FUZZY MODELLING FOR DISCRIMINATION AND MERIT FACTOR OF RADAR SIGNALS FOR RANGE RESOLUTION

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ABSTRACT

The coded waveforms like binary Barker, ternary, quinquenary and Costas find their applications in radar. The best sequences are binary sequences. But binary Barker codes are not known to exist beyond length 13. However, ternary sequences exist with Barker autocorrelation for length beyond 13. Several sieves are available for generating larger length binary, ternary sequences, viz., skew symmetry, terminal admissibility and so on. Evolutionary algorithm plays an important role for generating good offspring at larger lengths. In this paper, we proposed fuzzy modeling approach for the offspring obtained by evolutionary algorithm.

Key words: **Mamdani Fuzzy Model, Sugeno Fuzzy models, Tsukamoto Fuzzy Model, Discrimination and Merit factor**

1. INTRODUCTION

For range resolution radar, a coded waveform or a sequence of the form

$$X = x_0, x_1, x_2, ..., x_{N-1} \tag{1}$$

with aperiodic autocorrelation

$$r(k) = \sum_{i=0}^{N-1-k} x_i \, x_{i+k} \quad k = 0,1, 2,\dots, N-1 \tag{2}$$

For a sequence to be good, it should exhibit peaky autocorrelation function that is r(0) to be very large and r(k≠0) to be ideally zero.

In this autocorrelation domain, the goodness of a sequence is judged by the discrimination D and merit factor F. Discrimination D is defined as the ratio of main peak in the autocorrelation to absolute maximum amplitude among side lobes, Moharir [1]. That is

$$D = \frac{r(0)}{\underset{k \neq 0}{\mathrm{Max}} |r(k)|} \tag{3}$$

Merit factor F is defined as the ratio of energy in the main peak of the autocorrelation to the energy in the side lobes, Golay [2]. That is

$$F = \frac{r^2(0)}{2 \sum_{k=1}^{N-1} r^2(k)} \tag{4}$$

For the above equation, the factor 2 appears in the denominator as the autocorrelation is an even function. D and F should be as large as possible for sequences to be good.

Fuzzy logic has been applied successfully in hundreds of application domains including VLSI design, mobile robot navigation image processing, high energy physics , medicinal chemistry, robot manipulators, optimization of machining processes, control of permanent-magnet synchronous motors, electric power systems, and power converters [3].

Good research work on fuzzy concepts has been reported by Dash [4, 5]. A new fuzzy concept for post detection signal integration is also reported [6]. Using evolutionary algorithm some good sequences have been reported [7].

Every classical set is having a crisp boundary. Even though classical sets are suitable for various applications like mathematics and computer science, they do not reflect the nature of human concepts and thoughts.

A fuzzy set, as name implies, is a set without a crisp boundary. That is, the transition is gradual and this smooth transition is characterized by membership functions. The fuzzy inference system or fuzzy model is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning.

The basic structure of a fuzzy inference system consists of three conceptual components which are rule base, database and reasoning mechanism. A rule base, which contains a selection of fuzzy rules and a data base, which defines the membership functions used in the fuzzy rules.

A reasoning mechanism, which performs the fuzzy reasoning based on the rules and given facts to derive a reasonable output or conclusion.
Although, there are several fuzzy models available, we have considered three types of fuzzy models which have been widely used in various applications. These are Mamdani fuzzy model, Sugeno fuzzy model and Tsukamoto fuzzy model.

2. TYPES OF FUZZY INFERENCE SYSTEMS

2.1. Mamdani Fuzzy Models:

Initially Mamdani fuzzy inference system [8] was proposed by Mamdani to control a steam engine and boiler combination by a set of linguistic control rules obtained from experienced human operators.

Mamdani used two fuzzy inference systems as two controllers to generate the heat input to the boiler and throttle opening of the engine cylinder, respectively, to regulate the steam pressure in the boiler and the speed of the engine. Since the plant takes only crisp values as inputs, a defuzzifier is required to convert a fuzzy set to a crisp value.

A two-rule Mamdani fuzzy inference system derives the overall output z when subjected to two crisp input x and y. An example of a single-output single-input Mamdani fuzzy model with three rules can be expressed as

$$\begin{cases} \text{If X is small then Y is small.} \\ \text{If X is medium then Y is medium.} \\ \text{If X is large then Y is large.} \end{cases}$$

An example of a two-input single-output with four rules can be expressed as

$$\begin{cases} \text{If X is small and Y is small then Z is negative large.} \\ \text{If X is small and Y is large then Z is negative small.} \\ \text{If X is large and Y is small then Z is positive small.} \\ \text{If X is large and Y is large then Z is positive large.} \end{cases}$$

2.2. Sugeno Fuzzy Models:

Sugeno fuzzy model (also known as the TSK fuzzy model) was proposed by Takagi, Sugeno, and Knag [9, 10] in an effort to develop a systematic approach for generating fuzzy rules from a given input-output data set.

A typical fuzzy rule in a Sugeno fuzzy model has the form

If x is A and y is B then z = f (x, y),

where A and B are fuzzy sets in the antecedent, while z = f(x, y) is a crisp function in the consequent.

Generally f(x, y) is a polynomial in the input variables x and y, but it can be any function as long as it can appropriately describe the output of the model within the fuzzy region specified by the antecedent of the rule.

When f (x, y) is a first-order polynomial, the resulting fuzzy inference system is called a **First-order Sugeno fuzzy model,** which was originally proposed in [2,3].

When f is a constant, then it is a **zero-order Sugeno fuzzy model,** which can be viewed either as a special case of the Mamdani fuzzy inference system, in which each rule's consequent is specified by a fuzzy singleton, or a special case of the Tsukamoto fuzzy model, in which each rule's consequent is specified by an MF of a step function centre at the constant.

The output of a zero-order Sugeno model is a smooth function of its input variables as long as the neighboring MFs in the antecedent have enough overlap that determines the smoothness of the resulting input-output behavior.

In other words, the overlap of MFs in the consequent of a Mamdani model does not have a decisive effect on the smoothness.

Unlike the Mamdani fuzzy model, the Sugeno fuzzy model cannot follow the compositional rule of inference strictly in its fuzzy reasoning mechanism. This poses some difficulties when the inputs to a Sugeno fuzzy model are fuzzy.

However, the resulting overall output via either weighted average or weighted sum is always crisp; this is counterintuitive since a fuzzy model should be able to propagate the fuzziness from inputs to outputs in an appropriate manner.

2.3 Tsukamoto Fuzzy Models:

In the Tsukamoto fuzzy models [11], the consequent of each fuzzy if-then rule is represented by a fuzzy set with a monotonical MF.

As a result, the inferred output of each rule is defined as a crisp value induced by the rule's firing strength. The overall output is taken as the weighted average of each rule's output.

Since each rule infers a crisp output, the Tsukamoto fuzzy model aggregate each rule's output by the method of weighted average and thus avoids the time consuming process of defuzzification.

However, the Tsukamoto fuzzy model is not used often since it is not as transparent as either the Mamdani or Sugeno fuzzy models.

3. PROBLEM FORMULATION

Here in this work, discrimination and merit factor are considered as two input parameters for all the fuzzy inference systems.

In Mamdani single-output single-input fuzzy model, by considering discrimination alone is expressed as

If D is small then Y is small.
If D is medium then Y is medium.
If D is large then Y is large.

where Y represents goodness of the sequence. Similarly, the same notation can be applied for merit factor also. In Mamdani two-input single-output with four rules can be expressed as

If D is small and F is small then Z is negative large.
If D is small and F is large then Z is negative small.
If D is large and F is small then Z is positive small.
If D is large and F is large then Z is positive large.

where Z represents the goodness of the sequence. These same notions are applied for the other fuzzy models also.

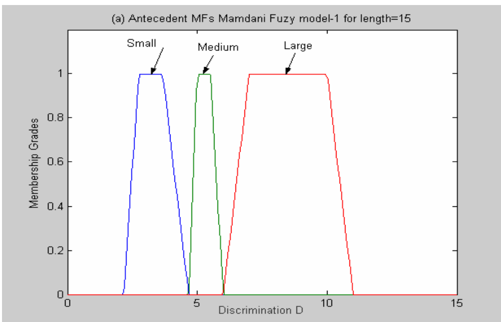

Figure3.1: Antecedent MFs Mamdani fuzzy model- for sequence length=15 and for Discrimination

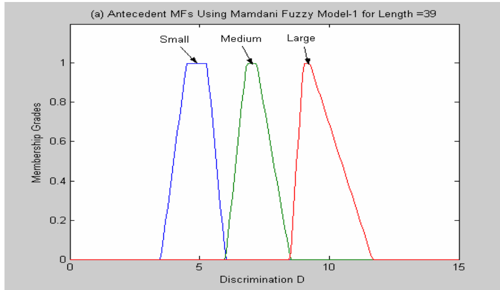

Figure3.2: Antecedent MFs Mamdani fuzzy model-1 for sequence length=15 and for Merit Factor

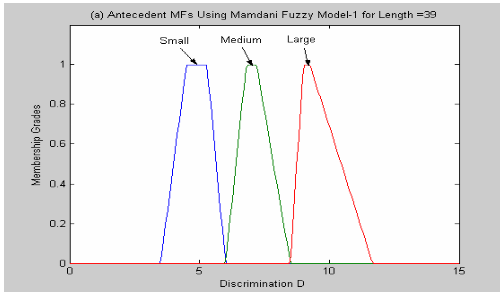

Figure3.3: Antecedent MFs Mamdani fuzzy model-1 for sequence length=39 and for Discrimination

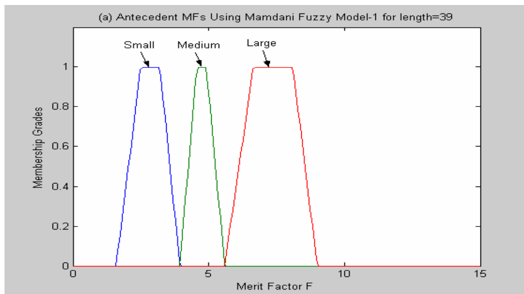

Figure3.4: Antecedent MFs Mamdani fuzzy model-1 for sequence length=39 and for Merit Factor

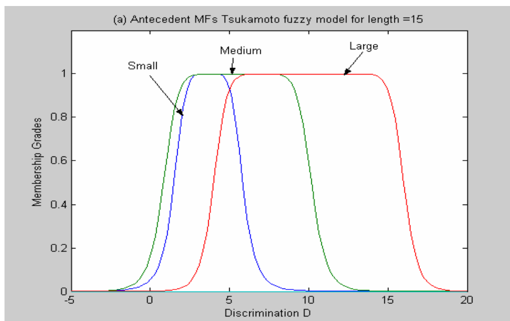

Figure3.5: Antecedent MFs Tsukomoto fuzzy model for sequence length=15 and for Discrimination

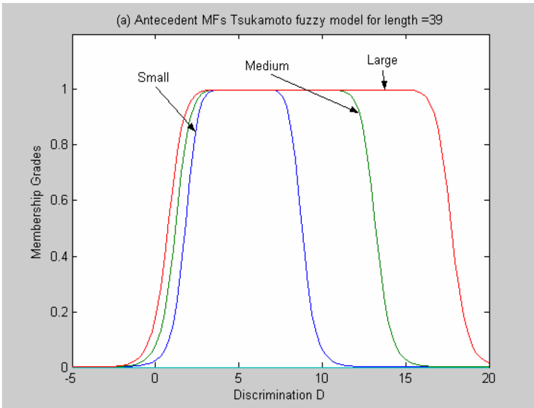

Figure3.6: Antecedent MFs Tsukomoto fuzzy model for sequence length=39 and for Discrimination

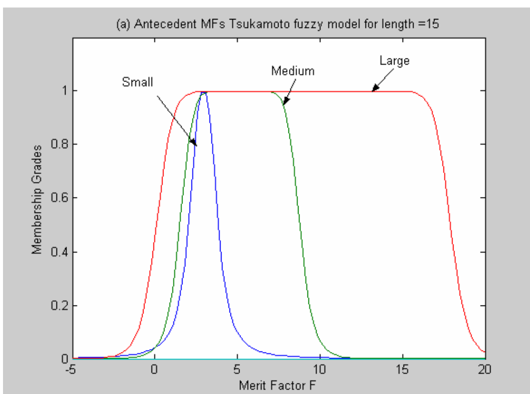

Figure3.7: Antecedent MFs Tsukomoto fuzzy model for sequence length=15 and for Merit Factor

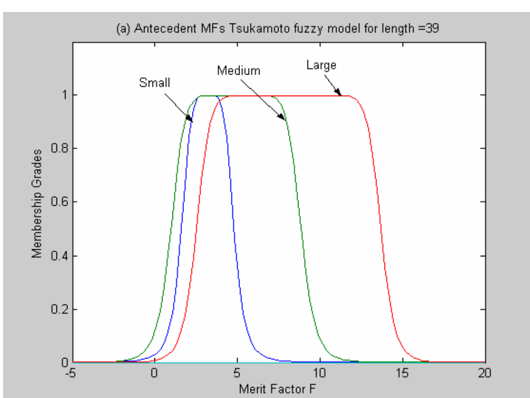

Figure3.8: Antecedent MFs Tsukomoto fuzzy model for sequence length=39 and for Merit Factor

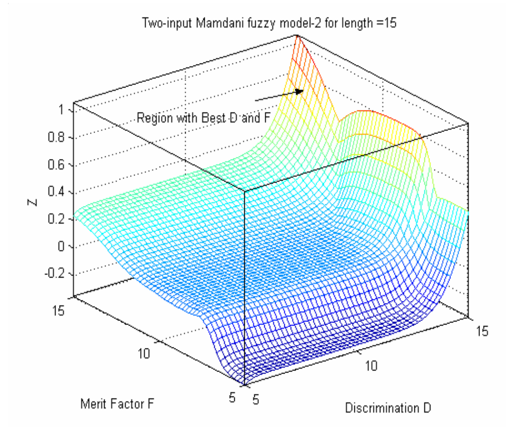

Figure3.9: Two-input Mamdani fuzzy model for sequence length=15 and for Merit Factor and Discrimination

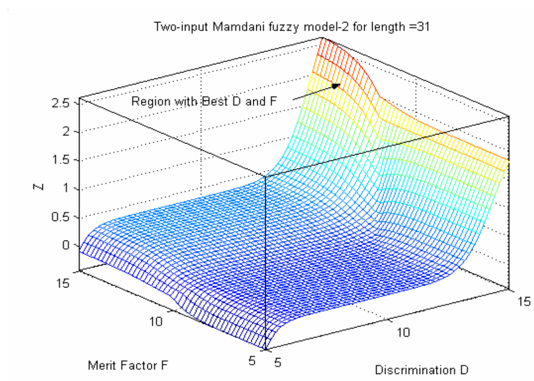

Figure3.10: Two-input Mamdani fuzzy model for sequence length=39 and for Merit Factor and Discrimination

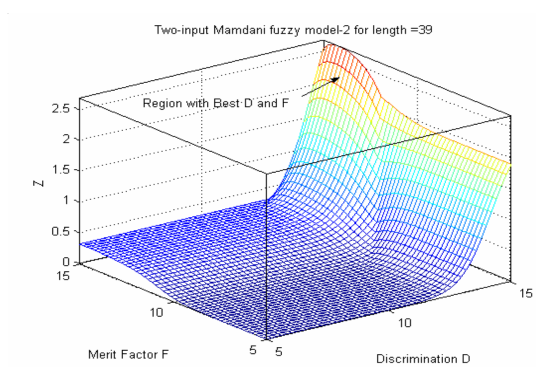

Figure3.11: Two-input Mamdani fuzzy model for sequence length=39 and for Merit Factor and Discrimination

4. Defuzzification

Defuzzification refers to the way a crisp value is extracted from a fuzzy set as a representative value. In general, there are five methods for defuzzifying a fuzzy set A of a universe of discourse Z, as shown in fig. 4.1. A brief explanation of each defuzzification strategy follows. Defuzzification of the discrimination and merit factor values was carried out for various lengths of sequences and the values have been tabulated in table 4.1 and table 4.2

4.1. Centroid of area z_{COA}:

$$z_{COA} = \frac{\int_z \mu_A(z)\, z\, dz}{\int_z \mu_A(z)\, dz}$$

Where $\mu_A(z)$ is the aggregated output MF. This is most widely adopted strategy.

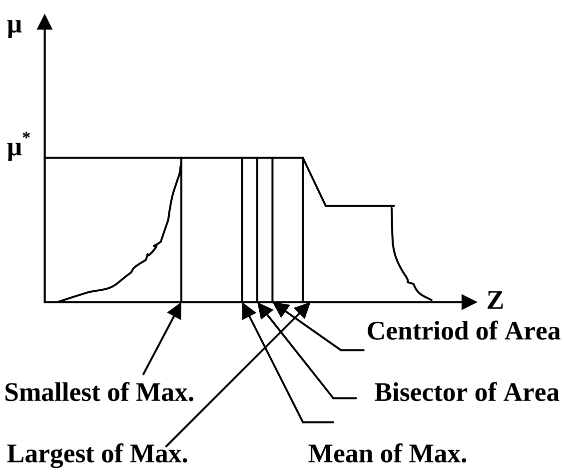

Fig. 4.1 Various defuzzication schemes for obtaining a crisp output

4.2 Bisector of area z_{BOA}: z_{BOA} satisfies

$$\int_{\alpha}^{z_{BOA}} \mu_A(z)dz = \int_{z_{BOA}}^{\beta} \mu_A(z)dz$$

where $\alpha = \min\{z/z \in Z\}$ and $\beta = \max\{z/z \in Z\}$

4.3 Maen of Maximum z_{MOM} : z_{MOM} is the average of the maximumizing z at which the MF reach a maximum μ^* in symbols

$$z_{MOM} = \frac{\int_{z^1} z\, dz}{\int_{z^1} dz}$$

4.4. Smallest of Maximum z_{SOM}: z_{SOM} is the maximum (in terms of magnitude) of the maximizing z

4.5 Largest of Maximum z_{LOM} : z_{LOM} is the maximum (in terms of magnitude) of the maximizing z.

Table 4.1 Defuzzication values for Discrimination for different lengths

Defuzzication method	Length 15	Length 31	Length 39
Centroid	7.6550	8.3410	8.0600
Bisector	7.7000	8.3000	8.1000
Mean of maximum	7.7500	7.9500	8.0000
Smallest of maximum	5.5000	6.3000	6.8000
Largest of maximum	10	9.6000	9.2000

Table 4.2 Defuzzication values for Merit factor fordifferent lengths

Defuzzication method	Length 15	Length 31	Length 39
Centroid	7.3197	6.2248	6.3326
Bisector	7.3000	6.2000	6.4000
Mean of maximum	7.1000	6.3500	6.8500
Smallest of maximum	5.2000	5.2000	5.6000
Largest of maximum	9	7.5000	8.1000

5. OBSERVATIONS FROM THE PLOTS

Sequences generated as offspring by using Evolutionary Algorithm have been fuzzified using different fuzzy models.

As discrimination and merit factor are the sieves for goodness of the sequence, these two parameters have been fuzzified for sequence lengths 15, 31 and 39 using Mamdani single input-single out put, Mamdani two input single out put, Tsukamoto single input-single out put fuzzy model, Sugeno single input-single out put and Sugeno two input-single out put fuzzy models.

For the sequence lengths of 15, 31 and 39, we have fuzzified D and F using the above notions and these are plotted in figures 3.1 through 3.11.

From the figures 3.1 and 3.3 and figures 3.2 and 3.4 it is observed that the parameters discrimination 'D' and Merit Factor 'F' have been fuzzified using Mamdani single input- single out put fuzzy model in to three regions 'small', 'medium' and 'large', for sequence lengths =15 and 39 respectively.

The minimum value of discrimination 'D' and Merit Factor 'F' is increasing when the sequence lengths are increasing. And also it is seen that discrimination 'D' has a higher minimum value than Merit Factor 'F'.

From the figures 3.5 and 3.6 and figures 3.7 and 3.8 it is apparent that the parameters discrimination 'D' and merit factor 'F' have been fuzzified using Tsukamoto single input- single out put fuzzy model in to three regions 'small', 'medium' and 'large', for sequence lengths =15 and 39 respectively.

The minimum value of discrimination 'D' and merit factor 'F' is increasing when the sequence lengths are increasing. The significant difference between Mamdani and Tsukamoto is that the regions are overlapping more in Tsukamoto than in Mamdani.

In addition, in Tsukamoto fuzzy model the three regions 'small' , 'medium' and 'large' has been extended to a larger region. And also, it is apparent that the regions of 'small', 'medium' and 'large' have increased when the sequence length is increasing.

The parameters merit Factor 'F', discrimination 'D' have been fuzzified together using Mamdani two input-single out put fuzzy model for sequence lengths =15, 31 and 39 as shown in the figures 3.9, 3.10, and 3.11 respectively.

From the figures it is observed that the region with best discrimination 'D' and merit Factor 'F' is increasing with increase in sequence length.

6. CONCLUSION:

By using these models, we can easily assess the discrimination or merit factor whether it is in the small, medium or large range over the given span. This helps to choose the best radar code readily. From the 3-D plots the best regions for D and F at once can be viewed. Defuzzification values of Discrimination and Merit factor were tabulated for different lengths. From the tables 4.1 and 4.2 it is seen that using centroid and bisector fuzzification methods for Discrimination as well as Merit Factor, very close results are obtained for different lengths 15,31and 39. For our study it is directly useful to judge the performance of the code under radar and sonar scenario.

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