Measurement: Sensors 27 (2023) 100780

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

Support vector machine and neural network for enhanced classification algorithm in ecological data

Ravi Prasad B [a,*], Mohammed Ashfaq Hussain [b], Sridharan K [c], Ricardo Fernando CosioBorda [d], Geetha C [e]

[a] Marri Laxman Reddy Institute of Technology and Management, India
[b] Computer Science & Information Technology Department, Jazan University, Saudi Arabia
[c] Department of IT, Panimalar Engineering College, Chennai, India
[d] Universidad Privada del Norte, Peru
[e] Sathyabama Institute of Science and Technology, Chennai, India

A R T I C L E I N F O

Keywords:
Hidden markov model
Vector machines
Algorithms
Systems
Matlab
BP neural Network
Evaluation index
Accuracy

A B S T R A C T

The current economic scale is bigger and bigger, the social material living standard also along is also getting higher and higher with the rapid economic growth. However, the problems caused by economic development are also increasing, on the one hand, there is the contradiction between supply and demand caused by resource consumption and shortage of resources; on the other hand, there also is contradiction between the great pollution and destruction in the ecological environment and the public's increasingly demanding ecological environment. Especially, the contradiction between the ecological environment and the social environment has become the focus of attention of the Chinese public. Therefore, the ecological environment protection becomes the current consensus either from the national level or the social level, how to manage and protect the ecological environment is also a question of the current social thinking. The common practice of ecological environment protection is to control and protect, at the same time, governance is to restore the damaged environment. There are many means for protection, such as energy conservation, emission reduction, monitoring and so on. Energy saving and emission reduction not only mean that the consumption of resources is reduced, but also mean that the discharge of pollutants and destroy the ecological environment are reduced. And monitoring refers to the existing ecological environment monitoring; the change of ecological environment is detected by real-time observation, so that counter measures are made according to the changes.

1. Introduction

The ecological environment sound is used to monitor the ecological environment, the sound in ecological environment is the identified and classified, and the situation of ecological environment is judged according to the results of identification and classification [1–4]. Any kind of sound can be divided into pitch, timbre and intensity and others according to their characteristics [5–7]. At present, the use of audio to retrieve information is the focus of current sound research, but the digital signals of intelligent disposal of computer can't recognize sounds directly, therefore, audio is often used for i identification in the process of voice recognition [8]. Because the audio is a digitally converted sound signal, the sound can be identified by classification and identification of audio signal [9].

The common methods for classifying and identifying audio signals are hidden Markov, nearest feature line, neural networks, and support vector machines and so on [10]. In order to minimize the recognition error rate, the resolution of some unknown audio data of the hidden Markov model is poor [11]. Nearest feature line method classifies audio by means of discrete quantization techniques, but audio signals are non-stationary signals, so classification isn't ideal [12]. The support vector machine model is classified by the principle of structural risk minimization, which is suitable for the classification of static data [13].

* Corresponding author.
E-mail addresses: rprasad.bodu@gmail.com (R.P. B), ashfaqksa2012@gmail.com (M.A. Hussain), sridharank.p@gmail.com (S. K), ricardo.cosio.borda@gmail.com (R.F. CosioBorda), gitakannan.2010@gmail.com (G. C).

https://doi.org/10.1016/j.measen.2023.100780
Received 12 February 2023; Accepted 4 May 2023
Available online 15 May 2023

2. Literaure survey

2.1. BP neural network model and working principle

The neural network is a feed-forward network of the learning algorithm using error back propagation algorithm in neural network. The feed forward network is usually composed of input layer, output layer and hidden layer. Each neuron accepts the input of the former layer and outputs the layer to the next layer, without feedback. In the research on ecological environment sound classification algorithm based on support vector machines, currently, it's found that sound is classified by means of audio classification after all research literature on sound classification algorithms is queried. At present, there are many common models and methods, such as HMM, BP neural network, nearest feature line and support vector machines. Therefore, audio classification is used to classify the sounds of the environment [14]. However, there are obvious defects in the existing classification methods or models. First of all, hidden Markov and support vector machines of the two algorithms for audio classification are introduced. Hidden Markov model is also called $^{\mathrm{HMM}}$, which is a kind of automaton with double stochastic process in finite state, it must follow the variation of the observation sequence because it's in a random state [14]. The following formula can be used to express its basic elements.

$$\lambda=(\pi,A,B,N,M) \quad (1)$$

The $^{\pi}$in the formula represents the distribution of the initial probability of the model. ^{A} and^{B} represent the matrix of probability of model state transition and the probability of observed number respectively, ^{N}represents the number of Markov chain states, ^{M}stands for the number of value observed corresponding to each state of the model.

$^{\mathrm{HMM}}$ can be divided into Markov chains expressed by $^{\pi}$ and ^{A}, or the randomized procedure represented by ^{B}in accordance with characteristics. Markov chains output the sequence of states; the randomized procedure outputs the sequence of observations, as shown in Fig. 1. $^{\mathrm{HMM}}$ can be abbreviated as follows (see Fig. 2).

$$\lambda=(\pi,\ A,B) \quad (2)$$

2.2. Prediction model of specific sports performance based on neural network

The amounts of measured data is collected and filtered to be promoted to establish a sample set in effective pattern. Since there exists certain regulations and associations between model input and model output, which data should be kept and which data should be filtered are mainly determined through practical situation, experience and statistical calculation results. However, this sample base can be gradually supplemented and improved with increasing historical data [15].

The determined modeling index P in this paper includes: standing long jump, 800 m race, sit-ups, 15 s fast leg kicking, right angle support, and 15 s single-arm push up. They are encoded as P1, P2, P3, P4, P5 and P6, and their corresponding specific performance is signaled as T. Data of man and woman is individually normalized and the normalized function selects linear normalized function whose function formula is:

$$y=(x-\text{Min Value})/(\text{Max value}-\text{Min Value}) \quad (3)$$

By repeated training and predicting test, it discovers that some testing data addition will affect convergence speed and predicting accuracy of model such as some athletes with insufficient training years or some athletes with difference of certain index test because of some special situations. Thus, this type of data will be deleted to obtain the final normalization results, which are shown as Table 1 and Table 2.

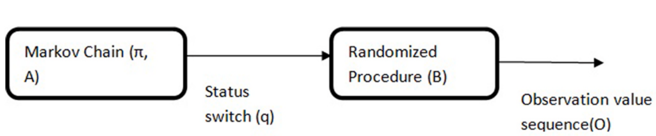

Fig. 1. Schematic diagram of HMM.

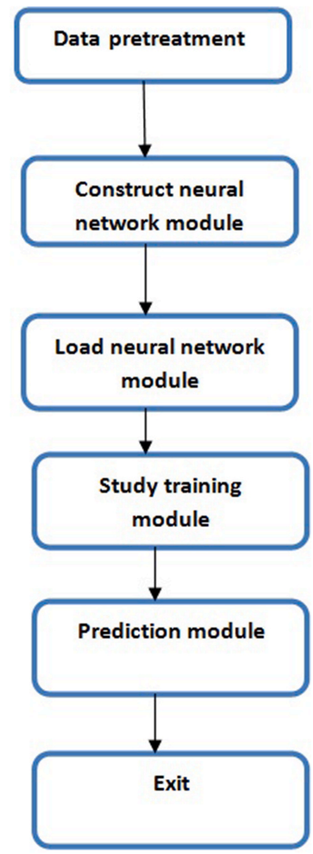

Fig. 2. Training prediction process framework.

Filtered physical quality indexes and normalized data of specific performance are taken as training samples in neural network. Levenberg-Marquardt-based improved learning algorithm is applied to learn training sample. Standard BP algorithm adopts the fastest grads descent method to correct the weight value. Training is from one point to reach the smallest point along slope of error function to promote error to be zero. Thus, its existence is associated with input sample order with slow convergence speed so it is easy to fall into local minimum. The specific structure of this neural network is shown: input neural element number in neural network is 6. They respectively matches the filtered 6 physical quality shape indexes and input matrix P is the matrix with 21 rows and 6 columns. Correspondingly, output neural element number is

Table 1
Normalization result of woman group.

Sample NO.	Evaluation(P)						Evaluation object (T)
	P1	P2	P3	P4	P5	P6	
1	0.17	0.66	0.45	0.25	1.01	0.45	1.000
2	0.40	1.00	0.58	0.22	1.00	0.15	0.335
3	0.00	0.78	0.94	0.12	0.77	0.08	0.415
4	0.06	1.02	0.47	0.00	0.07	0.00	0.225
5	1.00	0.77	0.01	0.38	0.42	0.15	0.285
6	0.82	0.77	0.67	0.25	0.91	0.33	0.275
7	0.06	0.82	1.00	0.25	0.44	0.69	0.304
8	0.41	0.56	0.03	0.66	0.00	0.67	0.324
9	0.55	0.43	0.06	0.61	0.28	0.31	0.007
10	0.29	0.00	0.18	0.09	1.00	1.00	0.00

Table 2
Normalization result of man group.

Sample NO.	Evaluation(P)						Evaluation object (T)
	P1	P2	P3	P4	P5	P6	
11	0.00	1.01	0.72	0.10	0.62	0.34	0.065
12	0.90	0.74	0.53	1.00	0.41	1.00	0.003
13	1.00	0.96	0.72	1.01	0.00	0.85	0.356
14	0.49	0.12	0.90	0.44	0.60	0.24	0.755
15	0.52	0.06	0.00	0.44	1.00	0.00	0.065
16	0.60	0.65	1.00	0.77	0.00	0.98	1.000
17	0.52	0.64	0.80	0.00	1.00	0.44	0.157
18	0.46	0.00	0.52	0.64	0.00	0.65	0.905
19	0.36	0.06	0.44	0.43	0.50	0.42	0.231
20	0.34	0.76	0.85	0.33	0.39	0.52	0.007

1 which stands for specific performance. Output matrix T is the matrix with 1 row and 21 columns. To construct a BP neural network with 3 layers, activation function in hidden layer is tan sig and activation function in output layer is log sig. The largest number of training times is 80000 and objective error is 0.1.

3. Methods and materials

3.1. Performance predicting model results and reliability test

Data at input layer and output layer after neural network training is shown as Table 3. The results show that predicting error scope of network model on specific performance of aerobics athletes is within 0.1. It hash ig her predicting accuracy, so this model is accurate and effective (see Table 4).

3.2. Predicting errors analysis

11 groups of data are extracted from sample data. Neural network models are respectively applied to calculate their predicting values of specific performance and compare with practical value to calculate predicting error [16]. The simulation accuracy of the obtained predicting model is shown as the following table.

An excellent group of female athletes' physical quality index in practical test is performed to test predicting accuracy of predicting model. Data is performed normalized process to input according to female group standard and it is signaled P_test = [0.12,0.32,0.20,0.75,0.77,0.77]. In addition, sim function is used to adjust the trained neural network and it can calculate athletes' specific performance T_test = 0.182. After reverse normalized treatment, predicting value of specific performance is T = 9.197, which is shown as Table 5.

Based on above table, to compare to practical specific value 9.201, predicting error of neural network model is very small. It indicates that neural network model can effectively simulate function relationship between quality training and specific performance and it has high predicting accuracy [17]. The contrast between networked output and target output in training set and test set can be visually expressed in Fig. 3. From this figure, it can be seen that neural network has better approximation capability to predict sports performance and it has better generalization capability. However, since there has noise in sample data, this may be caused by coachers when they record performance or measure performance.

The support vector machine model is also referred to as ^{SVM}, the model has a great advantage in the two-dimensional classification problem, the two dimensional classification problem is simplified by mapping the two-dimensional classification problem into the high-dimensional space, and using the optimal hyperplane classification,

Table 4
Fitting accuracy of prediction model.

NO	Evaluation target	Neural network		
		Output value	Prediction value	error
1	9.890	0.976	93869	−0.021
2	9.361	0.438	9.407	0.046
3	9.390	0.444	9.412	0.022
4	9.261	0.132	9.144	−0.117
5	9.275	0.395	9.371	0.096
6	9.268	0.314	9.301	0.033
7	9.291	0.298	9.228	−0.004
8	9.313	0.305	9.239	−0.020
9	9.092	0.085	9.104	0.012
10	9.031	0.029	9.056	0.025

Table 5
Prediction accuracy of prediction model.

Actual data	Actual value	BP neural network model	
		Prediction value	Error
Y_test	9.201	9.197	−0.004

Table 3
Data results of input and output layer after neural network training.

SampleNO.	Evaluation(P)						Outputsample(T)	Predictionerror (ΔT)
	P1	P2	P3	P4	P5	P6		
1	0.18	0.68	0.45	0.22	1.00	0.45	0.975	0.023
2	0.42	1.00	0.59	0.25	1.00	0.15	0.438	−0.053
3	0.00	0.75	0.93	0.13	0.77	0.08	0.445	−0.025
4	0.06	1.00	0.75	0.00	0.08	0.00	0.133	0.136
5	1.00	0.77	0.00	0.39	0.45	0.11	0.369	−0.111
6	0.83	0.77	0.67	0.25	0.90	0.33	0.314	−0.038
7	0.06	0.82	1.00	0.25	0.42	0.66	0.296	0.005
8	0.41	0.55	0.03	0.63	0.00	0.69	0.305	0.023
9	0.53	0.45	0.06	0.63	0.25	0.31	0.084	−0.014
10	0.29	0.00	0.14	1.00	1.00	1.00	0.029	−0.029
11	0.00	0.51	0.71	0.13	0.77	0.85	0.354	0.028
12	0.00	1.00	0.73	0.11	0.62	0.35	0.125	0.063
13	0.90	0.76	0.52	1.00	0.41	1.00	0.008	0.005
14	1.00	0.95	0.71	1.00	0.00	0.82	0.314	−0.013
15	0.18	0.12	0.91	0.44	0.60	0.24	0.760	−0.008
16	0.52	0.06	0.00	0.45	1.00	0.00	0.072	0.005
17	0.61	0.55	1.00	0.75	0.00	0.85	0.964	−0.037
18	0.50	0.65	0.80	0.00	1.00	0.47	0.166	0.014
19	0.46	0.00	0.52	0.67	0.00	0.65	0.893	−0.008
20	0.35	0.05	0.44	0.43	0.51	0.48	0.302	0.007

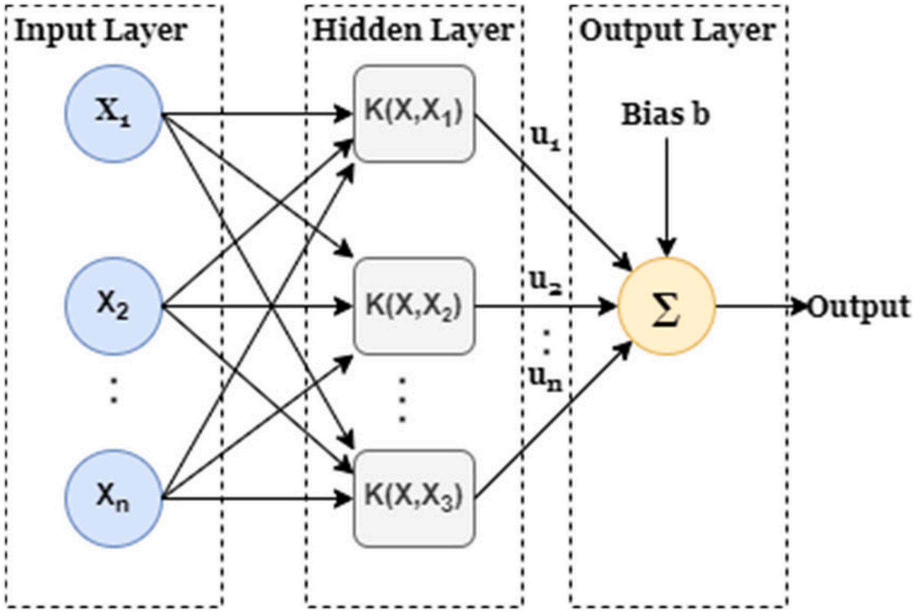

Fig. 3. Sketch map of support vector machines.

and finally the classification is achieved [18]. This classification is simpler than other categories. In the process of using ^{SVM}, there are two situations: linearly separable and linearly non-separable according to the different audio samples of ecological environment, linearly separable problems can be solved directly, the linear non-separable problem is mapped into a high dimensional space and becomes a linear separable problem to be solved. From the above, it can be seen that the linear separable problem is solved, it's supposed that figure is dyadic linear separable sample, the equation of straight line ^{H} crossing the straight line^{H1} of support vector machines with linearly separable and linearly non-separable samples, and being in parallel with ^{H2}

3.3. Result analysis and discussion

After the completion of design and implementation of the system, the test was done in the computer Windows XP operating platform, the memory of the computer was 4G, and CPU was Interl 2.1 GHz, and the audio signal was then normalized by using the Cool Edit2.0. The audio data source contained a variety of sounds in ecological environment, including a variety of sounds of insects, birds, wind blowing leaves; all sounds were processed in advance by Cool Edit2.0. Experiments were carried out after the correlation threshold and parameters were selected [19,20]. The first was the experiment of the effect of the pre-weighting coefficient on the classification results, as shown in Table 6.

The MFCC dimension reflected the characteristics of human hearing; therefore, the effect of MFCC coefficients on audio classification was very large. As can be seen from Table 7, as the MFCC coefficient continued to increase, the accuracy of the system with respect to the sound classification of the ecological environment was steadily increasing, and the classification accuracy increased by a large margin, when the MFCC coefficient was increased from 8 to 14, the accuracy of the system classification was increased from 84.86% to 88.94%, with about 4% increase. Similarly, in terms of the system$^{SVM-HMM}$ based on support vector machines, with the increasing of MFCC coefficient, the classification accuracy of the sound of ecological environment was also increasing, and the amplitude of the increase was relatively large. With the same increase of MFCC coefficients, the classification accuracy of the system $^{SVM-HMM}$ based on support vector machines was increased from 85.26% to 90.56%, with an increase of about 5%. Comprehensive analysis shows that with the increase of MFCC coefficient, the classification accuracy of the two systems increased greatly, and the classification results were also excellent. But the system$^{SVM-HMM}$ based on support vector machines has an advantage of about 1% in classification accuracy and growth.

Table 6
Accuracy of classification under different pre-weighting coefficients.

Pre-emphasis coefficient	0.90	0.92	0.94	0.96	0.98
Accuracy of classification of HMM system	88.22%	88.38%	88.60%	88.67%	88.69%
The accuracy of classification SVM-HMM system	89.20%	89.39%	89.59%	89.61%	89.70%

The accuracy of the classification of acoustic sounds increased continuously with the increase of the pre-emphasis factor, however, the added value slowed down with the increase of the pre-emphasis factor. For the system$^{SVM-HMM}$ based on support vector machines, the growth and trend growth of the classification accuracy of the sound of the ecological environment were basically similar to these of the single system ^{HMM}.

Table 8 shows the classification accuracy of three systems ^{HMM}, ^{SVM} and $^{SVM-HMM}$ based on support vector machines for different sounds, as can be seen from Table 8, the classification accuracy of the three systems was exactly the same in silent state, and all of them were 96.20%. For pure bird calls, the classification accuracy of the three systems varied considerably, the classification accuracy of the system ^{HMM} and ^{SVM} was 90%, while system$^{SVM-HMM}$ based on support vector machine was about 95%. The classification accuracy of the sound with windblowing leaves of the three systems was declined, that of systems^{HMM} and^{SVM}were about 84%, and system $^{SVM-HMM}$ based on support vector machine was 92%. For the sound with background, the classification accuracy of systems ^{HMM} and ^{SVM} were about 88%, while system $^{SVM-HMM}$ based on support vector machine was 94%.Comprehensive analysis shows that in silent state, the classification accuracy of the three systems is same, but either the sound classification in the sound with background, the call, or in complex background, the system $^{SVM-HMM}$ based on support vector machine has more advantages than the other two systems, the more complex the sound is, the higher the classification accuracy of the system $^{SVM-HMM}$ based on support vector machine.

Table 7
Accuracy of classification under different MFCC dimensions.

MFCC dimension	8.00	9.00	10.00	11.00	12.00	13.00	14.00
Accuracy of classification of HMM system	84.86%	86.65%	87.42%	88.20%	88.75%	88.83%	88.94%
Accuracy of classification of SVM-HMM system	85.26%	87.17%	87.87%	88.69%	89.96%	90.44%	90.56%

Table 8
Accuracy of classification based on different models.

Audio categories	Loud speaker mute	Simple bird	The wind blowing the leaves	Background sound (sound of the wind in the leaves + birds)
Classification accuracy of HMM system	96.20%	90.36%	84.36%	87.81%
Classification accuracy of SVM system	96.20%	90.21%	84.74%	88.26%
The classification accuracy of SVM-HMM system	96.20%	95.58%	92.47%	94.31%

4. Conclusion

The results prove that compared with the system ^{HMM}, the $^{SVM-HMM}$ ecological environment sound classification algorithm has more advantages in classification accuracy under different pre-emphasis coefficients and MFCC coefficients. Then, in the sound of the ecological environment under different backgrounds, the systems ^{HMM} and ^{SVM} were compared and verified. The result of verification shows that the more complex the environment is, the higher the classification accuracy of$^{SVM-HMM}$voice classifier based on support vector machines will be, and with the advantage over the other two systems. It proves that the computer sound classifier $^{SVM-HMM}$ based on support vector machines is very suitable for the monitoring of sound of ecological environment. Artificial neural network has advantages such as strong self-training learning and fault tolerance ability. Meanwhile, learning algorithm of BP network is simple with strong learning ability so it is broadly applied in practice. Because of this, BP neural network is applied to predict sports performance and combines practical cases to illustrate implementation and application of this method. Numerical value experiment shows that model has high prediction accuracy and provides a new method to predict sports performance. However, we also discover there is limitation for BP neural network model prediction on performance prediction. Therefore, algorithm of BP neural network training model should select according to practical situation. It not only needs guarantee networked stability but it also needs consider other convergence speed and learning time.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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