Improving signal detection accuracy at FC of a CRN using machine learning and fuzzy rules

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ABSTRACT

The performance of a cognitive radio network (CRN) mainly depends on the faithful signal detection at fusion center (FC). In this paper, the concept of weighted fuzzy rule in Iris data classification, as well as, four machine learning techniques named fuzzy inference system (FIS), fuzzy c-means clustering (FCMC), support vector machine (SVM) and convolutional neural network (CNN) are applied in signal detection at FC taking signal-to-interference plus noise ratio of secondary users as parameter. The weighted fuzzy rule gave the detection accuracy of 86.6%, which resembles the energy detection model of majority rule of FC; however, CNN gave an accuracy of 91.3% at the expense of more decision time. The FIS, FCMC and SVM gave some intermediate results; however, the combined method gave the best result compared to that of any individual technique.

Keywords: Co-operative CRN, Data classification, Entropy, Fusion center, Fuzzy system

1. INTRODUCTION

In Cognitive Radio Network (CRN), there exists two types of users such as Primary User (PU) called licensed user and Secondary User (SU) called unlicensed user. A PU can access a traffic channel of the network when the channel is free; however, a SU is an opportunist user who can access a channel when the channel is not occupied by any PU. Moreover, a SU in service has to release the channel when it is claimed by a PU. Therefore, the detection accuracy of the presence of a PU is a key factor to avoid any misdetection and false alarm. Hence, the concept of co-operative CRN comes forth where the received signals of several SUs are combined at a Fusion Center (FC) to expedite the detection accuracy.

In contemporary works, Fuzzy logic and various machine learning techniques are used at a FC to improve the detection accuracy. The weighted Fuzzy rule or Fuzzy system is widely used in data classification problem of combined Membership Functions (MF) of input variables. It is used to classify Iris data where the weight of an input variable is determined from the range of a variable and its non-overlapping parts [1]. Since accuracy depends on labels, authors found the classification accuracy of 96.7% under 11 labels. The Fuzzy rule-based classification of coronary artery disease data is analyzed in [2]; where trapezoidal MFs are used as input variables. It is found that classification accuracy is varied on weighting rules with a maximum of 92.8% and a minimum of 71.8%. A simulation work is done with relayed link communication to generate input data instead of importing them from a database. Seven different methods and Fuzzy c-Means Clustering [FCMC] are applied in magnetic resonance brain image classification problem and found a moderate performance [3]. A similar algorithm is applied for the classification of farms

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Table 1. Input parameters and output type of the SU data from simulation

| Hypothesis $H_0$ | SU_1 | SU_2 | SU_3 | Output | SU_1 | SU_2 | SU_3 | SU_4 | Output |
|------------------|------|------|------|--------|------|------|------|------|--------|
| 0.064            | 1.688| 0.824| 0.314| 1      | 2.820| 2.151| 3.224| 5.221| 2      |
| 0.889            | 0.664| 1.152| 1.902| 1      | 3.653| 2.412| 1.356| 4.122| 2      |
| 0.553            | 0.079| 0.221| 0.981| 1      | 4.312| 3.443| 3.089| 1.209| 2      |
| 0.763            | 1.306| 1.514| 0.320| 1      | 3.438| 1.121| 2.667| 2.072| 2      |
| 0.453            | 0.919| 0.231| 1.331| 1      | 2.494| 3.411| 4.108| 3.109| 2      |

Figure 1. The MFs of the fuzzy system

Table 2. Input parameters and output type simulation data

| Hypothesis $H_0$ | SU_1 | SU_2 | SU_3 | Output | SU_1 | SU_2 | SU_3 | SU_4 | Output |
|------------------|------|------|------|--------|------|------|------|------|--------|
| $A$              | $B$  | $A$  | $B$  | $A$    | $C$  | $C$  | $C$  | $E$  | $2$    |
| $B$              | $A$  | $B$  | $B$  | $1$    | $D$  | $C$  | $B$  | $D$  | $2$    |
| $A$              | $A$  | $A$  | $B$  | $1$    | $D$  | $C$  | $B$  | $D$  | $2$    |
| $B$              | $B$  | $B$  | $A$  | $1$    | $C$  | $B$  | $C$  | $C$  | $2$    |
| $A$              | $B$  | $A$  | $B$  | $1$    | $C$  | $C$  | $D$  | $C$  | $2$    |

Now, the rule for $H_0$ is $R_0 = ((\{A, B\}, \{A, B\}, \{A, B\}, \{A, B\}), H_0)$ and the rule for $H_1$ is $R_1 = ((\{C, D\}, \{B, C\}, \{B, C, D\}, \{C, B, D, E\}), H_1)$. We will explain the Fuzzy weighted rule through data validation techniques in a different way, specially using line diagrams and numerical examples.

2.1.1. Numerical example-1

Show that $(SU_1, SU_2, SU_3, SU_4) = (0.72, 0.83, 1.71, 0.134)$ belongs to output $H_0$.

From the membership function of SU signal, we get $(0.72, 0.83, 1.71, 0.134) \leftrightarrow (\{A\}, \{B\}, \{B\}, \{A\})$. Considering the sets of rule $R_0, A \in \{A, B\}, B \in \{A, B\}, B \in \{A, B\}, A \in \{A, B\}$. Therefore, $(0.72, 0.83, 1.71, 0.134)$ belongs to the class $H_0$.

Using the theoretical analysis of [1, 2], we determine the Fuzzy weight factors. From the input of Table 1, the range of $SU_1$ for output $H_0$ is 0.064 to 0.889 and for output $H_1$ is 2.494 to 4.312 as shown in Figure 2(a). For the convenience of analysis, the range of input data can be shown by line diagram as follows.

(a) Range of $SU_1$
(b) Range of $SU_2$
(c) Range of $SU_3$
(d) Range of $SU_4$

Figure 2. Range of input parameters of Table 1
For input parameter of SU₁, the line diagram becomes Figure 2(a). There is no overlapping part; therefore, the entire range S and non-overlapping part, S₀ will be the same. Now, S = (0.064 − 4.312) = S₀ = 4.248; therefore, the ratio becomes, \( V₁ = 4.248/4.248 = 1 \). For SU₂ of Figure 2(b), the sum of non-overlapping part, S₂ = (1.121-0.079) + (3.443-1.688) = 2.797. The entire range is S = (3.443 - 0.079) = 3.364. Then the ratio becomes, \( V₂ = S₂/S₀ = V₂ = 2.797/3.364 = 0.831 \). With similar calculations of Figure 2(c) and Figure 2(d), we get \( V₃ = 3.729/3.887 = 0.96 \) for SU₃, and \( V₄ = 4.208/4.901 = 0.85 \) for SU₄, respectively.

Now, \( V_{max} = Max(V₁, V₂, V₃, V₄) = Max(1, 0.831, 0.96, 0.85) = 1 \). From the theory, we know that, \( W₁ = \left(\frac{V₁}{Max(V₁, V₂, V₃, V₄)}\right)^2 \). Therefore, \( W₁ = (1/1)^2 = 1 \), \( W₂ = (0.831/1)^2 = 0.69 \), \( W₃ = (0.96/1)^2 = 0.92 \), and \( W₄ = (0.85/1)^2 = 0.722 \)

2.1.2. Numerical example-2

We take test data as (SU₁, SU₂, SU₃, SU₄) = {(0.92, 0.51, 1.61, 1.72), 1}. From the membership function of SL,

\[ \Psi₀(SU₁=0.92) = 0.62 \iff B \in \{ A, B \} \text{ i.e., } B \text{ belongs to the first set of } R₀ \]
\[ \Psi₀(SU₂=0.51) = 0.91 \iff A \in \{ A, B \} \text{ i.e., } A \text{ belongs to the second set of } R₀ \]
\[ \Psi₀(SU₃=1.61) = 0.74 \iff B \in \{ A, B \} \text{ i.e., } B \text{ belong to the third set of } R₀ \]
\[ \Psi₀(SU₄=1.72) = 0.78 \iff B \in \{ A, B \} \text{ i.e., } B \text{ belong to the fourth set of } R₀ \]

The weighted co-variance of Fuzzy rule \( R₀ \),

\[ R = \sum_{i=1}^{4} (\Psi₀(X_i)W_i = 1*0.62 + 0.69*0.91 + 0.92*0.74 + 0.722*0.78 = 2.49 \]

\[ \Psi₁(SU₁=0.92) = 0.62 \iff B \notin \{ C, D \} \text{ i.e., } B \text{ does not belong to the first set of } R₁ \]
\[ \Psi₂(SU₂=0.51) = 0.91 \iff A \notin \{ B, C \} \text{ i.e., } A \text{ does not belong to the second set of } R₁ \]
\[ \Psi₃(SU₃=1.61) = 0.74 \iff B \notin \{ B, C, D \} \text{ i.e., } B \text{ belong to the third set of } R₁ \]
\[ \Psi₄(SU₄=1.72) = 0.78 \iff B \notin \{ B, C, D, E \} \text{ i.e., } B \text{ belong to the fourth set of } R₁ \]

The weighted co-variance of Fuzzy rule \( R₁ \),

\[ R = \sum_{i=1}^{4} (\Psi₁(X_i)W_i = 0 + 0 + 0.92*0.74 + 0.722*0.78 = 1.24 \]

The maximum value of \( R \) is found for rule \( R₀ \); therefore, (0.92, 0.51, 1.61, 1.72) supports \( R₀ \) i.e., the testing data is under hypothesis \( H₀ \), which is found to be correct.

2.2. Fuzzy inference system

Fuzzy Inference System (FIS) relates input vectors \( X = [C₀ C₁ C₂ \ldots Cₙ] \), each of size \( k \), to output variable \( Y \) using Fuzzy logic. A FIS consists of three blocks named Fuzzification block, Inference engine and De-fuzzifier block as explained in [18-21] for different applications. In this paper, we use the following steps to relate the signals of SUs at FC with the decision of hypothesis \( H₀ \) or \( H₁ \).

a) Take M samples from the signal \( s(t) \) of each of SUs at FC.

b) Apply recurrent discrete wavelet transform on the sample vector until reducing it to a size of 4 as \( V = [C₀ C₁ C₂ C₃] \)

c) Apply vectors \( V \) to FIS

d) Generate crisp output \( Y \) as 0 or 1 against the hypothesis \( H₀ \) or \( H₁ \)

The result section reveals the signal vector \( V \) and corresponding output \( Y \) in a tabular form.

2.3. Fuzzy c-means clustering

Here, data is separated into several clusters, which may be overlapping or non-overlapping. The distance between the center of a cluster and the point under consideration governs the grade of a MF. The shorter the distance, the higher the grade of a MF. The steps of Fuzzy c-Means Clustering algorithm is available in [22-24]. In this paper, we take the received signal of PUs at FC under three categories: Hypothesis \( H₀ \) (absence of PU), Hypothesis \( H₁ \) (presence of PU) and Hypothesis \( H₀' \) (intermediate result, usually applicable to malicious attack); where SUs are used as the relay stations. Next, we apply Fuzzy c-Means Clustering algorithm to get the scatterplot of data after convergence of three degree of belongings: \( Uₐ(k) \), \( Uₙ(k) \) and \( U₀(k) \) of three hypotheses.

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2.4. Support vector machine

A Support Vector Machine (SVM) is a machine learning model for the classification of response data of a system. The basic concept of SVM is to construct a linear or non-linear hyperplane to separate the data points under different conditions. As an example, let us consider a set of data \( \{x_i, d_i \} \), \( i = 0, 1, 2, \ldots, (N-1) \), and corresponding desired response of a system is, \( d_i \in \{+1, -1\} \), which is represented as the set of ordered pair, \( \{x_i, d_i\}_{i=0}^{N-1} \). The equation of hyperplane, \( \mathbf{w}^T \mathbf{x} + b = 0 \) (where \( \mathbf{x} \) is input vector, \( \mathbf{w} \) is weight vector and \( b \) is a bias) satisfies, \( \mathbf{w}^T \mathbf{x} + b \geq 0 \) for \( d_i = +1 \) and \( \mathbf{w}^T \mathbf{x} + b < 0 \) for \( d_i = -1 \). Higher degree polynomial or even a special function like Gaussian Radial Basis Function is used as a hyperplane to segregate complex data [10-11]. We also consider three types of data under hypothesis \( H_0 \), hypothesis \( H_1 \) and hypothesis \( H_0^\prime \). Here, the input vector is SINR at FC and we determine SINR at receiving end as a random variable using the concept of [25-26].

2.5. Convolutional neural network

A Convolutional Neural Network (CNN) is one kind of Deep Neural Network (DNN) that acquires immense popularity in object recognition. The main functional block of a CNN is convolutional layer in which a Linear Time Invariant (LTI) system is activated as \( y(t) = x(t) * h(t); \) where \( x(t) \) is input signal, \( h(t) \) is impulse response of LTI system and \( y(t) \) is output of the system. If LTI system is a filter, then the convolutional operation provides filtered signal. In CNN, we use the term “convolutional filter” or “kernel” against the impulse response \( h(t) \) and feature map for output signal \( y(t) \).

Each convolutional layer is followed by a pooling layer and we consider an average pooling technique. Next, the Rectified Linear Unit (ReLU) works as an activation function like the threshold of signal. The output of the ReLU is connected to a fully connected NN to produce feature corresponding to hypothesis \( H_0 \) and \( H_1 \) as shown in Figure 3. The received signal at FC from several SUs are converted into an image. The noisy image is applied to CNN to take the decision about the presence or absence of a PU taking the expression as shown in (4) and (8) of SINR of single user and multiuser model of [27-28].

![Convolutional Neural Network Diagram](image)

**Figure 3.** Basic building block of CNN to recognize signal at FC

2.5.1. Simulation algorithm

a) Set the link parameters as mention in result section and \( \varepsilon = 2 \)
b) Assign the transmitted power, \( P = \text{rand}(); \) % average power of 0.5 under \( H_0 \)
c) \( N = 49; \) % size of image is 49×49
   for \( i=1:N \)
   for \( j=1:N \)
   Store SINR for multi user as, \( \text{Gamma}_m(i, j) \) using eq. (8) of [27]
   Store SINR for single user as, \( \text{Gamma}_s(i, j) \) using eq. (4), of [27] as mentioned before
   end
   end

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d) Repeat step c taking \( P = \text{rand()+5} \); % average Power of 5 under \( H_1 \)
e) Repeat step a to d for \( \epsilon = 2.25 \) and 2.5
f) Create image for matrices \( \text{Gamma}_s \) and \( \text{Gamma}_m \)
g) Store 10 images for each category in a folder
h) Apply the image to a CNN taking appropriate parameter of NN.
i) Acquire the features of the image and take decision about hypothesis \( H_0 \) or \( H_1 \)

3. RESULTS AND DISCUSSION

First, we concentrate on the results of Fuzzy weighted rule. However, our prime focus is on the results of four machine learning techniques. Here, we consider four SUs as a relay station under a FC. Only a few received data under hypothesis \( H_0 \) and \( H_1 \) are shown in Table 1. About 100 data sets representing the received signal under a Rayleigh fading channel along with AWGN like [29] are taken for simulation. Working on 12 data sets (each data set contains 100 records like Table 1), we get the outcome of Fuzzy weighted rule for five different experiments on simulated signal as shown in Table 3.

The next part of the experiment deals with FIS. The signal vectors corresponding to section 2.2 are shown in Table 4 for both \( H_0 \) and \( H_1 \) using 16-QAM signal with AWGN and Rayleigh fading of [30] at FC, and simulation is done 500 times for each hypothesis and only 9 of them are shown. The verification of Fuzzy rules is carried out against \( H_0 \) and \( H_1 \) with three numerical values for vector \( V \) as \( V_1 = [1 \ 0.0198 \ 0.0588 \ 0.1806] \) and Output \( \approx 0 \) \((H_0)\); \( V_2 = [1 \ 0.8039 \ 0.6069 \ 0.4168] \) and Output \( \approx 1 \) \((H_1)\); and \( V_3 = [0.6082 \ 0.1989 \ 0.3649] \) and Output \( \approx 0 \) \((H_0)\), respectively.

### Table 3. Signal detection with Fuzzy weighted rule

| Experiment No. | Detection of \( H_0 \) (2 SUs at FC) | Detection of \( H_1 \) (2 SUs at FC) | Detection of \( H_0 \) (4 SUs at FC) | Detection of \( H_1 \) (4 SUs at FC) |
|----------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| 1              | 0.832                               | 0.858                               | 0.873                               | 0.892                               |
| 2              | 0.803                               | 0.869                               | 0.886                               | 0.883                               |
| 3              | 0.838                               | 0.876                               | 0.865                               | 0.874                               |
| 4              | 0.847                               | 0.811                               | 0.869                               | 0.867                               |
| 5              | 0.823                               | 0.832                               | 0.847                               | 0.881                               |

### Table 4. Signal vectors for FIS

| \( c_0 \) | \( c_1 \) | \( c_2 \) | \( c_3 \) | \( H_0 \) | \( c_0 \) | \( c_1 \) | \( c_2 \) | \( c_3 \) | \( H_0 \) |
|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 0.1500   | 0.1445   | 1.0000   | 0.0426   | 1        | 1.0000   | 0.0198   | 0.0588   | 0.1806   | 0        |
| 0.2140   | 0.8811   | 0.6402   | 1.0000   | 1        | 1.0000   | 0.0233   | 0.1348   | 0.1856   | 0        |
| 1.0000   | 0.0148   | 0.2177   | 0.0845   | 1        | 0.9467   | 0.2666   | 0.0756   | 1.0000   | 0        |
| 0.2458   | 0.1493   | 1.0000   | 0.5703   | 1        | 1.0000   | 0.0881   | 0.0381   | 0.4125   | 0        |
| 1.0000   | 0.8039   | 0.6069   | 0.4168   | 1        | 1.0000   | 0.0684   | 0.4053   | 0.1556   | 0        |
| 1.0000   | 0.0571   | 0.2505   | 0.2533   | 1        | 0.6082   | 0.1989   | 1.0000   | 0.3649   | 0        |
| 0.1565   | 0.3330   | 0.4324   | 1.0000   | 1        | 1.0000   | 0.0293   | 0.6662   | 0.0993   | 0        |
| 1.0000   | 0.3667   | 0.1601   | 0.1698   | 1        | 0.9793   | 0.0692   | 0.4300   | 1.0000   | 0        |
| 1.0000   | 0.0111   | 0.3373   | 0.1485   | 1        | 0.6517   | 0.5511   | 0.7855   | 1.0000   | 0        |

Now, the experiment deals with Fuzzy c-Means Clustering (FCMC). The scatterplot of data set of \( H_0 \), \( H_1 \) and \( H_{0^+} \) under FCMC is shown in Figure 4. After 61 iterations, we get three distinct regions on scatterplot; where the function \( U(k) \) takes the numerical values of \( U(56)=594.730209, U(57)=594.730207, U(58)=594.730205, U(59)=594.730204, U(60)=594.730203, U(61)=594.730202 \), which are very close. We run simulation 50 times in Matlab v.18 and get the detection accuracy of 78.246% as the best case and of 73.215% as the worst case. If we use two hypothesis model i.e., excluding the data set of intermediate level \( H_{0^+} \), then we get the detection accuracy of 94.113% as the best case and of 88.512% as the worst case.

Next, we apply SVM on the simulated random data of SINR and the corresponding scatterplot is shown in Figure 5(a) and the region of \( H_0 \), \( H_1 \) and \( H_{0^+} \) is shown in Figure 5(b). The SVM seems to be more successful approach than that of FCMC. The success rate for 200 random data is of 96.234% as the best case and of 92.678% as the worst case.

Finally, we apply CNN on received signal under Rayleigh fading and AWGN channel captured at FC. We consider 16-QAM signal and the duration of six consecutive symbols as time slot. The fading signal of length 4900 (one time slot) is converted to an image of 49x49 using the algorithm of section 2.5.1. The signal of a time slot and the corresponding images are shown in Figure 6(a) and 6(b) under hypothesis \( H_1 \) and \( H_0 \), respectively. We make 100 images for each category, and then apply deep learning algorithm e.g., CNN. Running CNN several times, we measure the accuracy of detection for three cases as shown in Figure 7.

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Figure 4. Scatterplot of Fuzzy c-mean clustering with three distinct region

Figure 5. Scatterplot of two hypothesis model under SVM
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(a) Noisy signal and image under $H_1$
(b) Noisy signal and image under $H_0$

Figure 6. 16-QAM signal and corresponding image at FC

(a) Worst case
(b) Intermediate result
(c) Best case

Figure 7. Accuracy of detection from CNN

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Finally, the outcomes of five different methods are combined together to achieve a decision about the presence or absence of a PU in CRN. To combine five methods, we use the following algorithm based on the idea of [29]:

a) If the accuracy of recognition of ith method (for example SVM) is $a_i$, then the accuracy vector of 5 methods is $V_i = [a_1, a_2, a_3, a_4, a_5]$.

b) Normalize the accuracy vector as, $V_n = [a_1, a_2, a_3, a_4, a_5]/\sum_{i=1}^{5} a_i = [b_1, b_2, b_3, b_4, b_5]$

c) Determine the entropy of elements of $V_n$. $E = \sum_{i=1}^{k} b_i \log \left( \frac{1}{b_i} \right)$, which has the maximum value of 2.3219.

d) If $E > 2.2$ and majority of the methods (3 out of five) has $a_i > 0.75$, we consider the detection is correct.

e) Repeat all steps M time and determine the ratio of correct decision and M, which the accuracy of combined method.

f) The correct decision about $H_0$ and $H_1$ are averaged.

The combined result of above algorithm is shown in Table 5, where we found that the combined method gives a better result than that of any individual classification technique.

| Experiment Number | Weighted Fuzzy System | FIS Fuzzy c-Means Clustering | SVM | CNN | Combined |
|-------------------|-----------------------|-------------------------------|-----|-----|----------|
| 1                 | 0.836                 | 0.873                         | 0.782          | 0.763 0.894 | 0.962    |
| 2                 | 0.811                 | 0.849                         | 0.765          | 0.724 0.873 | 0.958    |
| 3                 | 0.829                 | 0.881                         | 0.791          | 0.783 0.901 | 0.967    |
| 4                 | 0.802                 | 0.847                         | 0.752          | 0.772 0.843 | 0.925    |
| 5                 | 0.866                 | 0.891                         | 0.787          | 0.782 0.913 | 0.971    |

4. CONCLUSION

In this paper, Fuzzy system and four different machine learning techniques are used at FC to detect the presence or absence of a PU. Here, CNN shows the best result among all classification techniques whereas SVM shows the worst. However, the combined method gives the best classification outcome with an accuracy of detection about 96.7%. Still, we have the scope to observe the performance of other machine learning algorithms such as Principal Component Analysis, Linear Discriminant Analysis, Speeded-Up Robust Features, Scale-Invariant Feature Transform, etc. In future, we will include malicious user attack into CRN using three hypothesis model under different machine learning algorithms.

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