## A Comparison of Mamdani and Sugeno Inference Systems for a Satellite Image Classification

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#### ABSTRACT.

This research provides a comparison between the performances of Sugeno type versus Mamdani-type fuzzy inference systems. The main motivation behind this research was to assess which approach provides the best performance for satellite image classification. The performance of each approach has been evaluated for six bands (from Landsat-5) for West Iraq image classification and compared with traditional method (Maximum likelihood), based on pixel-by-pixel technique. Due to the importance of performance in online systems we compare the Mamdani model, used previously, with a Sugeno formulation using four types of membership function (MF) generation methods. The first method triangular membership function using the mean, minimum and maximum of the histogram attribute values. The second approach generates triangular membership function using the mean and the standard deviation of the histogram attributes values. The third procedure generates Gaussian membership function using the mean and the standard deviation of the histogram attributes values. The results show that the Mamdani models perform better in most of the case under study.

# Keywords: Fuzzy Inference system; classification; Membership function; Remote sensing, West Iraq images.

#### **1. INTRODUCTION.**

Classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification. Although much previous research and some books are specifically concerned with image classification [1,2].

Generally, supervised classification is involving three distinct stages; training, allocation and testing. Whether the goal is to produce a crisp or a fuzzy classification, the assessment of classification performance is a critical step as it allows a degree of confidence to be attached to the classifications for their effective end use. The performance of crisp classifications may be assessed in a number of ways [3].

In this paper the performance of four direct rule generation methods that involve no timeconsuming tuning procedures have been examined. The first method generates triangular membership function using the mean, minimum and maximum of the histogram attribute values. The second method generates triangular membership function using the peak and the standard deviation of attributes values. The third method generates Gaussian membership function using the mean and the standard deviation of the histogram attributes values. In the fourth method, generates Gaussian membership function using the mean and the standard deviation of the histogram attributes values. These methods has been used, previously with Mamadani type [4], and in this paper with we used Takagi type of inference system to generate a single fuzzy if-then rule for each class by specifying the membership function of each fuzzy set using the information about attribute values of training patterns. The performance of each approach is evaluated for West Iraq image classification in compare with traditional method (more specific Maximum likelihood method). That is, the number of fuzzy if-then rules is the same as the number of classes. The main advantage of fuzzy rule-based systems is that they do not require large memory storage, their inference speed is very high and the users can carefully examine each fuzzy if-then rule [5].

The paper is organized as follows. The next section presents the motivation for the comparison of Mamdani versus SUGENO types of inference systems. In section 3 the study area is introduced. In section 4 the results of comparing the performance of the two inference schemes are discussed and finally in section 5 we present the conclusions.

### 2. MOTIVATION FOR COMPARING MAMDANI AND SUGENO FIS.

In terms of inference process there are two main types of Fuzzy Inference Systems (FIS): the Mamdani-type [6] and the SUGENO-type [7].

In terms of use, the Mamdani FIS is more widely used, mostly because it provides reasonable results with a relatively simple structure, and also due to the intuitive and interpretable nature of the rule base [8]. Since the consequents of the rules in a SUGENO FIS are not fuzzy this interpretability is lost; however, since the SUGENO FIS's rules' consequents can have as many parameters per rule as input values, this translates into more degrees of freedom in the design than a Mamdani FIS thus providing the system's designer with more flexibility in the design of the system [9]. However, it should be noted that the Mamdani FIS can be used directly for either MISO systems (multiple input single output) as well as for MIMO systems (multiple input multiple output), while the SUGENO FIS can only be used in MISO systems (we explain below this issue).

In many decision support applications, it is important to guarantee the expressive power, easy formalization and interpretability of Mamdani-type fuzzy inference systems (FIS), while ensuring the computational efficiency and accuracy of Sugeno-type FIS[11]. Hence, The fact that a Mamdani FIS can be seen as a function that maps the system's input space into its output space ensures that there exists a SUGENO FIS that can approximate any given Mamdani FIS with an arbitrary level of precision. It is beyond the scope in this paper to explain in detail the formalisms of this comparison. For a comprehensive comparison and description on several approximate reasoning methods, including Mamdani FISs and Sugeno FISs, see [11].

Summarizing, our main motivations for testing the classification developed with Mamdani FIS and with a Sugeno FIS and to compare the results are:

• The Sugeno FIS is more flexible because it allows more parameters in the output and since the output is a function of the inputs it expresses a more explicit relation among them;

• In computational terms the Sugeno FIS is more effective because the complex defuzzification process of the Mamdani FIS is replaced with a weighted average;

• Because of the structure of the Sugeno FIS rule outputs, it is more adequate for functional analysis than a Mamdani FIS.

From the above, it seems that any Sugeno FIS is always more efficient than a Mamdani FIS and the question to ask is "why wasn't the Space monitoring application developed from scratch with a Sugeno FIS?" There are two important reasons for this:

1. For classification problems, where the rules outputs are usually independent of each other, i.e. MIMO systems, it does not make any sense to aggregate different nature outputs with a weighted average. However, to "select" the output with the best match (max-min inference), as in Mamdani FIS, makes perfect sense. Sugeno FIS is ONLY suitable for MISO problems, i.e. systems with the same output linguistic variable. Of course, any MIMO can always be divided into several MISO's

2. The monitoring tool developed included two MISO FIS (the gyroscopes fault detection and the data quality fault detection) but only the generic system level of the alarms is a MISO system. Hence, we selected the latter to develop all modules with the same type of FIS.

In summary, in this research only the "generic system level alarms" module is considered for the performance comparison.

#### **3. STUDY AREA DATA.**

In our work, satellite images are available in, to the area of west of Iraq (flight path 169 and row 37) comprises seven main classes. These are Water (two elements Deep and Shallow), Urban, Bare and Agricultural (three elements Tree, Crop and Vegetation) [4]. This digitally represented by six bands ( $512 \times 512$ ) pixel (The resolution of TM is  $30 \times 30$  m<sup>2</sup>).

As it was later used for fuzzy logic classification, the selected training area of supervised image classification will be given in brief. Selected land covers are: Shallow Water, Deep Water, tree, urban, vegetable and crop. For these classes, training areas were pointed on the image **Fig.(1)** 

In determination whether the training areas that have been selected are well represented, histogram was used.

#### 4. RULE GENERATION PROCEDURE.

In this section, Takagi fuzzy inference system with a single fuzzy if-then rule generated for each class based on training areas attribute values used in [4] for generating the input membership function is done with four approaches.

Creation of the output membership functions (8 with unknown class) is done as variable for all approaches since this is Takagi fuzzy inference system as shown in **table (1)**.

To compare the performance of the two types of rule base models, we use four kinds of membership function generation, as mentioned in the introduction. Details about each test and discussion of results are presented in the next sub-sections.

Due to paper size limitations only Sugeno of the fuzzified images for each type is shown, since the Mamadni type previously worked are similar.

### 5. RESULT.

In order to compare the two type of Fuzzy logic classification with traditional method (Maximum likelihood) produced by TNTmips 2010 software. These grayscale images are produced in such way that pixels coming from the same band have the same digital numbers in both images: Deep water (1), Shallow water (2), Urban (3), Vegetable (4), Crop (5), Tree(6), Bare (7) and Unknown (8). This is the basis for image comparison (the difference between the images compared). Number of classified pixels (White) and misclassified pixels (black) can be found and the similarity percent is computed in the areas covered as summarized in **fig.(2**), **fig.(3)**, **fig.(4)** and **fig.(5**).

It should be noted, that we slightly modified the original model outputs (they were almost uniform functions) to highlight the comparison between both FIS. Further, we used the centers of gravity of the output membership functions as the Sugeno output parameters. The input variables are identical in both FIS and the difference is in the consequents of the rules as can be observed in **Table(1)**. The min operator is used for the implication in both FIS. For the Mamdani FIS, the aggregation was done using the max operator and for defuzzifier the center of gravity was used. For the Sugeno FIS the aggregation was done with the classical weighted average using singletons output.

As shown in **table (2)**, in band1 the performance of Mamdani FIS is better than Sugenos except in type2. But in band2, band3 and band6 the performance of Mamdani FIS is better than Sugenos (or equal as in type2). In band4, the Mamdani performance better in all types. And finally the performance of Mamdani FIS in band5 is better in type1 and type4 while it's equal in type2 and worse in type3.

At last Mamdani FIS is the best choice for classification purpose and easy to implement as it depends only on the attribute values of the training area with a good performance.

### 6. CONCLUSIONS AND FUTURE WORKS.

In this paper, we examined the performance of two type of Fuzzy logic Inference system: Mamdani and Sugeno for classification purpose of landsat satellite images. This has been done using four types of fuzzy membership function generation methods that could generate fuzzy ifthen rules directly from training data.

It may be noted that a single fuzzy if-then rule for each class is not always sufficient for realworld pattern classification problems. While each approach is very simple and has some drawbacks as discussed above, fuzzy rule-based systems have high classification ability as shown in this paper. The performance of fuzzy rule based systems can be further improved by feature selection and optimizing the rule selection and various rule parameters for future works.

This research showed that for this case study Mamdani FIS does not only works better in case of processing time but also perform better in the other tests, showing that the structure of the Mamdani FIS is more robust in the presence of noisy input data (until a certain point, obviously). Furthermore, when we tested the sensitivity of both FIS systems we observe that the Sugeno FIS is more sensitive in areas where there is significant imprecision in the input representation, i.e. when the fuzzy sets overlap.

In summary, we believe that the Mamdani FIS should be used whenever we have applications with a single output variable (MISO systems). For MIMO systems (usual in classification problems) the Mamdani FIS is maybe more appropriate, i.e. it can deal directly with MIMO, while Sugeno FIS would require dividing the MIMO into as many MISO systems as the number of output variables; often a cumbersome and time consuming task. We are presently studying ways to optimize the fuzzy rules for a MISO Mamdani FIS.

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| Output | Name          |
|--------|---------------|
| 1      | Deep Water    |
| 2      | Shallow Water |
| 3      | Tree          |
| 4      | Vegetable     |
| 5      | Urban         |
| 6      | Crop          |
| 7      | Bare          |
| 8      | Unknown       |

 Table (1): Output Variable.



Figure (1): Training areas.



Figure (2) Sugeno Classification results using type1: triangular (MF) with mean and min&max



Figure (3) TSK Classification results using type2: triangular (MF) with Peak and min. &max



Figure (4) TSK Classification results using type3: Gaussian (MF) with mean and standard deviation



**Figure (5)** TSK Classification results using type4: Gaussian (MF) with peak and standard deviation

| مقارنة انظمة الاستنتاج لطريقتي MAMDANI و SUGENO في تصنيف صور الاقمار الاصطناعية |                                           |
|---------------------------------------------------------------------------------|-------------------------------------------|
| منتصر عبد الواحد سلمان                                                          | نزار عصمت سينو                            |
| قسم نظم المعلومات                                                               | قسم الفيزياء                              |
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#### الخلاصة.

الحافز الرئيسي في هذا البحث هو المقارنة بين اداء نوعي الانظمة الضبابية (SUGENO) مع نوع ( MAMDAMI ) لتحديد ومعرفة النوع الافضل لاستخدامه في تصنيف صور الاقمار الصناعية. ولاهمية اداء الانظمة في التطبيقات المباشرة on-line تم اعتماد النظام الضبابي نوع MAMDAMI المستخدم سابقا لتصنيف صور الاقمار الصناعية للقمر لاندسات on-line (ست اطوال موجية) لمنطقة في غرب العراق كدراسة حالة ومقارنة نتائجه مع صيغة الـ SUGENO المقابلة له ومدى تقارب (ست اطوال موجية) لمنطقة في غرب العراق كدراسة حالة ومقارنة نتائجه مع صيغة الـ MAMDENO المقابلة له ومدى تقارب (ست اطوال موجية) لمنطقة في غرب العراق كدراسة حالة ومقارنة نتائجه مع صيغة الـ SUGENO المقابلة له ومدى تقارب انتائجهما مع نتائج الطريقة التقليدية (Maxinum likelihood) وقد تم استخدام اربعة طرق توليد لدوال الاتنماء المعاني المنات المتلث باستخدام قيمة المعدل والقيم الصغرى والعليا الانتماء المعروي. النوع الثاني الدالة ذات الشكل المتلث باستخدام قيمة المعدل والقيم الصغرى والعليا المدرج التكراري. النوع الثاني الدالة ذات الشكل المتلث باستخدام قيمة المعدل والقيم الصغرى والعليا والانتماء المدرج الثاني الدالة ذات الشكل المتلث باستخدام ويمة المعدل والقيم الصغرى والعليا المدرج التكراري. النوع الثاني الدالة ذات الشكل المتلث باستخدام وهمة المعدل والقيم الصغرى والعليا والانتماء المدرج الثاني الدالة ذات الشكل المتلث باستخدام ويمة المعدل والقيم الصغرى والعليا والانتماء والانوي الثاني الدالة ذات الشكل المتلث باستخدام قيمة المعياري المدرج التكراري. النوع الثالث المدرج التكراري. النوع الثالث المدرج التكراري. النوع الثالث والانتراف المعياري المدرج التكراري. النوع الثالث والانتراف المعياري المدرج التكراري. النوع الثالث والانحراف المعياري المدرج التكراري. النوع الثالث والانحراف المعياري المدرج التكراري. النوع الرامية المدرج المعياري والاخير دالة كاوس باستخدام قيمة القمة والانتراف المعياري المدرج التكراري. النوع الثالية منوع الزاني والانتراف المعياري المدرج التكراري. النوع الانتيام والانتراف والالي والالغمة الضابية نوع والانحراف المعياري المدرج التكراري. النوع الزالي مدرع التكراري. والانتراف المعياري المدرج التكراري. والانتراف المعياري والالني والانتراف الميامي والانتيام والالنماء والانتيا والانتيالانفمة الضابية