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# A weighted selection combining scheme for cooperative spectrum prediction in cognitive radio networks

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**Abstract:** A weighted selection combining (WSC) scheme is proposed to improve prediction accuracy for cooperative spectrum prediction in cognitive radio networks by exploiting spatial diversity. First, a genetic algorithm-based neural network (GANN) is designed to perform spectrum prediction in consideration of both the characteristics of the primary users (PU) and the effect of fading. Then, a fusion selection method based on the iterative self-organizing data analysis (ISODATA) algorithm is designed to select the best local predictors for combination. Additionally, a reliability-based weighted combination rule is proposed to make an accurate decision based on local prediction results considering the diversity of the predictors. Finally, a Gaussian approximation approach is employed to study the performance of the proposed WSC scheme, and the expressions of the global prediction precision and throughput enhancement are derived. Simulation results reveal that the proposed WSC scheme outperforms the other cooperative spectrum prediction schemes in terms of prediction accuracy, and can achieve significant throughput gain for cognitive radio networks.

**Key words:** cognitive radio network; cooperative spectrum prediction; genetic algorithm-based neural network; iterative self-organizing data analysis algorithm; weighted selection combining

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Cognitive radio (CR) has been viewed as a promising technology to alleviate the spectrum scarcity problem. Secondary users (SUs) are allowed to opportunistically access the licensed channels allocated for the primary users (PUs) to improve spectrum utilization efficiency. Spectrum sensing is an essential functionality of the SUs to timely detect spectrum holes for data transmission. In the interweave mode, the licensed channels can only be accessed by the SUs when they are sensed to be in an idle state, otherwise, the SUs should wait until spectrum holes are detected. However, the incapability of spectrum sensing to eliminate false alarms due to interference will reduce spectrum sensing efficiency and waste available spectrum resources[1]. To tackle this shortcoming, spectrum prediction has been proposed as an effective approach to help weaken the impact of improper spectrum detection by providing the dependable knowledge of available licensed channels.

Spectrum prediction in CR mainly targets channel availability, i. e. predicting whether the licensed channel is idle or busy. Various types of machine learning techniques have been adopted in spectrum prediction, and neural network (NN)[2] has in particular received much attention due to its good nonlinear quality, high fitting accuracy, fully distributed storage structure and the hierarchical quality of the model structure. A wavelet neural network (WNN)[3] has been studied to show that the nature of discrete transform can help build a more accurate prediction model with less complexity. Channel estimation in predictive modeling scenarios and multi-secondary-user scenarios has been investigated by using two types of artificial neural networks (ANNs)[4]. Apart from the "hard decision" models, a "soft decision" model[5] for spectrum prediction based on back-propagation (BP) neural networks has also been studied. Since the parameters of NN, i. e., weights and biases, are determined by gradient search algorithms and are sensitive to initial values, the genetic algorithm (GA)[6] has been employed to solve the problem that the NN-based spectrum prediction models are always trapped in local optimal solutions.

Based on various types of local spectrum prediction techniques, the design of cooperative spectrum prediction schemes with high prediction accuracy has attracted more and more attention recently[7]. A spectrum prediction scheme has been proposed based on the coalitional game theory[8]. It shows an outstanding performance of cooperative spectrum prediction but lacks the detailed analysis of the relationship between SUs' characteristics and cooperative spectrum prediction performance. Cooperative spectrum prediction has been analyzed in both pre-fusion and post-fusion scenarios[9]. The $M$-out-of-$N$ rule has been extended for cooperative spectrum prediction in this paper and the results show that cooperative spectrum prediction can lead to a significant improvement in prediction accuracy.

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However, to the best of our knowledge, the existing works have not considered the heterogeneity of predictors for combination. To this end, we propose an efficient weighted selection combining (WSC) scheme for cooperative spectrum prediction, by selecting a subset of predictors for optimal combination according to the priority of each predictor, and present an analysis of the scheme in terms of both prediction precision and throughput enhancement. The mean prediction precision of the WSC scheme is simulated against traffic intensity and compared with other combining schemes to show its outstanding effectiveness. It can also be proven that the WSC scheme can provide evident throughput enhancement from both the analysis and simulation results.

## 1 System Model

A time slotted system with one PU and $N$ pairs of secondary transceivers is assumed in this paper. SUs are randomly distributed around the PU, and opportunistically access the licensed channel for data transmission. PU traffic on the licensed channel is assumed to follow a Poisson process, and the ON (busy) and OFF (idle) times of the channel are drawn from geometric distributions. When the ON and OFF times of the channel are, respectively, denoted by $t_{\mathrm{ON}}$ and $t_{\mathrm{OFF}}$, the traffic intensity can be calculated by[2]

$$\rho = \frac{t_{\mathrm{ON}}}{t_{\mathrm{ON}} + t_{\mathrm{OFF}}} \tag{1}$$

Let $H_1$ represent the ON state and $H_0$ represent the OFF state. The probability of the licensed channel being busy and idle can be, respectively, estimated by

$$P(H_1) = \rho \tag{2}$$

$$P(H_0) = 1 - \rho \tag{3}$$

We assume that the received PU signal at SU $j$ is complex phase shift keying (PSK) with zero mean and a variance$(\sigma_{\mathrm{s}}^j)^2$, and the noise is independent circular symmetric complex Gaussian (CSCG) with zero mean and a variance $(\sigma_{\mathrm{u}}^j)^2, j = 1, 2, \ldots, N$. Thus, the false alarm probability $P_{\mathrm{f}}^j$ and the detection probability $P_{\mathrm{d}}^j$ of spectrum sensing can be, respectively, approximated by[10]

$$P_{\mathrm{f}}^j = Q\left(\left(\frac{\varepsilon^j}{(\sigma_{\mathrm{u}}^j)^2} - 1\right)\sqrt{f_{\mathrm{s}}\tau_{\mathrm{s}}}\right) \tag{4}$$

$$P_{\mathrm{d}}^j = Q\left(\left(\frac{\varepsilon^j}{(\sigma_{\mathrm{u}}^j)^2} - 1 - \gamma^j\right)\sqrt{\frac{f_{\mathrm{s}}\tau_{\mathrm{s}}}{2\gamma^j + 1}}\right) \tag{5}$$

where $\varepsilon^j$ is the energy detection threshold for the $j$-th SU; $\gamma^j = (\sigma_{\mathrm{s}}^j/\sigma_{\mathrm{u}}^j)^2$ is the average signal noise ratio (SNR) of the PU signal measured at the $j$-th SU; $\tau_{\mathrm{s}}$ is the available sensing time and $f_{\mathrm{s}}$ is the sampling frequency; $Q(x)$ is the tail probability of the standard normal distribution. For a target detection probability $\overline{P_{\mathrm{d}}^j}$, the false alarm probability is related to the target detection probability as

$$P_{\mathrm{f}}^j = Q\left(\sqrt{2\gamma^j + 1}\,Q^{-1}(\overline{P_{\mathrm{d}}^j}) + \gamma^j\sqrt{f_{\mathrm{s}}\tau_{\mathrm{s}}}\right) \tag{6}$$

In centralized cooperative spectrum sensing, all the participating SUs send their spectrum sensing results to the fusion center (FC) for combination, and the final results will be sent back as a guide for action. Thus, a cloud computing unit[11] is disposed at the FC to provide storage for the spectrum sensing results and computational capacity. Since the prediction duration is comparable with the sensing duration[12], we redesign the frame structure as a three-phase frame structure as shown in Fig. 1. During the spectrum prediction and spectrum sensing phase, spectrum prediction is performed at the FC based on the historical sensing results. Meanwhile, local spectrum sensing is performed by SUs. Afterwards, the FC collects all the sensing results from participated SUs and makes final decisions according to the cooperative prediction results and cooperative sensing results in the reporting phase. Finally, if the licensed channel is decided to be idle, data transmission is performed by a selected SU during the data transmission phase; otherwise, no SU is allowed to transmit on the licensed channel.

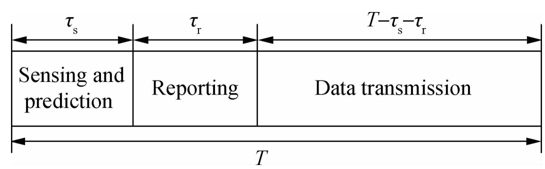


**Fig. 1** Three-phase frame structure

## 2 Cooperative Spectrum Prediction

### 2.1 Design of the WSC scheme for cooperative spectrum prediction

In this section, we propose a WSC scheme for cooperative spectrum prediction by selecting a subset of local predictors for optimal combination according to the reliability of each predictor, and analyze the performance of the proposed scheme. The scheme consists of three parts as shown in Fig. 2. $N$ GANN-based predictors are designed for local spectrum prediction in the first part. An ISODA-

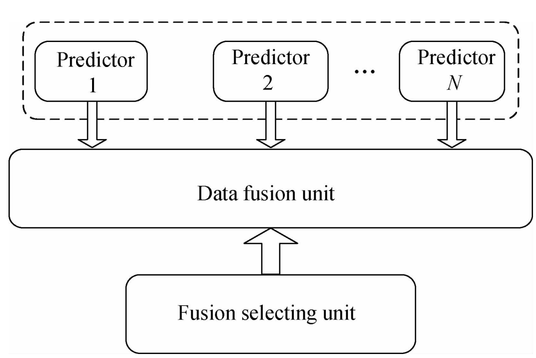


**Fig. 2** The structure of WSC scheme

TA-algorithm-based fusion selection unit is designed to choose a subset of predictors for combination in the second part. A data fusion unit is designed to make optimal weighted combination in the third part.

### 2.1.1 GANN-based predictors

Each GANN-based predictor in the WSC scheme is designed to make spectrum prediction based on the historical spectrum sensing results of a particular SU. Take the $j$-th ($j=1,2,\dots,N$) predictor as an example, the time series forecasting task consists of predicting the real-state value $x_{t+1}$ of the PU at time $t$ based on the historical spectrum sensing results $(\boldsymbol{S}^j)_{t-t_0+1}^{t} = \{s_{t-t_0+1}^j, s_{t-t_0+2}^j, \dots, s_{t-1}^j, s_t^j\}$ composed of $t_0$ observations. When $(\boldsymbol{S}^j)_{t-t_0+1}^{t}$ is presented to the NN, it will come up with an output $\hat{x}_{t+1}^j$ and it can be viewed as an estimate of the desired output $x_{t+1}$. The difference between $\hat{x}_{t+1}^j$ and $x_{t+1}$ will be used to adjust the parameters of the NN in the training phase[2]. The training phase will only terminate when the difference between the desired output and its estimate drops down below some given threshold or the predefined training time is over. However, for the nonconvex NN, the training phase often stops at a local optimal solution, which results in low prediction accuracy. Thus, the GA is employed to solve the local optimal solution problem for its excellent global search ability.

The GA is an evolutionary algorithm which applies the search principles of natural evolution for parameters optimization[13]. It is used to initialize the weights and biases of the NN in this paper since the accuracy of prediction is sensitive to the initial values. The main steps of the GA-based parameter initialization are given as follows:

1) Each set of weights and biases is encoded as a string to denote a specific chromosome, and a population of chromosomes is created.

2) The fitness value of each chromosome is calculated by the mean absolute error (MAE) as

$$\mathrm{MAE} = \frac{1}{t_2 t_1}\sum_{t=t_1}^{t_2} \left| \hat{x}_{t+1}^j - x_{t+1} \right| \tag{7}$$

3) Genetic operations of selection, crossover and mutation are performed among individuals to generate the next generation of chromosomes.

4) The generated offspring replace their parents in the initial population. They are decoded back into weights and biases as the result of parameter initialization.

After training of the GANN, a testing phase is needed to evaluate the performance. The performance evaluation is done by judging the difference between the estimate value $\hat{x}^j$, which is obtained by presenting the testing patterns to the trained GANN and the corresponding real-state information $x$. The testing patterns are obtained in the same way as the training patterns but the data used in the training phase should be eliminated in the testing phase to ensure valid evaluation[14]. We define two probabilities, i. e. miss-prediction probability $P_{\mathrm{p,md}}^j$ and false-alarm prediction probability $P_{\mathrm{p,fa}}^j$, to evaluate the reliability of the $j$-th GANN-based predictor. The miss-prediction probability represents the chance that the licensed channel is predicted to be idle when its real-state is busy, while the false-alarm prediction probability represents the chance that the licensed channel is predicted to be busy when its real-state is idle. They are two important performance criteria for the spectrum prediction model, which can be, respectively, expressed as

$$P_{\mathrm{p,md}}^j = P(\hat{x}^j = -1 \mid x = 1) \tag{8}$$

$$P_{\mathrm{p,fa}}^j = P(\hat{x}^j = 1 \mid x = -1) \tag{9}$$

where $x=-1$ denotes that the real-state of the licensed channel is idle, and $x=1$ denotes that the real-state of the licensed channel is busy.

Therefore, the prediction precision of the $j$-th GANN-based predictor can be calculated by

$$P_{\mathrm{pre}}^j = P(H_0)(1-P_{\mathrm{p,fa}}^j) + P(H_1)(1-P_{\mathrm{p,md}}^j) \tag{10}$$

After training and testing, the GANN-based predictors are established and then they can be used to perform spectrum prediction. By presenting the latest $t_0$-length spectrum sensing results of the $j$-th SU to the predictor, the spectrum prediction result is obtained for each frame.

### 2.1.2 ISODATA-algorithm-based fusion selection unit

Since the SUs are randomly located around the PU, they have various spectrum sensing performance, and therefore, the reliability of the predictors is not equal. In this part, we propose an ISODATA-algorithm-based fusion selection method to select a subset of appropriate predictors for further combination. The ISODATA algorithm[15] is an unsupervised machine learning classification algorithm. It is an extension of the K-means classification algorithm by selecting the number of clusters automatically. Our main idea is to use the ISODATA algorithm to find out which predictors are most frequently clustered together with the PU, and choose these predictors for further combination. For the $k$-th($k=1,2,\dots,N$) predictor, its prediction results obtained at the testing phase are stored at the FC as a binary series and is denoted by $\hat{\boldsymbol{X}}^k$, and the corresponding real-state information is also denoted by $\boldsymbol{X}$. The ISODATA-algorithm-based fusion selection method can be described as follows:

1) A clustering pattern which contains $N+1$ vectors is obtained in each round, and the length of each vector is chosen as $l_0$. The first $N$ vectors in the clustering pattern are the prediction results of $N$ predictors and the last vector in the clustering pattern is the corresponding real-state information. To make this clear, we take the $l$-th clustering round as an example. The clustering pattern established for the $l$-th round can be denoted by $\boldsymbol{C}^l = \{(\hat{\boldsymbol{X}}^1)_{l-l_0+1}^{l}, (\hat{\boldsymbol{X}}^2)_{l-l_0+1}^{l}, \dots, (\hat{\boldsymbol{X}}^N)_{l-l_0+1}^{l}, (\boldsymbol{X})_{l-l_0+1}^{l}\}$, where

$(\hat{\boldsymbol{X}}^k)_{l-l_0+1}^{l} = \{\hat{x}_{l-l_0+1}^k, \hat{x}_{l-l_0+2}^k, \dots, \hat{x}_{l-1}^k, \hat{x}_l^k\}$ is a $l_0$-length vector coming from $\hat{\boldsymbol{X}}^k$, and $(\boldsymbol{X})_{l-l_0+1}^{l} = \{x_{l-l_0+1}, x_{l-l_0+2}, \dots x_{l-1}, x_l\}$ is a $l_0$-length vector coming from $\boldsymbol{X}$.

2) The $N+1$ vectors in the clustering pattern are clustered by using the ISODATA algorithm. The clustering result $c_k(l)$ denotes whether or not the $k$-th predictor is clustered together with the PU in the $l$-th clustering round, and is recorded by

$$c_k(l) = \begin{cases} 1 & u_k = u_{N+1} \\ 0 & u_k \neq u_{N+1} \end{cases} \tag{11}$$

where $u_k$ denotes the cluster the $k$-th vector is assigned to, and $u_{N+1}$ denotes the cluster the PU is assigned to.

3) Suppose that the clustering process is performed for $N_s$ rounds, and $N_s$ is large enough. The clustering frequency which denotes the frequency of each predictor being clustered together with the PU can be calculated by

$$f_k = \frac{\sum_{l=1}^{N_s} c_k(l)}{N_s} \tag{12}$$

4) Sort the clustering frequency of all the predictors in a descending order, and select the first $K$ predictors for further combination.

### 2.1.3 Reliability-based weighted combination unit

To make full use of the diversity among different predictors, a reliability-based weighted combination scheme is employed. In this scheme, the weighting factor for each selected predictor represents its contribution towards the global prediction decisions. The weighted combination rule in this paper is considered as[16]

$$\left.\begin{aligned} H_1 &: R_p = \sum_{i=1}^{K} \alpha_i \hat{x}^i + \beta \geqslant 0 \\ H_0 &: R_p = \sum_{i=1}^{K} \alpha_i \hat{x}^i + \beta < 0 \end{aligned}\right\} \tag{13}$$

where $\hat{x}^i$ is the prediction result of the $i$-th selected predictor; $\alpha_i$ is the weighting factor; and $\beta$ is the correction factor, $i = 1, 2, \dots, K$.

To achieve the maximum cooperative spectrum prediction precision, the weighting factor $\alpha_i$ and the correction factor $\beta$ are estimated according to the likelihood ratio test (LRT) as[17]

$$\frac{P(\hat{x}^1, \hat{x}^2, \dots, \hat{x}^K \mid H_1)}{P(\hat{x}^1, \hat{x}^2, \dots, \hat{x}^K \mid H_0)} = \frac{P(\hat{X} \mid H_1)}{P(\hat{X} \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)}{P(H_1)} \tag{14}$$

The corresponding log-LRT can be expressed as

$$\log \frac{P(H_1 \mid \hat{X})}{P(H_0 \mid \hat{X})} \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{15}$$

Suppose that $\boldsymbol{A}_0$ contains all the selected predictors whose prediction results are idle, and $\boldsymbol{A}_1$ contains all the selected predictors whose prediction results are busy. Since

$$\log \frac{P(H_1 \mid \hat{X})}{P(H_0 \mid \hat{X})} = \log \frac{P(H_1)}{P(H_0)} + \log \frac{P(\hat{X} \mid H_1)}{P(\hat{X} \mid H_0)} = \log \frac{P(H_1)}{P(H_0)} + (+1) \sum_{m \in \boldsymbol{A}_1} \log \frac{1 - P_{\mathrm{p,md}}^m}{P_{\mathrm{p,fa}}^m} + (-1) \sum_{n \in \boldsymbol{A}_0} \log \frac{1 - P_{\mathrm{p,fa}}^n}{P_{\mathrm{p,md}}^n} \tag{16}$$

The optimum weighting factor $\tilde{\alpha}_i$ and the optimum correction factor $\tilde{\beta}$ can be expressed as

$$\tilde{\alpha}_i = \begin{cases} \tilde{\alpha}_i^+ = \log \dfrac{1 - P_{\mathrm{p,md}}^i}{P_{\mathrm{p,fa}}^i} & \text{if } \hat{x}^i = +1 \\ \tilde{\alpha}_i^- = \log \dfrac{1 - P_{\mathrm{p,fa}}^i}{P_{\mathrm{p,md}}^i} & \text{if } \hat{x}^i = -1 \end{cases} \tag{17}$$

$$\tilde{\beta} = \log \frac{P(H_1)}{P(H_0)} \tag{18}$$

When a large number of predictors are selected for further combination, a Gaussian approximation of the test statistic $R_p$ in (13) can be made according to the central limit theorem. The expectations and variances of the Gaussian distribution under different hypotheses can be, respectively, expressed as

$$E(R_p \mid H_0) = \sum_{i=1}^{K} \left[ \tilde{\alpha}_i^+ P_{\mathrm{p,fa}}^i - \tilde{\alpha}_i^- (1 - P_{\mathrm{p,fa}}^i) \right] + \tilde{\beta} \tag{19}$$

$$E(R_p \mid H_1) = \sum_{i=1}^{K} \left[ \tilde{\alpha}_i^+ (1 - P_{\mathrm{p,md}}^i) - \tilde{\alpha}_i^- P_{\mathrm{p,md}}^i \right] + \tilde{\beta} \tag{20}$$

$$\mathrm{Var}(R_p \mid H_0) = \sum_{i=1}^{K} \mathrm{Var}(\tilde{\alpha}_i \hat{x}^i \mid H_0) = \sum_{i=1}^{K} \left[ (\tilde{\alpha}_i^+ + \tilde{\alpha}_i^-)^2 P_{\mathrm{p,fa}}^i (1 - P_{\mathrm{p,fa}}^i) \right] \tag{21}$$

$$\mathrm{Var}(R_p \mid H_1) = \sum_{i=1}^{K} \mathrm{Var}(\tilde{\alpha}_i \hat{x}^i \mid H_1) = \sum_{i=1}^{K} \left[ (\tilde{\alpha}_i^+ + \tilde{\alpha}_i^-)^2 P_{\mathrm{p,md}}^i (1 - P_{\mathrm{p,md}}^i) \right] \tag{22}$$

Therefore, the false-alarm prediction probability and the miss-prediction probability of the cooperative spectrum prediction process can be calculated by

$$\Psi_{\mathrm{p,fa}} = Q\left( \frac{E(R_p \mid H_0)}{\sqrt{\mathrm{Var}(R_p \mid H_0)}} \right) \tag{23}$$

$$\Psi_{\mathrm{p,md}} = 1 - Q\left( \frac{E(R_p \mid H_1)}{\sqrt{\mathrm{Var}(R_p \mid H_1)}} \right) \tag{24}$$

The prediction precision of the proposed WSC scheme can be expressed as

$$P_{\mathrm{pre}} = P(H_0)(1 - \Psi_{\mathrm{p,fa}}) + P(H_1)(1 - \Psi_{\mathrm{p,md}}) \tag{25}$$

## 2.2 Enhanced throughput by using the WSC scheme

The $M$-out-of-$N$ rule is employed at the FC to fuse the spectrum sensing results from all the SUs for cooperative spectrum sensing. In this paper, $M = \left\lceil \frac{N}{2} \right\rceil$ is used. The false-alarm probability and miss-detection probability of cooperative spectrum sensing can be expressed as[18]

$$P_{\mathrm{F}} = \sum_{w=\lceil \frac{N}{2} \rceil}^{N} \sum_{\sum u = w} \prod_{j=1}^{N} (P_{\mathrm{f}}^{j})^{(1+u)/2} (1 - P_{\mathrm{f}}^{j})^{(1-u)/2} \quad (26)$$

$$P_{\mathrm{M}} = 1 - \sum_{w=\lceil \frac{N}{2} \rceil}^{N} \sum_{\sum u = w} \prod_{j=1}^{N} (P_{\mathrm{d}}^{j})^{(1+u)/2} (1 - P_{\mathrm{d}}^{j})^{(1-u)/2} \quad (27)$$

Thus, the probability distributions of cooperative spectrum prediction, cooperative spectrum sensing, and the true channel state are illustrated in Tab. 1.

**Tab. 1** Probability distributions considering true channel state, prediction, and sensing

| True channel state | Prediction | Sensing | Probability |
|---|---|---|---|
| Idle | Idle | Idle | $P_1 = (1 - P_{\mathrm{F}}) P(H_0)(1 - \Psi_{\mathrm{p,fa}})$ |
| Idle | Idle | Busy | $P_2 = P_{\mathrm{F}} P(H_0)(1 - \Psi_{\mathrm{p,fa}})$ |
| Idle | Busy | Idle | $P_3 = (1 - P_{\mathrm{F}}) P(H_0) \Psi_{\mathrm{p,fa}}$ |
| Idle | Busy | Busy | $P_4 = P_{\mathrm{F}} P(H_0) \Psi_{\mathrm{p,fa}}$ |
| Busy | Idle | Idle | $P_5 = P_{\mathrm{M}} P(H_1) \Psi_{\mathrm{p,md}}$ |
| Busy | Idle | Busy | $P_6 = (1 - P_{\mathrm{M}}) P(H_1) \Psi_{\mathrm{p,md}}$ |
| Busy | Busy | Idle | $P_7 = P_{\mathrm{M}} P(H_1)(1 - \Psi_{\mathrm{p,md}})$ |
| Busy | Busy | Busy | $P_8 = (1 - P_{\mathrm{M}}) P(H_1)(1 - \Psi_{\mathrm{p,md}})$ |

The cooperative spectrum sensing results can be revised by combining the cooperative spectrum prediction results to mitigate the effect of false-alarm detection, and an OR-rule is adopted. The average throughput of the proposed scheme is calculated by

$$\bar{R}_{\mathrm{p}} = (P_1 + P_2 + P_3)\bar{C}_0 + (P_5 + P_6 + P_7)\bar{C}_1 \quad (28)$$

where $\bar{C}_0$ and $\bar{C}_1$ are the average throughput of the SUs when they transmit on an idle channel and a busy channel, respectively. For the sake of easy comparison, the normalized average throughput is denoted by

$$\bar{R}_{\mathrm{p,norm}} = \frac{\bar{R}_{\mathrm{p}}}{\bar{R}_{\max}} \quad (29)$$

where $\bar{R}_{\max}$ is the SUs' maximum average throughput and is given by

$$\bar{R}_{\max} = P(H_0)\bar{C}_0 + P(H_1)\bar{C}_1 \quad (30)$$

To make a comparison, the normalized average throughput of the SUs when adopting the same cooperative spectrum sensing scheme without cooperative spectrum prediction is calculated by

$$\bar{R}_{\mathrm{s,norm}} = \frac{(P_1 + P_3)\bar{C}_0 + (P_5 + P_7)\bar{C}_1}{\bar{R}_{\max}} \quad (31)$$

Therefore, the throughput enhancement of the proposed scheme can be expressed as

$$\bar{R}_{\mathrm{enh}} = \bar{R}_{\mathrm{p,norm}} - \bar{R}_{\mathrm{s,norm}} \quad (32)$$

## 3 Simulation Results

The performance of the proposed WSC scheme is illustrated by simulation results in this section. Three different simulations are performed based on MATLAB: 1) Investigating the prediction precision of an individual predictor; 2) The prediction precision of cooperative spectrum prediction; 3) The throughput enhancement of the WSC scheme.

Some fundamental parameters are chosen as follows. The number of the participated SUs is $N = 100$. Frame duration $T$ is 100 ms, spectrum sensing duration $\tau_{\mathrm{s}}$ and reporting duration $\tau_{\mathrm{r}}$ are both 2.5 ms, and sampling frequency $f_{\mathrm{s}}$ is 100 kHz. The transmitting SU is randomly selected here and its average throughput on the idle channel and the busy channel are $\bar{C}_0 = 1$ Kbit/s and $\bar{C}_1 = 0.05$ Kbit/s, respectively.

In the first simulation, we evaluate the performance of the GANN-based predictor. In the parameter initialization process, the population contains 50 individuals. The iterative process of selection, crossover and mutation is performed $I_{\max}$100 times, where the crossover factor and the mutation factor are, respectively, set to be 0.4 and 0.2 to adjust the diversity and convergence of the population. A three-layer-NN-model with 6 neurons in the hidden layer is exploited in each predictor. The length of training/testing patterns is set to be $t_0 = 4$ and the input layer of the GANN model is of the same size. Assuming that the spectrum sensing SNR of the SUs varies from −25 to 5 dB, Fig. 3 shows the impact of fading on the mean prediction precision with different traffic intensities of the PU. The mean prediction precision is obtained by assuming that SU's target probability of detection is uniformly distributed between 0.7 and 0.95. Fig. 3 shows that, for a given traffic intensity $\rho$, the mean prediction precision increases with the enhancement of SNR, that is, a predictor can make more precise prediction based on the sensing results from SUs with a higher SNR. It is also shown that the mean prediction precision converges to $|\rho - 0.5| + 0.5$ as SNR decreases. This is because the predictor predicts the licensed channel to be always idle ($\rho < 0.5$) or busy ($\rho \geqslant 0.5$) when the input patterns become quite irregular and unpredictable. In this case, the predictor can be viewed as incapable of spectrum prediction and may be abandoned for further combination.

In the second simulation, the parameters for the ISODATA-algorithm-based fusion selection scheme are set as follows. The length of clustering vectors is set to be $l_0 = 10$. The maximum number of clusters is 8, the maximum number of clusters that can be merged at one time is 1, the maximum number of iterations is 10, the threshold of number of vectors for cluster elimination is 1, the threshold of distance for cluster merging is 4, the threshold of standard deviation for cluster splitting is 1, and the mini-

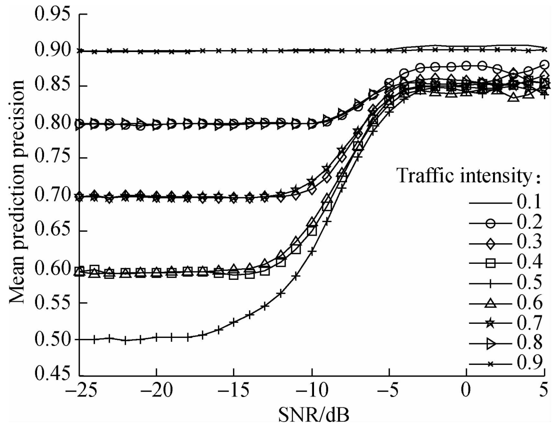


**Fig. 3** Mean prediction precision of the predictor vs. SNR

mum distance between a vector and each cluster center is 100. The number of selected predictors in the ISODATA-algorithm-based fusion selection process is set to be $K = \left\lceil \frac{N}{2} \right\rceil = 50$ and the target detection probability is also assumed to be uniformly distributed between 0.7 and 0.95. Fig. 4 displays the mean prediction precision of the proposed WSC scheme, a single predictor, and other data fusion rules such as the AND rule, the OR rule and the Majority rule[9] for comparison. As depicted in Fig. 4, the mean prediction precision of the WSC scheme exceeds the other schemes for any traffic intensity, which indicates the superior performance of the WSC scheme at the cost of higher computational complexity. It is also shown in Fig. 4 that the WSC scheme has comparable effectiveness as the real-state-information-based (RS) ANN spectrum prediction model[4].

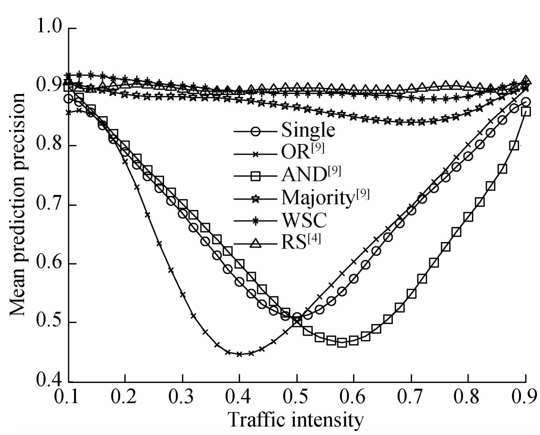


**Fig. 4** Mean prediction precision of different schemes vs. traffic intensity

In the last simulation, the normalized average throughput $\bar{R}_{\mathrm{p,norm}}$ of the WSC scheme and the normalized average throughput $\bar{R}_{\mathrm{s,norm}}$ of the cooperative spectrum sensing scheme[1] versus the traffic intensity $\rho$ are plotted in Fig. 5. It is observed that $\bar{R}_{\mathrm{p,norm}}$ outperforms $\bar{R}_{\mathrm{s,norm}}$ regardless of the traffic intensity. This is because the WSC scheme can help weaken the impact of false-alarm detection in the process of spectrum sensing and provide more opportunities for the SUs to perform data transmission. It also needs to be mentioned that the gap between the two normalized average throughputs, i. e. the throughput enhancement $\bar{R}_{\mathrm{enh}}$, decreases as the traffic intensity increases. This is because few extra available frequency resources can be obtained when the PU is extremely busy on the licensed channel.

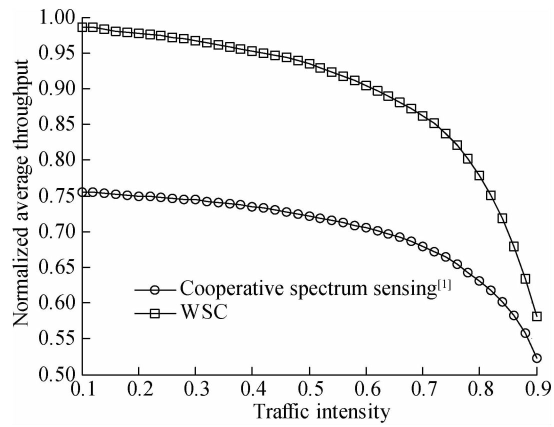


**Fig. 5** Normalized average throughput vs. traffic intensity

## 4 Conclusions

1) A genetic algorithm-based neural network (GANN) is designed to perform spectrum prediction in consideration of both the characteristics of the PU and the effect of fading.

2) A fusion selection method based on the iterative self-organizing data analysis (ISODATA) algorithm is designed to select the best local predictors for combination.

3) Considering the diversity of the predictors, a reliability-based weighted combination rule is proposed to make an accurate decision based on local prediction results.

4) A Gaussian approximation approach is employed to study the performance of the proposed WSC scheme, and the expressions of the global prediction precision and throughput enhancement are derived. Simulation results reveal that the proposed WSC scheme can provide higher prediction precision and significant throughput enhancement for any traffic intensity environment.

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# 认知无线网络中基于加权选择融合的协作频谱预测策略

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**摘要:**为了进一步提高认知无线网络中频谱预测的准确性,提出一种利用空间多样性进行加权选择融合的协作频谱预测策略. 首先,综合考虑主用户行为特点以及信号衰落的影响,设计一种基于遗传算法的神经网络进行本地预测. 然后,设计一种基于迭代自组织数据分析算法的融合筛选方法来选择性能最好的本地预测器进行协作融合. 此外,考虑到本地预测器之间的空间多样性,提出了一种基于预测可靠性的加权融合规则. 最后,采用高斯近似方法对所提出的基于加权选择融合的协作预测策略的性能进行分析,并给出了全局预测精度和吞吐量的表达式. 实验结果表明,基于加权选择融合的协作频谱预测策略相比于其他的协作频谱预测策略具有更高的预测准确性,并且能够使得认知无线网络中的吞吐量得到很大程度的提高.

**关键词:**认知无线网络;协作频谱预测;基于遗传算法的神经网络;迭代自组织数据分析算法;加权选择融合

**中图分类号:**TN915