WNN	RSLFN	RBF-ELM	LIBSVM	kNN	RBF-ELM
Iris	96.00	96.67	96.67	96.67	96.67	98.00	96.00
Glass	65.03	65.38	66.29	69.23	63.48	57.50	63.98
Vehicle	82.50	81.68	80.61	84.17	71.51	78.47	70.21
Vowel	94.44	93.54	93.84	94.65	91.21	60.81	84.75
Satimage	87.35	87.26	87.99	90.57	89.91	82.70	88.66
Letter	62.78	62.65	61.99	69.96	46.56	33.01	67.31
Shuttle	99.74	99.57	99.72	99.90	98.59	85.30	99.81

comparable. As for RSLFN, the accuracy of RVT-WNN is significantly better RSLFN only in “Letter” dataset while the rest of them are not significantly different ($p < 0.05$).

Furthermore, Tables 4 and 5 indicate that RBF-ELM is the most accurate classifier across seven datasets except the “Iris” dataset. Nevertheless, the accuracy of RVT-WNN is comparable to RBF-ELM in all datasets ($p > 0.05$) except in “Letter” dataset ($p < 0.05$). Moreover, RVT-WNN has the same performance as LIBSVM except on Vehicle and Letter datasets in which RVT-WNN is better. For the rest of the classifiers, Tables 4 and 5 show that RVT-WNN is significantly better than LDA in two datasets: Vowel and Letter. Moreover, RVT-WNN is better than kNN in Vowel dataset while kNN is better than RVT-WNN in Letter datasets ($p < 0.05$). Overall, RVT-WNN is comparable to RBF-ELM and LIBSVM and slightly better than LDA and kNN in most datasets.

Table 5. One way ANOVA test results on the comparison of RVT-WNN and other classifiers (the black box shows $p < 0.05$)

	p-value					
RVT-WNN -->	RWNN	RSLFN	RBF-ELM	LIBSVM	LDA	kNN
Iris	0.771	1.000	1.000	1.000	0.524	0.809
Glass	0.942	0.835	0.377	0.682	0.075	0.755
Vehicle	0.585	0.424	0.080	0.000	0.121	0.000
Vowel	0.432	0.807	0.354	0.064	0.000	0.005
Satimage	0.999	0.980	0.922	0.934	0.885	0.966
Letter	0.765	0.043	0.000	0.000	0.000	0.000
Shuttle	0.996	0.997	0.993	0.980	0.679	0.995

In addition to the classification performance, the processing time of classifiers is one of the discussion objectives. Table 6 presents the training time while Table 7 provides the testing time. Table 6 shows that the training time of RVT-WNN is one of the slowest classifiers, compared to other classifiers over all datasets. It becomes worse when RVT-WNN works on big data like “Letter” dataset. The RVT-WNN is the slowest classifier taking around 40 s to learn Letter datasets. However, an anomaly occurred when RVT-WNN worked on Shuttle datasets. RVT-WNN took around 33 s,

Table 6. The training time of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data

Dataset	Training time (ms)						
	RWNN	RVT-WNN	RSLFN	RBF-ELM	LIBSVM	LDA	kNN
Iris	45.20	48.33	41.33	3.51	0.00	15.61	38.53
Glass	69.53	68.40	31.93	1.81	2.00	1.83	9.62
Vehicle	403.13	353.67	438.13	16.03	56.00	2.76	40.11
Vowel	776.00	1,014.80	1,334.67	20.95	30.00	4.82	28.72
Satimage	6,412.22	6,236.67	5,436.33	562.04	723.33	49.07	799.55
Letter	29,202.20	40,664.33	17,541.87	11,442.31	20,140.00	72.39	4,618.73
Shuttle	62,114.33	33,069.22	47,162.44	123,161.44	10,820.00	49.54	1,472.41

Table 7. The testing time of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data

Dataset	Testing time (ms)						
	RWNN	RVT-WNN	RSLFN	RBF-ELM	LIBSVM	LDA	kNN
Iris	10.00	16.27	6.47	0.99	0.00	1.74	6.28
Glass	10.73	17.20	6.60	0.46	2.00	1.47	5.80
Vehicle	38.07	46.00	28.07	2.47	56.00	1.88	9.88
Vowel	51.40	72.67	34.47	3.69	30.00	2.93	12.43
Satimage	709.00	1,082.00	134.67	112.45	723.33	14.85	375.33
Letter	2,391.53	4,751.87	276.87	873.45	20,140.00	28.72	1,177.10
Shuttle	11,241.89	8,536.11	1,001.22	10,101.54	10,820.00	36.02	786.39

faster than RWNN, RSLFN even much more quickly than RBF-ELM that took 123 s. Similar results happen on the testing time. This happened because RVT-WNN used a lower number of nodes than RSLFN or RVT-WNN when working on the Shuttle dataset.

One thing that is not normal on LIBSVM; the training time and the processing time of LIBSVM is the same while the other classifiers took a shorter testing time than training time. The fastest classifier is LDA, which took only around 72 ms on Letter dataset and about 49 ms on Shuttle dataset. Overall, the training time of RVT-WNN is slow, but it can be compensated by using less number of nodes with comparable performance to other classifiers.

5 Discussion and Conclusion

RVT-WNN has been implemented in wide range classification problems using UCI machine learning datasets. The experimental results show that RVT-WNN could work on a wide range of datasets from small size to large size data. RVT-WNN is comparable to RWNN in all datasets, and it is better than RSLFN on the Letter dataset.

Moreover, RVT-WNN attained better accuracy than LDA in Vowel and Letter datasets while it shows the same performance as LDA with the other datasets. Comparison with RBF-ELM indicates that RVT-WNN is comparable to it except on the Letter dataset. On this dataset, RBF-ELM is better than RVT-WNN.

Other results show that RVT-WNN has the same performance as LIBSVM except on Vehicle and Letter datasets in which RVT-WNN is better. Finally, the comparison with kNN indicates that RVT-WNN is better than kNN on Vowel dataset while kNN is better than RVT-WNN on Letter dataset. Overall, RVT-WNN is a promising classifier for many classification applications.

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