

Application of Fuzzy Logic to Cognitive Radio Systems

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SUMMARY This paper reviews applications of fuzzy logic to telecommunications and proposes a novel fuzzy combining scheme for cooperative spectrum sensing in cognitive radio systems. A summary of previous applications of fuzzy logic to telecommunications is given outlining also potential applications of fuzzy logic in future cognitive radio systems. In complex and dynamic operational environments, future cognitive radio systems will need sophisticated decision making and environment awareness techniques that are capable of handling multidimensional, conflicting and usually non-predictable decision making problems where optimal solutions can not be necessarily found. The results indicate that fuzzy logic can be used in cooperative spectrum sensing to provide additional flexibility to existing combining methods.

key words: cognitive radio, cooperative sensing, efficient spectrum use, fuzzy logic, radio resource management, spectrum sensing

1. Introduction

Cognitive radio systems (CRS) are emerging as a new paradigm for more efficient use of radio and network resources. These systems are capable of obtaining information of the underlying radio operational environment and policies, dynamically adjusting their actions accordingly and learning from the results to further improve the performance.

The design of future CRS will face new challenges as compared to traditional cellular systems. The operational environment is heterogeneous consisting of several access technologies with diverse sets of terminals with the common goal of providing high user satisfaction [1]. Moreover, an eclectic array of services will be provided. Distributed network architectures will appear alongside with centralized structures. The conventional network design by considering only one isolated network will no longer be sufficient. Indeed, joint resource management across networks will be required for more efficient use of distributed resources, such as spectrum. The decision making problems in radio resource management of CRS will have more degrees of freedom due to the increased dimensionality and the dynamic operational environment. As a result of the conflicting requirements and restrictions an engineering compromise needs to be sought, particularly for the decision making process. In fact, in the complex environment with compressed time scales, optimal

solutions cannot be found and the design challenge will be to find good enough solutions. Thus in the envisaged scenario for CRS, novel design techniques are needed.

The decision making for resource management in future CRS is heavily based on the knowledge of the operational environment. Environment awareness techniques for collecting information on the current resource use and state of nature will be important. In particular, information on the current spectrum use with e.g. spectrum sensing techniques will be critical for the successful deployment of CRS. Obtaining reliable information in the dynamic and uncertain environment is a true challenge for future CRS.

Fuzzy logic is an attractive technique particularly in cases where target problems are difficult to model with traditional mathematical methods, but are at the same time easier for human people to understand. In industrial control systems, fuzzy logic control has proven useful when linearity and time-invariance of the controlled process cannot be assumed, when the process lacks a well posed mathematical model, or when the human understanding of the process differs from its mathematical model [2]. Fuzzy logic resembles human like thinking being thus efficient for compromise centric decision making, and therefore it is well suited for multidimensional decision making problems. The rule-based decision making achievable by fuzzy logic enables efficient inclusion of incomplete information. The flexibility provided by the decision making architecture has proven to be suitable for dynamic and distributed environment [3]. In addition, it provides savings in computational complexity.

With the characteristics of future CRS in mind, the capabilities of fuzzy logic offer good potential to be applied in CRS as suggested in e.g. [1] and [4] for cross-layer design and reconfiguration, respectively. In this paper, we review applications of fuzzy logic to telecommunications and focus on CRS. While previous work on fuzzy logic for CRS has focused on radio resource management and cross-layer design, in this paper we extend the approach to radio environment recognition techniques. In particular, we propose a novel fuzzy logic-based cooperative spectrum sensing technique where the cooperative decision making process is implemented using fuzzy logic. The proposed fuzzy decision making technique includes traditional combining schemes as special cases and is therefore particularly beneficial in realistic operational environments as it can be flexibly adjusted to the changing conditions.

The remainder of this paper is organized as follows.

Manuscript received June 1, 2009.

Manuscript revised September 3, 2009.

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DOI: 10.1587/transcom.E92.B.3572

Section 2 provides an overview of fuzzy logic and its applications to telecommunications and in particular to CRS. Section 3 describes cooperative spectrum sensing for CRS and proposes a new fuzzy combining for the decision making process. Section 4 presents performance evaluation of the proposed fuzzy decision scheme. Section 5 outlines future research directions for the use of fuzzy logic in CRS. Finally, Sect. 6 draws the conclusions.

2. Overview of Applications of Fuzzy Logic to Telecommunications

Modern telecommunications is more oriented to mathematical knowledge than to any kind of experience or human understanding based knowledge. However, fuzzy logic has been proposed to solve many typical telecommunications problems since the 1990's. Application areas vary greatly from radio interface algorithms to resource management. Here we provide an overview of fuzzy logic and its use in telecommunications including receiver algorithms, radio resource management and cognitive radio systems.

2.1 Introduction to Fuzzy Logic

Fuzzy logic was first introduced by L.A. Zadeh, who studied methods to extend binary logic to cover more general linguistic notation [5]. The research started first with fuzzy mathematics, and first engineering applications were developed later, see for example [6]. In generally, fuzzy logic and fuzzy decision making is divided into three consecutive phases [2]:

1. Fuzzification: The input variables (e.g. measurement results) are fuzzified using predefined membership functions (MBF). Unlike in binary logic where only 0 and 1 are accepted, also numbers between 0 and 1 are used in fuzzy logic. This is accomplished with the MBFs to which the input variables are compared. The output of the fuzzification is a set of fuzzy numbers.
2. Fuzzy reasoning: Fuzzy numbers are fed into a predefined rulebase that presents the relations of the input and output variables with IF-THEN clauses. The output of the fuzzy reasoning is a fuzzy variable that is composed of the outputs of the THEN clauses.
3. Defuzzification: The output of the fuzzy reasoning is changed into a non-fuzzy number that represents the actual output of the system, e.g. control action.

There exist many mathematical methods for the above mentioned phases, but the most used methods fit well for most cases [2]. The advantage of fuzzy logic has been the capability to exploit human knowledge into computer based decision making. Additionally, the computational simplicity of fuzzy logic has been seen as a strength in embedded systems [3].

2.2 Fuzzy Logic in Receiver Algorithms

Fuzzy logic has been applied in receiver algorithms includ-

ing e.g. beamforming, decoding of error-correction codes, channel equalization, channel estimation, interference cancellation, synchronisation, and multiuser detection. For example, in [7] authors show that the implemented fuzzy logic equalizer can reach or even exceed the results of the traditional equalizer. A more recent approach is presented in [8], where fuzzy logic is applied to channel estimation in multiple input multiple output (MIMO) orthogonal frequency division multiplexing (OFDM) system.

In general, the benefit of exploiting fuzzy logic in receiver algorithms is not outperforming conventional schemes but rather achieving similar performance with less computational complexity. This clearly results in power saving, reduced costs and less development work.

2.3 Fuzzy Logic in Radio Resource Management

Fuzzy logic has found many applications in resource management including for instance handoff, call admission control, channel allocation, buffer management, congestion control, routing, scheduling, power control, and radio access technology (RAT) selection. An early review of the applications of fuzzy logic to radio resource management from 1998 is given in [9]. In the following we review some of the applications.

One of the first works using fuzzy logic in telecommunications was the handoff problem in cellular network studied in [10]. The approach to the solution is pattern-recognition type of fuzzy algorithms that are based on training vectors that represent pilot cases for tuning the MBFs. The use of fuzzy logic for vertical handoff with radio and optical wireless systems was studied in [11]. Both networks have good performance under certain conditions, but may lead to poor quality of service (QoS) when used in unclear or dynamically changing conditions. The fuzzy vertical handover algorithm is capable of adapting to network and traffic changes and incorporating the uncertain conflicting metrics to carry out a comprehensive decision with little cost.

An example of managing simultaneously several resources is found in [12], where a neural fuzzy control for radio resource management is presented for hierarchical cellular systems. The main target is to maintain a good QoS by using and controlling several influential radio and network parameters, e.g., handoff failure probabilities, resource availabilities, and data rate. This is done by two-layered decision making architecture where the first layer handles the cell selection, and the second layer performs the call-admission and rate control using a neural network with fuzzy logic control leading to improved channel utilization and reduced handoff rate.

In [13] resource management is extended to multiple networks and neural fuzzy control for joint radio resource management for balancing the traffic over several RATs is presented. In the two-phase decision making system the best cell of each radio network is first chosen, and then the selection between networks is done using criteria such as signal strength, resource availability, and estimated mobile speed.

Fuzzy logic is used for the decision making as it is good at explaining how to reach suitable decisions from inaccurate and distinct information. By means of defining reasonable rules, it is possible to simplify the large state space of solution possibilities existing in a complex problem. Neural networks were used for properly tuning MBFs of the fuzzy system since neural networks are good at recognising patterns using learning procedures. Additionally, the approach made it possible to use other existing heuristic information, such as user and operator policies, as a guideline to the fuzzy decision making. The joint radio resource management with fuzzy neural control [13] was extended to consider both intraoperator and interoperator levels and also economic aspects in [14].

The above examples show the potential of fuzzy logic techniques for resource management in communication systems. In particular, the joint radio resource management over multiple cells and RATs using fuzzy logic and learning capabilities of neural networks are promising building blocks for the future CRS.

2.4 Cognitive Radio Systems

Recently, research on fuzzy logic based CRS has emerged [1], [4], [15]–[19]. In [1] fuzzy logic is proposed for cross-layer optimisation in CRS. The challenges in cross-layer design include modularity, information interpretability, imprecision and uncertainty, complexity and scalability [1]. The goal is to optimize the parameters of different layers by taking into account the different needs of the different services. Since there is no individual solution that can achieve optimal quality for all applications, the CRS should have capabilities to understand the different service requirements and use artificial intelligence techniques to adapt the configuration of the systems in the time-variant operational environment. Fuzzy logic is proposed to be used as a generic knowledge presentation and control implementation base for the cross-layer optimisation in cognitive radios. This is achieved by describing the parameter values of the systems on the different layers as linguistic variables. Link layer information can be determined by measurements while upper layers might need to interpret cross-layer information.

The fuzzy logic cross-layer optimisation techniques [1] can achieve performance improvements and seems to be more modular and reusable than traditional cross-layer solutions. Additionally, the benefit of the technique is technology neutrality that allows independent implementations of the layers as the technology-specific information processing is kept within the layer and information required by other layers is presented using a common representation. Complexity of the approach is lower compared to other cross-layer solutions. However, it requires significant standardization efforts.

In [15] a cooperative spectrum sensing scheme is proposed. The technique takes into account the reliability of the sensing results at different cognitive radio nodes. The final decision on the presence of primary users (PU) is done based

on the combined results from several cognitive radio nodes whose decisions are weighted with the credibility. The credibility of the sensing node is determined in a training stage with fuzzy evaluation. However, the training process is not described well and the actual use of fuzzy techniques remains unclear.

In [16] fuzzy decision making is used for cognitive network access where cognition refers to the detection of the users' needs and the provision of wireless services most adequate to meet the requirements. Fuzzy decision making chooses the most appropriate access opportunity by using cross-layer information, past history, and shared knowledge among different devices through a knowledge base. Fuzzy decision making is used to process cross-layer communication quality metrics and to estimate the expected transport layer performance that is compared to QoS requirements of the application. The results indicate good performance and fairness as well as flexibility.

Early attempts of using fuzzy logic to channel selection in CRS are made in [17] and [18]. In [17] mobile ad hoc networks with cognitive radio capabilities are studied. Channel selection is done using fuzzy logic by taking into account the traffic conditions on the channels. In [18] fuzzy logic is used to select the most suitable secondary user (SU) for accessing the spectrum. The rule based decision scheme takes into account spectrum efficiency, user mobility, and distance to the PU under the constraint of not interfering with the PU. In [19] a fuzzy logic power control scheme is proposed to allow SUs to transmit simultaneously with the PUs on the same band.

In [20] spectrum handoff in CRS is considered where CRS can transmit during PU operation if it does not cause harmful interference to PU. Spectrum handoff denotes the vacation of the spectrum that the SU is using due to harmful interference generated to PU or too low QoS of the SU itself. In the first stage the transmission power of the cognitive radio is determined using fuzzy control based on qualitative estimations of the distance between the SU and the PU. In the second stage the handoff decisions or adjustments to SU's transmission power are made with fuzzy control based on determined transmission power, bit rate of SU and observed transmission power of PU.

In [4] the decision making for terminal reconfigurations for adapting to user needs, system resources and RAT availability is done with fuzzy logic. Fuzzy logic is found to be useful in taking into account multiple contradictory requirements as the reconfiguration decisions are multi-objective optimizations problems.

From the previous work on applications of fuzzy logic to CRS, the benefits of fuzzy logic are its capabilities to provide good results in multidimensional optimization problems with conflicting requirements. Moreover together with other intelligent algorithms, fuzzy logic can be used to provide learning capabilities to improve the performance. However, not much work exists on using fuzzy logic for environment awareness techniques e.g. spectrum sensing.

3. Cooperative Spectrum Sensing

3.1 Spectrum Sensing

Spectrum sensing is a fundamental technique for CRS for identifying spectrum opportunities. The goal in spectrum sensing is the detection of the presence of PUs which is done by simple two-hypothesis testing: signal present or signal absent. The performance of spectrum sensing is typically characterized by the receiver operating characteristics (ROC) that capture the relations of the probability of detection and the probability of false alarm. The probability of detection measures how well the CRS can detect the presence of primary systems. It is thus a critical design parameter as it indicates how often the primary system can be susceptible to harmful interference from the CRS if they are deployed on the same spectrum bands. The probability of false alarm describes the chances on which the spectrum sensing unit detects a primary user when none is actually present, thus indicating how efficiently the spectrum opportunities can be perceived.

A fading environment significantly influences the performance of spectrum sensing as the propagation path between the primary user and the cognitive radio node might experience the fluctuations of the channel during the sensing process. To guarantee high enough probability of detection acceptable to the primary users, cooperation between cognitive radio nodes can be exploited as indicated in [21].

3.2 Combining Rules

In cooperative spectrum sensing the decisions on the presence of the primary user are based on observation results from several cognitive radio nodes. The final decision making process can be classified into data fusion and decision fusion [22]. In data fusion the measurements from the nodes are collected by a fusion centre and the final decision is made based on the combined measurements. The observed information is combined following a given rule, e.g., equal gain, signal-to-noise ratio (SNR) based weighting, etc. Data fusion is often also called soft combining. Reporting of the measurement results from several nodes to a fusion centre requires considerable signaling as well as efficient quantization.

In decision fusion the individual nodes report their decisions to a fusion centre that combines the decisions with some rule (e.g., AND, OR or majority combining). The reporting of only the decisions instead of the individual measurements requires less signaling. The general combining rule for cooperative spectrum sensing is “ m out of N rule” that can be presented as [22]

$$D = \sum_{n=1}^N D_n \begin{cases} \geq m : \text{signal present} \\ < m : \text{signal absent} \end{cases} \quad (1)$$

where D_n is the decision of the n th cooperative cognitive

radio node (i.e., 1 or 0 denoting signal present or absent), N is the total number of the cooperative nodes, and m is the number of users that is set as the threshold. OR, AND and majority combining rules are obtained from (1) by setting $m = 1$, $m = N$, or $m = \lceil N/2 \rceil$ corresponding to the cases that PU is declared present if one node, all nodes, or most of the nodes detect the PU.

The above mentioned decision fusion scheme uses one bit hard decisions. To improve the overall performance, quantized soft decisions using more bits to represent the decision of each cooperative node can be used. By using more than one bit it is possible to give an indication on the reliability of the observation. In [23] two-bit quantized soft decisions are formed by using three thresholds instead of one. The decisions are combined by summing up the individual two-bit decisions obtained using Welch's periodogram and comparing them to a threshold that corresponds to majority combining. The results of the two bit quantized decisions are compared to AND, OR and majority rules as well as to a non-quantized case. The results indicate that the performance is improved by the two-bit decisions in additive white Gaussian noise (AWGN) channel and that the performance with two-bit quantized decisions is comparable to non-quantized soft decisions.

Two-bit quantized soft decisions are also investigated in [24] and the performance is compared to non-quantized soft combining and hard decision combining using OR rule. The paper investigates the performance in a Rayleigh fading channel using traditional energy detectors. The results are given both as probability of detection and SNR wall reduction. SNR wall refers to an SNR threshold below which the energy detection is impossible. The results in [24] indicate that almost all the achievable benefit from soft decision combining can be obtained by using just two bits which was also described in [23]. In [25] energy detection is used and the information between cooperative users is sent using one bit. However, the reliability of the information is indicated so that only the users that evaluate their information to be reliable report their decisions.

3.3 Cooperative Fuzzy Combining Scheme

To test the feasibility of fuzzy logic for the mathematical cooperative spectrum sensing combining schemes given in (1), we constructed a simple fuzzy decision making algorithm for decision fusion for the simple case of three cooperative cognitive radio nodes. The fuzzy combining scheme is constructed using basic methods in fuzzy reasoning and defuzzification. The proposed scheme takes as an input the decisions from the individual cooperative cognitive radio nodes and produces as an output the combined sensing result, i.e., PU present or absent.

The developed fuzzy system is simple and includes three inputs with three MBFs each and one output with five MBFs. The names of the input MBFs describing the strength of the individual sensing nodes' decisions are *low*, *med* and *high* indicating the likelihood of the presence of

PU signal. The names of the output MBFs describing the strenght of the combined sensing result are *low*, *quite low*, *med*, *quite high*, and *high* indicating the combined likelihood of the presence of PU signal.

The inference method used is the Max-Product and the defuzzification method is the center of area [26]. The input variable MBFs are triangular and the output MBFs are triangles of equal shape and size. Both input and output MBFs are normalized between 0 and 1, corresponding to the sensing decisions that 0 is *signal absent* and 1 *signal present*. Positions of output MBFs are in 0, 0.25, 0.5, 0.75, and 1.0 describing the joint decision. The MBFs are constructed such that they implement the majority combining from (1), i.e. $m = 2$. Alternatively, the MBFs could be selected to implement OR or AND rules. The output from the fuzzy inference system is compared to threshold equal to 0.5 and the PU is declared present if the output is equal to or exceeds the threshold.

The rules are of the form IF X_1 IS A_{1a} AND X_2 IS B_{2a} AND X_3 IS C_{3a} THEN Y_1 IS D_{1y} , where A_{ia} , B_{ia} , C_{ia} and D_{iy} are linguistic labels of variables X_i and Y_i used in the rules respectively. The number of rules is 27. Table 1 presents a part of the rulebase, from which all combinations can be derived due to the symmetry of the rulebase. For example, the rule in the first row in Table 1 denotes that if all three cognitive radio nodes report *low* (i.e. likelihood of PU presence is low), the combined fuzzy decision is *low* and the signal is declared to be absent. The rule in the last row denotes that if one node reports *low* (i.e. likelihood of PU presence is low) and two nodes report *high* (i.e. likelihood of PU presence is high), the combined decision is *quite high* and the signal is declared to be present. The remarkable aspect of fuzzy inference is that several rules can be partially true at the same time because the input variables can partially belong to several input MBFs at the same time. The system output is then a combination of outputs from several rules which allows to take into account the uncertain observations, i.e., signal not clearly absent or present, but gives them only little weight.

Table 1 Rulebase for cooperative fuzzy combining.

<i>Input 1</i>	<i>Input 2</i>	<i>Input 3</i>	<i>Output</i>
low	low	low	low
low	low	med	quite low
low	low	high	quite low
low	med	low	low
low	med	med	quite low
low	med	high	med
low	high	low	quite low
low	high	med	med
low	high	high	quite high

4. Performance Evaluation

4.1 Description of System Model

The performance of the proposed cooperative fuzzy combining scheme is compared with AND, OR, and majority decision rules with simulations in terms of the ROC. In the simulations, complex quadrature phase shift keying (QPSK) signals are transmitted over a 1 MHz channel with symbol rate $R_s = 500$ Ksymbols/s over an AWGN channel or one-tap Rayleigh fading channel with AWGN. The fading is assumed to be slow compared to the observation interval of the sensing method. Thus, the channel is assumed to remain constant during the data block but it varies randomly between consecutive blocks. Spectrum sensing at the individual nodes is done with Welch's periodogram [27], see Fig. 1. For more details on the system model, see [28].

The received signal samples are divided into M segments (here $M = 8$) before the FFT. The segment length is equal to the FFT size (here 1024) which is also the length of the rectangular window. The number of frequency bins averaged around the assumed frequency of the baseband signals L is equal to 1. The block length is 410 symbols and the symbol length T is 20 samples. Thus, 8200 samples are taken from the PU signal. The product of the FFT size and M corresponds to the number of samples used for processing in Welch's periodogram, which is 8192. SNR is defined as $E/N_0 = (A^2T)/(2\sigma^2)$ where E is the symbol energy, N_0 is the noise spectral density, A is the signal amplitude, and the noise variance σ^2 is 0.5.

One cognitive radio node collects the sensing results from the other two cooperative cognitive radio nodes and performs the decision fusion with the fuzzy scheme presented in Sect. 3.3. To quantify all different combinations of the probability of detection and the probability of false alarm, we use several values for the sensing threshold. The performance of the fuzzy decision making scheme is evaluated in AWGN and Rayleigh fading channels with one-bit hard and two-bit quantized soft decisions. Comparisons are made to AND, OR and majority combining rules.

4.2 One-Bit Decisions

First, we study the performance of the proposed cooperative fuzzy combining scheme and the three other combining rules (AND, OR and majority) using one bit hard decisions for the three cooperative cognitive radio nodes. Each node is assumed to have the same SNR, -7 dB in AWGN channel

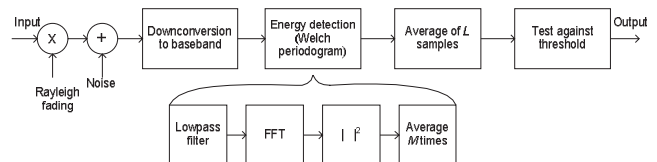


Fig. 1 Welch periodogram.

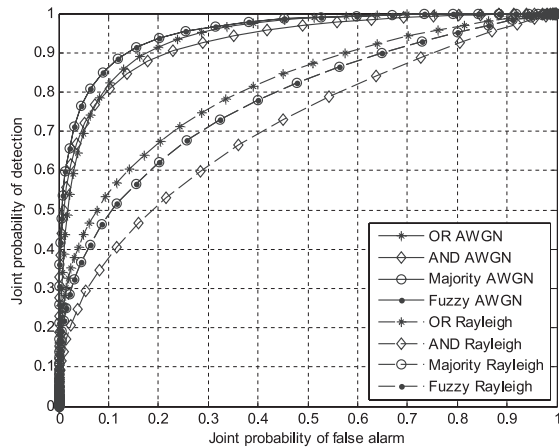


Fig. 2 Performance of one-bit decisions in AWGN and Rayleigh fading.

and -4 dB in Rayleigh fading channel. The sensing results are shown in Fig. 2. The results in AWGN channel are better than in Rayleigh fading channel even that higher SNR values are assumed for the Rayleigh fading channel. From the traditional combining rules, the majority combining is the best in AWGN channel while OR rule is the best in Rayleigh fading channel due to its conservative nature. The cooperative fuzzy combining rule takes the same decisions as the majority combining rule and thus their performances are equal. However, the decision making method is different.

The proposed fuzzy combining scheme acts similarly to the majority rule but alternatively, the fuzzy reasoning system can easily be made to resemble AND or OR rules by either changing the rule base or the positions of the output MBFs. The benefit of the fuzzy reasoning system is flexibility. It can easily be adjusted to fulfil different requirements in different operational environments.

4.3 Two-Bit Quantized Decisions

A more interesting case for fuzzy logic is the use of quantized soft decisions instead of single bit hard decisions. This situation is particularly attractive for fuzzy inference system where several rules are partially true at the same time, and the decision result is influenced by the outcomes of each rule. This takes into account the decisions that are not well described by the hard decisions.

To test the suitability of fuzzy combining with quantized decision, we use two-bit quantization with three thresholds as in [23]. The two outermost thresholds were placed equidistant from the central threshold with a distance of 0.13 in absolute terms in all cases as in [23].

The results of using two-bit quantized decisions with cooperative fuzzy combining rule and majority combining and one-bit decisions with OR and fuzzy rules are shown in Fig. 3. The results of two-bit AND and OR decisions are omitted because the ROC curve representation does not quantify the differences between one bit and two bit cases for AND and OR rules. The same SNRs are assumed as in the one-bit case. The plots from Fig. 3 show that both

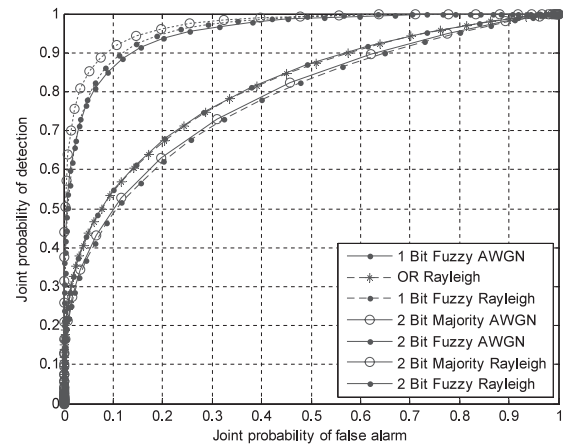


Fig. 3 Performance of two-bit decisions in AWGN and Rayleigh fading.

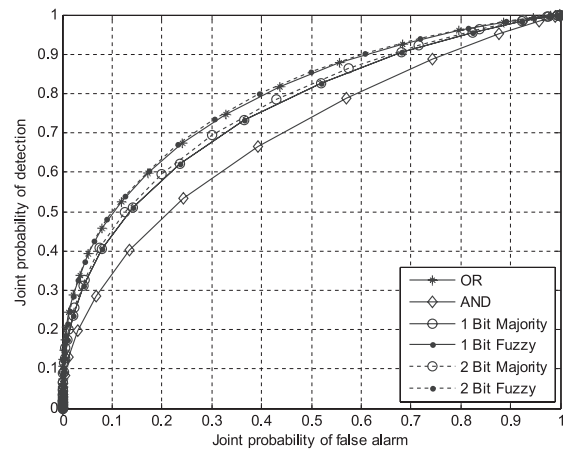


Fig. 4 Performance of two-bit decisions with unequal SNRs in and Rayleigh fading.

two-bit fuzzy and two-bit majority combining schemes improve the performance of spectrum sensing as compared to the one-bit case with the same combining rules. In AWGN channel the two-bit majority combining rule is better than the two-bit fuzzy combining scheme. In the more challenging Rayleigh fading channel the fuzzy combining scheme outperforms the two-bit majority rule. The two-bit fuzzy implementation achieves the same performance as OR rule. The results indicate that fuzzy combining scheme is applicable also in the more realistic channel conditions.

Next we study the performance when the three cooperative cognitive radio nodes have unequal SNR values in Rayleigh fading channel corresponding to more realistic operational environments. Two of the nodes have SNR -5 dB while one node has SNR -7 dB. The results of using unequal SNRs are shown in Fig. 4. The results indicate that cooperative fuzzy combining scheme is even better than the other techniques, including the 1 bit OR rule. It seems that when going to more complex operational environments with e.g. variable SNRs, the benefits of fuzzy logic include not only flexibility but also performance improvements.

5. Discussion and Future Directions

Fuzzy logic has been applied to solve different problems in telecommunications systems. Application areas vary greatly from radio interface algorithms to resource management, and even cross-layer optimization. It seems that telecommunications has been one application area for fuzzy logic, but it has not been any major source of new innovations in the development of fuzzy logic methods.

When analyzing different application areas, we found that in receiver algorithms there often exist an optimal mathematical solution, and there are no needs to find out more accurate or better algorithms. The main purpose has been to implement a fuzzy algorithm that approximate the mathematical solution, and in most cases satisfactory results have been achieved. Benefits of fuzzy logic are found in other aspects, such as requirements of less computational complexity, less development work required, or power saving. On the other hand, new arising requirements caused by CRS affect the requirements of radio interface related algorithms in a new way. In addition, there is not much work done on the more advanced systems exploiting OFDM and MIMO techniques, offering thus great potential for future research on fuzzy logic.

In resource management we found more similarities to knowledge based systems that have been a typical application area for fuzzy logic [3]. In resource management the decision making problems are typically multivariable, where compromises are inevitable. There appear conflicting requirements and the optimal solution does not exist or is very difficult to find. These conditions are very typical to knowledge engineering and to knowledge based fuzzy systems.

Complex operational environments and the characteristics of future CRS give rise to the need for decision making approaches that are capable of handling multifaceted, conflicting, and non-predictable resource management where no optimal solutions exist. The decision making process in future CRS will be based on obtaining knowledge of the radio operational environment which is challenging in the dynamic environment. Fuzzy logic appears to be useful for CRS as it has been applied in similar settings in other fields. One important reason to use fuzzy logic in industrial applications has been the presupposition that the exact optimal solution do not often exist for the problems to be solved due to e.g., the complex nature of the problem. In such cases knowledge-based fuzzy system can produce good enough results, but not optimal. Current trends in telecommunications emphasize more efficient use of resources and environmentally oriented solutions leading to finding computationally less consuming solutions and optimizing resources use.

Future CRS will need to take into account the underlying policies arising from the operational environment, e.g., spectrum regulation. The inclusion of the policies into the decision making process at different levels in the network could be accomplished with fuzzy logic. Learning from the past experience will be an essential part of dynamic network

management in future CRS. Together with other intelligent methods, fuzzy logic can be utilized as a part of learning mechanisms to further improve the system performance.

6. Conclusion

In this paper we have presented an overview of application of fuzzy logic to telecommunications. The characteristics of future cognitive radio systems offer great potential for applying fuzzy logic based techniques. We have proposed a new combining scheme for cooperative spectrum sensing based on fuzzy logic. Fuzzy logic can be used in cooperative spectrum sensing to provide additional flexibility to existing combining methods.

Acknowledgments

This work has been carried out in the framework of the Cognitive and Opportunistic Wireless Communication Networks (COGNAC) project which is partially funded by the Finnish Funding Agency for Technology and Innovation (Tekes) (decision number 40028/08).

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