Chapter 6

Conclusion

This thesis was divided into three main parts. In the first part, a signal classification technique was presented to monitor the transmission activity in TV bands. It has been proven through simulations that the presented approach is able to accurately differentiate between primary and secondary transmission using the fuzzy fusion between the results of the energy detection method and the correlation based method.

The second part of this thesis presents a fuzzy-based handover approach for cognitive radio networks. It consists of an initial setup phase which includes classifying the detected signal (whether primary or secondary signal) using the approach proposed in the first part of the thesis. This step is necessary to avoid unnecessary handover in case of detecting an active Secondary User (SU) where the high transmission priority is given only to Primary Users (PUs). The following phases include: *distance estimation phase*, in which a Fuzzy Inference system (FIS) is deployed taking two inputs, signal strength received from PU and signal-to-noise ratio and resulting in an estimate of the distance between PU and SU. Then, an *interference estimation phase* that applies a path-loss model to estimate the signal power received at the PU from the SU. Finally, the *handover decision phase*, another FIS is implemented that gives a decision of handover only if the interference on the PU's transmission is high or the QoS of SU's transmission is not satisfying. MATLAB simulations prove enhanced performance that outperforms the fixed threshold technique.

In the third part, two channel assignment schemes were proposed and compared for cooperative spectrum sensing in cognitive radio networks. The first approach is a FIS used to distribute the spectrum sensing task over a number of secondary users based on fusion of the sensing error of each node over every channel and the SNR of the reporting subchannel. The second approach applies the Hungarian algorithm in a task-agent assignment problem to assign the sensing task to the sensing nodes at the minimum cost. The cost here depends on the individual probability of sensing error that each node can calculate statistically. Both algorithms aim to assign the best k channels for each node to decrease the global probability of sensing error. MATLAB simulation results have shown that the performance of the proposed algorithms outperform the complete assignment and the random assignment with respect to global probability of error, time delay and overall energy consumption.

Future work can include applying an Adaptive Neuro-Fuzzy Inference System (ANFIS) instead of an FIS in the three applications of signal classification, spectrum handover and sensing task assignment. ANFIS is a kind of artificial neural network that is based on a certain type fuzzy inference systems. In other words, we can say that ANFIS is a fuzzy system that has the structure of a neural network.

The main advantage of ANFIS is that it does not depend on expert knowledge of the system under consideration. It depends on a set of training data. During the training phase, the system is able to put the whole setup of rules and universes of discourse. ANFIS is expected to give more accurate results than FIS provided that a training set of data is available.

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Appendix A

Fuzzy Logic Overview

Introduction:

Fuzzy logic is suitable for the representation of vague data and concepts on an intuitive basis, such as human linguistic description, e.g. the expressions: approximately, large, young. It is capable of expressing knowledge in a linguistic way and allowing a system to be described by simple, human-friendly rules. The purpose of fuzzy logic is to realize sophisticated control systems considering that many times real problems cannot be efficiently expressed by means of mathematical models. When the system under consideration is ruled by multiple variations or uncertainties, a fuzzy logic based model is capable of mitigating the effect of these uncertainties [5].

A fuzzy inference system (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy IF-THEN rules and fuzzy reasoning. It implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy IF-THEN rules, each of which describes the mapping behavior. The design of a fuzzy parameters and IF-THEN rules depends in most cases on expert knowledge of the nature of the system variables.

Why Fuzzy Logic ?

Fuzzy Logic *vs* Crisp Logic

Crisp logic, or *binary valued logic*, depends on the idea that an element either belongs or does not belong to a set. This means that its *membership* to a certain set can take only two values ”1” or ”0” [39]. On the other hand, fuzzy logic is able to imitate the human flexibility of using expressions. It depends on the idea that an element can belong to a certain set to some degree. The membership of an element to a set can take any value from the interval [0, 1].

Using the *crisp logic* method of deciding the nature of activity using thresholds only is not always sufficient due to the lack of flexibility in dealing with variables. This problem is solved in Fuzzy Reasoning. Utilizing an FIS to deal with parameters via a group of IF-THEN rules is flexible and highly accurate. It controls the decision making process and eliminates the problem of rigidity in dealing with values.

Fuzzy Logic *vs* Machine Learning

Machine learning deals with systems that can learn from data, rather than follow only explicitly programmed instructions [40]. The main problem that faces machine learning algorithms is the need to a training phase where the system is not yet ready for use and it is still using a training set of data to be completely constructed. This training phase can, sometimes, be challenging. First, the training phase needs to be repeated periodically to capture environmental changes. This can consume time and reduce the time available for operating. Second, The existence of a training set of data might not always be possible in real time applications.

The main advantage of using fuzzy fusion is the easy implementation. It requires no prior training phase. The system is set once the ranges of possible values of each input and output are determined and divided into subsets called universes of discourse which are mostly overlapping. Each universe of discourse is mapped into a membership function. How universes of discourse are designed and overlapped and the shape of the membership functions are determined in most cases by human knowledge of the nature of the system variables.

Basic Architecture:

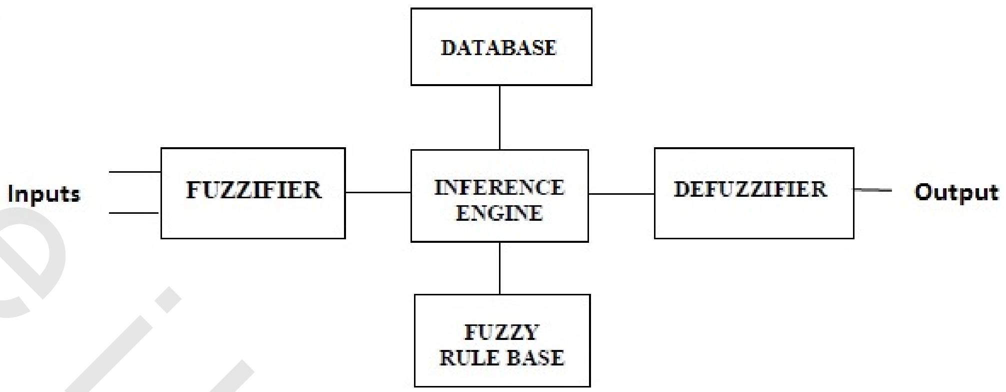

FIGURE A.1: Fuzzy Inference System

As noticed from Fig. A.1, the components of FIS are [5]:

a) **Rule Base**: Rules may be provided by experts or can be extracted from numerical data. In either case, they are a collection of IF-THEN statements. Each rule has a premise (antecedent) and a result (consequent). Each rule can be viewed as a local description of the system under consideration.
e.g. If x is low, then y is $large$.
Where x and y are the linguistic variables under consideration. "Low" and "large" are linguistic values or labels that are characterized by membership functions.

b) **Database**: It defines the membership functions of the fuzzy sets used in the fuzzy rules. Membership functions denote the degree to which a variable belongs to a certain fuzzy set (i.e to which degree a linguistic variable can be described by a certain linguistic value or label). That is, to what degree x is low and to what degree y is $large$. It is common to express degrees of membership in fuzzy sets by numbers on the closed interval [0,1]. The extreme values in this interval, 0 and 1, then represent, respectively, the total denial or affirmation of the membership in the fuzzy set.

c) **Fuzzifier**: It maps crisp numbers into membership functions. This is needed to activate rules.

d) **Inference Engine**: It handles the way in which rules are combined.

e) **Defuzzifier**: It maps output fuzzy sets into crisp numbers. The most popular defuzzification method is the centroid calculation (which is the center of area (COA) under curve).

Main Steps of Fuzzy Reasoning:
The general steps of fuzzy reasoning are:

a) Map the input values to the corresponding membership functions on the premise part. i.e. Singleton Fuzzification.

b) Combine through t-norm operator (multiplication or minimum) the membership values to get what is called the firing strength (activator) of each rule.

c) Generate the consequent of each rule depending on the firing strength.

d) Aggregate the consequent using t-conorm operator (usually maximum) to produce a fuzzy output.

e) Calculate a crisp output using defuzzification method. The defuzzification method used in this work is the COA method.

Fuzzy reasoning steps can be summarized in the following illustrative example [5]:
Assume x and y to be two crisp inputs to the FIS and z is the output. A_i, B_i and C_i are

linguistic variables.
Consider the following two IF-THEN rules:
If $x \in A_1$ and $y \in B_1$, Then $z \in C_1$.
If $x \in A_2$ and $y \in B_2$, Then $z \in C_2$.
Fig. A.2 shows the complete operation.

- Each row is the fuzzy set illustration of each rule.

- Fuzzification: Mapping crisp input values to the corresponding membership functions ($A_1(x)$ and $A_2(x)$ for input x and $B_1(y)$ and $B_2(y)$ for input y).

- The output of each row is taken to be the minimum (or product) of the two membership functions (t-norm).

- Using IF-THEN rules to find the membership function of the output ($C\prime_1$ and $C\prime_2$).

- The aggregation process of the two rules is the maximum of the two results (t-conorm).

- The defuzzification process takes place via the COA method (Center of the area $C\prime$).

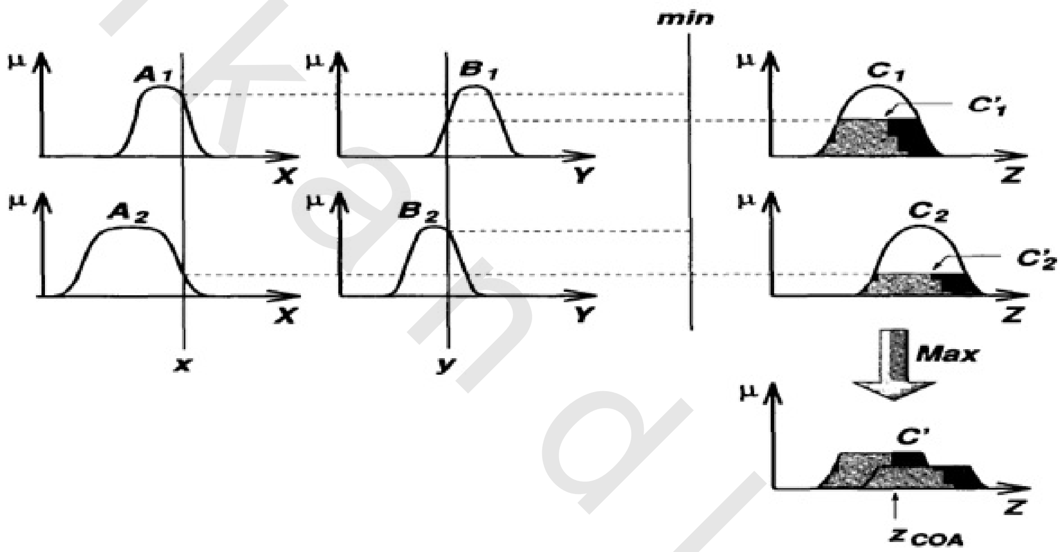

FIGURE A.2: Fuzzy Reasoning Illustrative Example

Appendix B

Derivation of Probability Density Function of Log-Likelihood Ratio

Consider X_i as the received signal at node i. Two hypothesis are possible:

a) No primary user

$$H_o : X_i \sim N(0, \sigma_{0_i}^2) \tag{B.1}$$

b) Active primary user

$$H_1 : X_i \sim N(0, \sigma_{1_i}^2) \tag{B.2}$$

where,

$\sigma_{0_i}^2$ is the noise variance at node i. $\sigma_{1_i}^2$ is the received signal variance at node i and

$$\sigma_{1_i}^2 > \sigma_{0_i}^2 \tag{B.3}$$

The measure on which the Fusion Center (FC) depends to choose the candidate nodes for the sensing process is the individual probability of error of each node. The decision metric of each node is the Log-Likelihood Ratio (LLR) which is the ratio of the probability of the observation given the presence of primary user to that given the absence of primary user.

$$LLR_i = log \frac{Pr(X_i/H_1)}{Pr(X_i/H_o)} \tag{B.4}$$

For each node, error occurs when the LLR is above the sensing threshold while no PU is present (False Alarm) or when the LLR is below the threshold while the PU is active (Misdetection). The individual probability of error at each node is computed as follows:

$$P_{e_i} \; = \; \pi_{o_i} \, P_{FA_i} \; + \; \pi_{1_i} \, P_{MD_i} \tag{B.5}$$

where,

- π_{o_i} is the probability of idle PU.
- π_{1_i} is the probability of active PU ($\pi_{1_i} \; = \; 1 - \pi_{o_i}$).
- π_{o_i} and π_{1_i} are assumed known for each node.
- P_{FA_i} is the probability of false alarm and given by: $P_{FA_i} = Pr(LLR_i \geq t_o | H_o)$.
- P_{MD_i} is the probability of misdetection and given by: $P_{MD_i} = Pr(LLR_i \leq t_o | H_1)$.
- t_o is the decision threshold.

To find P_{e_i} we need to find P_{FA_i} and P_{MD_i} which depend on the probability density function (pdf) of LLR_i.

Proof. Assuming Additive White Gaussian Noisy (AWGN) channel,

$$\begin{aligned} LLR &= log\frac{Pr(x/H_1)}{Pr(x/H_o)} \\ &= log\frac{\frac{1}{\sqrt{2\pi\sigma_1^2}}exp(-\frac{x^2}{2*\sigma_1^2})}{\frac{1}{\sqrt{2\pi\sigma_1^2}}exp(\frac{-x^2}{2*\sigma_0^2}} \\ &= log\frac{\sigma_0}{\sigma_1} \; + \; [\frac{-x^2}{2\sigma_1^2} + \frac{x^2}{2\sigma_0^2}] \end{aligned} \tag{B.6}$$

Eq. B.6 can be rearranged to become:

$$LLR_i \;=\; log\frac{\sigma_{0_i}}{\sigma_{1_i}} \;+\; \frac{x_i^2}{\sigma_{1_i}^2}[\frac{\sigma_{1_i}^2}{2\sigma_{0_i}^2} - \frac{1}{2}] \tag{B.7}$$

or,

$$LLR_i \;=\; log\frac{\sigma_{0_i}}{\sigma_{1_i}} \;+\; \frac{x_i^2}{\sigma_{0_i}^2}[-\frac{\sigma_{0_i}^2}{2\sigma_{1_i}^2} + \frac{1}{2}] \tag{B.8}$$

Remark:
There is a theorem [41] stating that:

Let $Z \sim N(0,1)$, then $Z^2 \sim {\chi^2}_1$ with 1 degree of freedom.
Similarly, let $Y \sim N(0,\sigma^2)$, the $Y = Z * \sigma$.
Therefore, $(\frac{Y}{\sigma})^2 \sim {\chi^2}_1$ with 1 degree of freedom.

Where ${\chi^2}_k$ is the Chi-squared distribution with k degrees of freedom and given by:

$$f(x) = \begin{cases} \frac{x^{\frac{k}{2}-1}\, e^{\frac{-x}{2}}}{2^{\frac{k}{2}}\, \Gamma\left(\frac{k}{2}\right)} & x \geq 0 \\ 0 & otherwise \end{cases} \tag{B.9}$$

at k=1 and x≥0:

$$f(x) = \frac{x^{\frac{1}{2}-1}\, e^{\frac{-x}{2}}}{2^{\frac{1}{2}}\, \Gamma\left(\frac{1}{2}\right)} \tag{B.10}$$

$$\begin{aligned} \because\; \Gamma\left(\frac{1}{2}\right) \;&=\; \sqrt{\pi} \\ \therefore\; f(x) \;&=\; \frac{1}{\sqrt{2\pi x e^x}} \end{aligned} \tag{B.11}$$

Now,

Assuming active primary user (H_1)
i.e.

$$X_i \sim N(0, \sigma_{1_i}^2) \tag{B.12}$$

Then, we can use eq. B.7 as a representation of LLR and $\frac{x_i^2}{\sigma_{1_i}^2}$ is a Chi-squared distributed random variable with k=1.

Assuming idle primary user (H_o)
i.e.

$$X_i \sim N(0, \sigma_{0_i}^2) \tag{B.13}$$

Then, we can use eq. B.8 as a representation of LLR and $\frac{x_i^2}{\sigma_{0_i}^2}$ is a Chi-squared distributed random variable with k=1.

Using the chi-squared pdf, we can obtain the pdf of LLR_i:

1. Put the LLR equation on the form $Y = a + bX$.
   Where, Y is the LLR, $a = log\frac{\sigma_0}{\sigma_1}$, $b = \frac{\sigma_1^2}{2\sigma_0^2} - \frac{1}{2}$ in case of H_1 and $b = -\frac{\sigma_o^2}{2\sigma_1^2} + \frac{1}{2}$ in case of H_o and X is the Chi-squared distributed Random Variable.

2. Let the last equation $Y = a + bX$ be called g(x). g(x) results in a new random variable Y that represents the LLR value. To find the distribution of Y we need to apply *Random Variable Transformation* [42].
   This can be applied using the following equation:

   $$f_Y(y) = f_X\{g^{-1}(y)\}|g^{-1'}(y)| \tag{B.14}$$

   which represents the pdf of the LLR.

3. To apply this equation, we need:

- $g^{-1}(y)$, which is $X = \frac{1}{b}\ (Y - a)$.
- $|g^{-1'}(y)|\ =\ |\frac{1}{b}|$.
- $f_X\{g^{-1}(y)\}$ which is Chi-squared distribution as mentioned before.

4.

$$\begin{aligned} f_X\{g^{-1}(y)\} &= \frac{1}{\sqrt{2\ \pi\ g^{-1}(y)\ e^{g^{-1}(y)}}} \\ &= \frac{1}{\sqrt{2\ \pi\ \frac{1}{b}(Y-a)\ e^{\frac{1}{b}(Y-a)}}} \end{aligned} \tag{B.15}$$

$$\therefore f_Y(y_i)\ =\ |\frac{1}{b_i}|\ \frac{1}{\sqrt{2\ \pi\ \frac{1}{b_i}(Y_i-a_i)\ e^{\frac{1}{b_i}(Y_i-a_i)}}} \tag{B.16}$$

Where, Y_i is the LLR_i, $a_i = log\frac{\sigma_{0_i}}{\sigma_{1_i}}$, $b_i = \frac{\sigma_{1_i}^2}{2\sigma_{0_i}^2} - \frac{1}{2}$ in case of H_1 and $b_i = -\frac{\sigma_{0_i}^2}{2\sigma_{1_i}^2} + \frac{1}{2}$ in case of H_o.

□

Appendix B
Publications

Mariam Nabil, Mustafa ElNainay and Mohamed Rizk, ”TV Signal Classification using Fuzzy Inference Fusion”, accepted at ICNC, IEEE, 2015.

ملخص الرسالة

ندرة الطيف الترددي, بسبب التخصيص الثابت لبعض أجزائه إلى تطبيقات معينة مرخصة, تسببت في جذب الإهتمام إل الشبكات الراديوية الإدراكية. الراديو الإدراكي يتم تعريفه على أنه الراديو القادر على الإستفادة من المعلومات المحيطة به وتغيير عوامل ومتغيرات الإرسال بناءً على التفاعل مع البيئة المحيطة, وذلك للوصول إلى الإستغلال الأمثل للطيف الترددي.

الفكرة الرئيسية هي أن الراديو الإدراكي قادرٌ على استشعار الطيف. ولذلك فإنه يسعى إلى وضع اشارته تحت مستوى اشارة المستخدم المرخص, أو تركيب إشارته مع إشارة المستخدم المرخص عن طريق تغيير المعاملات والمتغيرات, أو وضع إشارته في فراغات الطيف الترددي التي لا يستخدمها المستخدم المرخص, وذلك لزيادة كفاءة استخدام الطيف الترددي وتجنب أي تأثير سئ على إرسال هذا المستخدم.

الشبكات الراديوية الإدراكية تسمح للمستخدم الثانوي (الغير المرخص), والذي يطلق عليه أيضا المستخدم الإدراكي, أن يستخدم الأجزاء المرخصة من الطيف بشرط تجنب أي تداخل يؤذي المستخد الأساسي (المرخص).

الأولوية العالية المعطاه للمستخدم الأساسي تحتم على المستخدم الثانوي أن يستشعر الطيف لاكتشاف الفراغات التي يكون فيها المستخد الأساسي خاملاً, وذلك ليستطيع استخدام الطيف بدون التأثير على المستخدم الأساسي. وأيضا, في حالة أن يكون المستخدم الثانوي يضع إشارته تحت مستوى إشارة المستخدم الأساسي, يجب أن يكون هناك طريقة كفء لتسليم الطيف حتى يستطيع المستخدم الثانوي أن يخلي حزام الترددات المستخدم إذا كان التداخل المتسبب فيه يؤثر على الإشارات المرخصة.

الهدف الرئيسي من هذه الرسالة هو تطبيق المنطق الغيمي في عملية استشعار الطيف وتسليم الطيف للإستفادة من مميزات المنطق الغيمي في المرونة وسهولة الإعداد, وذلك لتحسين القدرة في استشعار الطيف وتقليل نسبة تسليم الطيف الغير ضروري بهدف زيادة كفاءة استغلال الطيف الترددي. بالإضافة إلى ذلك, تقدم الرسالة خوارزمية لتوزيع مهمة استشعار الطيف على المستخدمين الثانويين في الشبكة.

تطبيق المنطق الغيمي على استشعار الطيف وتسليم الطيف في الشبكات الراديوية الإدراكية

رسالة مقدمة من

مريم محمد نبيل عبد الحليم أبو الوفا

للحصول على درجة

ماجستير العلوم الهندسية

فى الهندسة الكهربية

لجنة المناقشة والحكم على الرسالة	التوقيع
الاستاذ الدكتور / سعيد السيد اسماعيل الخامي	
الاستاذ الدكتور / فتحي مبروك أبو العنين	
الاستاذ الدكتور / محمد حامد نافع	
الاستاذ الدكتور/ محمد رزق محمد رزق	

وكيل الكلية للدراسات العليا والبحوث
كلية الهندسة – جامعة الاسكندرية

أ.د. هبـه وائـل لهيـطه

لجنة الاشراف

الاستاذ الدكتور / فتحي مبروك أبو العنين

الاستاذ الدكتور / محمد رزق محمد رزق

الدكتور / هانيه حسن فرج

تطبيق المنطق الغيمي على استشعار الطيف وتسليم الطيف في الشبكات الراديوية الإدراكية

رسالة علمية

مقدمة الى قسم الهندسة الكهربية بكلية الهندسة – جامعه الاسكندرية

استيفاء للدراسات المقررة للحصول على درجة

ماجستير العلوم الهندسية

فى

الهندسة الكهربية

مقدمة من

مريم محمد نبيل عبد الحليم أبو الوفا

نوفمبر 2014