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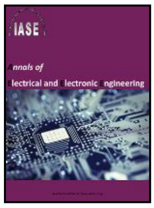

# Cloud identification and classification utilizing a new fuzzy intelligent system

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ABSTRACT

A Fuzzy Inference System with the specialists' knowledge of meteorology is designed in this paper and its aims are detection of the cloud type through extracting knowledge from satellite images of the cloud upper portions. The used data are extracted from the reputable website of UCI called Cloud Data set. This dataset is gathered by Philip Collard in two ranges of IR and VISIBLE. Using the experts' knowledge, this system determines the type of cloud with an accuracy level of 86% and according to experts' opinion; the results are suitable and acceptable.



## 1. Introduction

We know that the cloud is formed as the result of condensed moisture and water particles and is divided into different types according to its height. In this regard, the clouds are classified into three levels: low, middle and high-level clouds. Using satellite images of clouds and extracting their special features like mean, max, min, mean distribution, contrast, entropy, second angular momentum, we can determine some properties of the cloud such as brightness or darkness, etc. Since one of the most important parameters to detect cloud type is its brightness or darkness, the proposed system will have the capability to predict the cloud type. Detecting the cloud type requires specialized knowledge plus necessary sufficient experience and is considered as an important challenge in meteorological systems. The system is designed using the knowledge of experienced experts and can identify the cloud type in minimum time with minimum human costs. Following detection, the duration and amount of rainfall, storm hazards, lightning and so on are determined. Also, the system is fully functional in the places where the climatology staff cannot work due to difficult climatic and geographical situations. It is quite obvious that the results should be reviewed by an expert. As it can be mentioned, unlike the general programs, expert systems seek a reasonable and acceptable answer and not a precise and definitive solution. Table 1 helps to learn more about the cloud types and their properties.

## 2. Lecture review

This database was first gathered by Collard (1989) regarding data collection from satellite images and was loaded on the UCI website. Since then, numerous scientists and researchers developed various systems regarding this database. Various tools of artificial intelligence are used in these systems, such as neural networks, genetic algorithms, swarm intelligence, expert systems, etc.

One of the effective methods in cloud data classification is the CHC method; it is, in fact, the simple genetic algorithm with an adaptive uniform crossover which yields quite satisfactory results (Guerra-Salcedo and Whitley, 1998). Using combining multiple classifiers as a good method for increasing classification accuracy, Bay (1999) worked on cloud data and obtained good results as well. Others used a combination of methods such as bagging, boosting, or error-correcting output coding (Aha and Bankert, 1997) for improving the classifier. Another technique used in the classification of the cloud data is the boost-clustering-algorithm; it is a new, accurate clustering method. One of the classical classification methods is the k-mean with several weaknesses. The K-mean++ method improved it somewhat and is tested on the cloud data yielding satisfactory results (Arthur and Vassilvitskii, 2007).

One of the research studies done in the field of improved clustering procedures is the combined method of AICC and COBWEB. Given the extraction of effective features in the conceptual clustering, this method tries to yield an optimum method, and the results showed the good performance of this approach in the cloud data field (Devaney and Ram, 1997). The boost-clustering algorithm is a multi-clustering method. Toward every boosting repetition, a novel training set is produced by using weighted stochastic sampling from the original dataset and a simple clustering algorithm (e.g. k-means) has been implemented to supply a new data dividing (Frossyniotis et al., 2004).

The use of various Bayesian networks is very common in data estimation. The probability norm minimizing (PNM) method improved the Bayesian method and showed a good performance on cloud data (Pang, 2004). Bocaniala et al. (2005) presented a new method in fuzzy-classification. The main advantage of the mentioned method is its high accuracy gained by learning the topology structure of the problem features space. The proposed method had higher efficiency compared with neural networks. Drobics and Botzheim (2008) presented a new combined method of optimizing the fuzzy sets rules with the evolutionary algorithm of the bacteria. In this method, a large set of fuzzy rules is

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presented first and then, using the bacteria optimization algorithm, the optimal rules are extracted. Based on the results, this method proved efficient regarding the desired data.

**Table 1**
The various types of clouds and their features

| height | VIRGA | Cloud color | Cloud figure | Cloud substance | Cloud type |
|---|---|---|---|---|---|
| 0-1980 | VIRGA | Sometimes transparent or dark | Layers or sheets of clouds | Water drops sometimes snow particles | Stratocumulus (Sc) |
| 0-1980 | -------- | gray | Uniform layers | Small water drops | Stratus (St) |
| 0-1980 | VIRGA | White with dark bottom | Like to broccoli and domed shape | Water drops | Cumulus (Cu) |
| 0-1980 | VIRGA | dark | Very massive and like to anvil | Water drops | Cumulonimbus (Cb) |
| 1980-7000 | VIRGA | Visible shadow | Sequences rooted | Water drops | Altocumulus(ac) |
| 1980-7000 | VIRGA | gloomy | Very squatty | Water drops and ice crystals | Altostratus (As) |
| 1980-7000 | VIRGA | Gray and always dark | Thick, layered and continuous | Water drops | Nimbostratus (NS) |
| 4875-13715 | ----------- | white | Silk-like appearance | Ice crystals | Cirrus (ci) |
| 4875-13715 | VIRGA | white | A broad layer of small waves | Ice crystals | Cirrocumulus(CC) |
| 4875-13715 | ------------- | gloomy | Silk-like appearance | Ice crystals | Cirrostratus (Cs) |

Neural networks are also used in the diagnosis and classification of clouds. For example, a neural network is a new architecture combination used for data learning and testing through the merger of two neural networks. It is able to identify cloud types with an accuracy of 88.91% (Wanas and Kamel, 2001). An expert system using the Mild Cognitive Impairment method was used for the diagnosis of Alzheimer's disease as well as the accuracy of the cloud data classification. It is an inventive method and generally overcomes the following problems: (1) Appraisal missing data in the experiment by utilizing reciprocal data and Newton interpolation. (2) Validate the prior feature ordering in assembling the Bayesian network. (3) Build the Bayesian network (they term the method as MNBN). The mean square error of the system was 0.0173 (Sun et al., 2011). Predicted and examined learning time of classifier algorithms is designed and also various sets of specifications are studied according to their impact on assessing the learning time of the classifier algorithm. The results showed that cloud data are predicted with good accuracy (Reif et al., 2011).

Various researchers used a variety of evolutionary algorithms to determine the type of clouds, which include a nonstandard Crossover as a general model for design problems in specific functions. According to this research, for feature subset selection- a binary string optimization problem, the Common Features / Random Sample Climbing operator is improved. Although this problem is an ideal application of a Genetic algorithm with standard Crossover, it is helpful in finding the subsets' features for learning a clustering problem (Chen et al., 1999). Cloud data are accurately classified with the accuracy of %87.65 using Multi-objective Classification Rule Mining Using Gene Expression Programming (Dehuri and Cho, 2008). A case study on Cirrus cloud type is conducted by Lim et al. (1999) who worked on the data received from the satellite and obtained good results through analysis and extraction of semantic characteristics.

## 3. Methods

### 3.1. Fuzzy inference system

The fuzzy logic first appeared on the field of new calculations after formulating the fuzzy sets by Zadeh (1965). The fuzzy system is an advanced system using a set of rules and functions instead of the Boolean logic for accessing data. In the mid-1980s, the Japanese craftsmen understood the industrial meaning and value of this knowledge and hence, applied the fuzzy systems. Their first project plan was to direct and control the subway of Sendai city in an all-automated way, which was planned and built by Hitachi Co.

The advantages of fuzzy expert systems can be classified as follows:

- Cost reduction: The experience gaining costs by the user is significantly reduced.
- Risk Reduction: Expert systems can be used in environments that may be difficult or hazardous for humans.
- Increased reliability: Expert systems do not get sick or tired, do not strike or plot against their boss; but such situations arise frequently among the experts.

### 3.2. Proposed system

Cloud identification is vital in predicting weather and other atmospheric phenomena. In fact, clouds contain abundant information and one can gain much knowledge of climate change or its occurrence severity by observing them. But defining the type of cloud is a challenging task requiring specialized knowledge. Since these individuals are not always available, the proposed system can be an effective step in addressing this shortcoming. The goal of this system is to identify the various data obtained from a satellite called AVHRR in detecting the types of clouds. According to the available information sources, the proposed system has 7 inputs called mean, max, min, mean distribution, contrast, entropy, second angular momentum and one output called "cloud" which is the cloud brightness; because numerous studies and discussions with experts indicated that one of the simplest ways to identify the clouds is their color. The color of the clouds is a non-expressed language containing information such as humidity, altitude, thickness and even temperature. Considering the clouds' brightness, the proposed system identifies seven different types of clouds in the output.

#### 3.2.1. Fuzzification

***The first input (Mean)***

According to data derived from satellite images, the “mean” input values contain a general knowledge of the available space. In other words, one can estimate the average brightness level of the existing cloud and adopt decisions on that basis. According to Fig. 1, this input is divided into the three membership functions (low, median, and high), and the Eq. 1 shows the fuzzification of this variable.

***The second input (Max)***

According to the cloud data, the fuzzy membership functions of Max are designed as follows. This input is the maximum light intensity in the images. The statistical analyses revealed that the lowest and the highest values in this field were respectively 150 and 255. For this reason, the system fuzzification value is set on this basis (Fig. 2).

$$\left\{\begin{matrix} 0, x \le 80 \\ 1{,}80 \le x \le 110 \\ \dfrac{140-x}{140-110}, 110 \le x \le 140 \\ 0, d \le x \end{matrix}\right\} \quad \left\{\begin{matrix} 0, x \le 115 \\ \dfrac{x-115}{165-115}, 115 \le x \le 165 \\ \dfrac{215-x}{215-165}, 165 \le x \le 215 \\ 0{,}215 \le x \end{matrix}\right\} \quad \left\{\begin{matrix} 0, x \le 185 \\ \dfrac{x-185}{230-185}, 110 \le x \le 140 \\ 1{,}230 \le x \le 255 \\ 0{,}255 \le x \end{matrix}\right\} \tag{1}$$

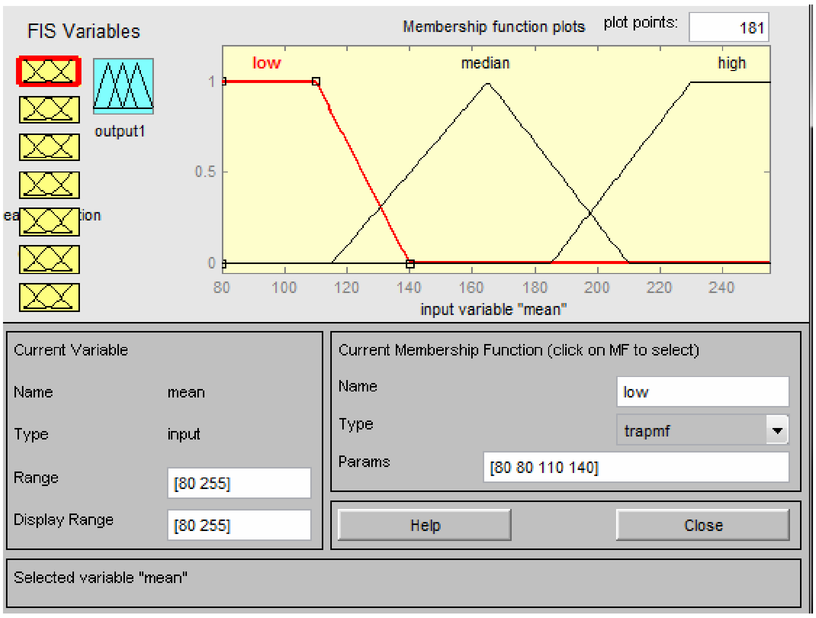


**Fig. 1.** The input fuzzy membership function of a mean variable.

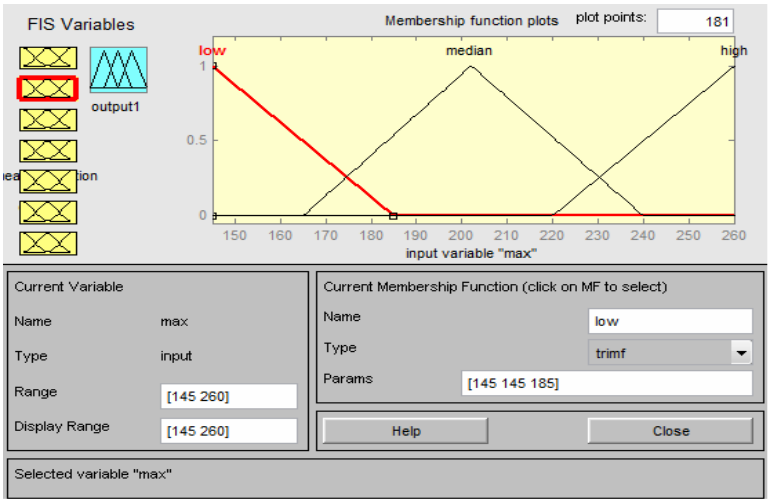


**Fig. 2.** The input fuzzy membership function of a max variable.

For fuzzification of this input, three triangular fuzzy membership functions were used, and the first and last functions were quasi-triangular (Eq. 2).

***The third input (Min)***

This variable refers to the lowest brightness level in the image taken by satellite and can give us good knowledge about the dark clouds. For this reason, this input is fuzzified with higher precision and is mapped onto four fuzzy membership functions. It applied the "low" and "very low" values in the detection of dark clouds and the values of "median" and "high" for detecting the lighter parts (Fig. 3 and Eq. 3).

$$\left\{\begin{matrix} 0, x \le 145 \\ \dfrac{185-x}{185-145}, 145 \le x \le 185 \\ 0{,}185 \le x \end{matrix}\right\} \quad \left\{\begin{matrix} 0, x \le 145 \\ \dfrac{x-165}{202-165}, 165 \le x \le 202 \\ \dfrac{240-x}{240-202}, 202 \le x \le 240 \\ 0{,}240 \le x \end{matrix}\right\} \quad \left\{\begin{matrix} 0, x \le 220 \\ \dfrac{x-220}{260-220}, 220 \le x \le 260 \\ 0{,}260 \le x \end{matrix}\right\} \tag{2}$$

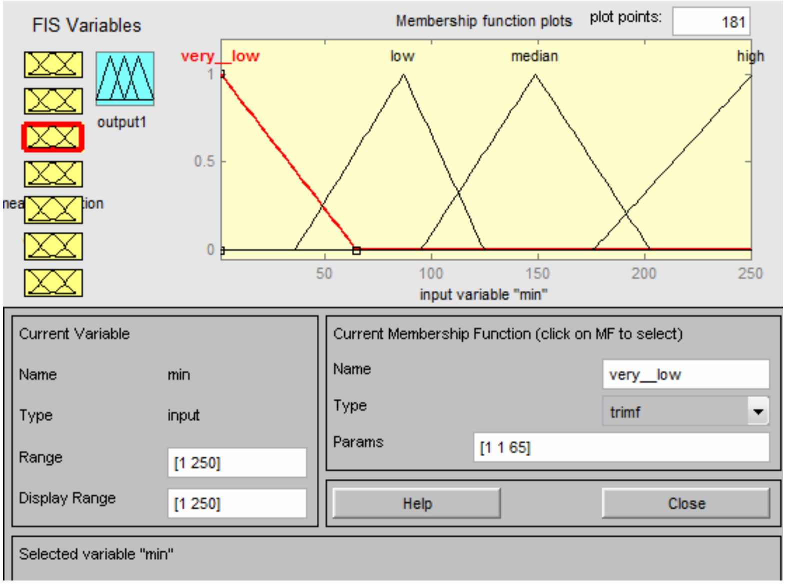


**Fig. 3.** The input fuzzy membership function of min variable.

$$\begin{Bmatrix} 0, x \leq 1 \\ \dfrac{65-x}{65-1}, 1 \leq x \leq 65 \\ 0,65 \leq x \end{Bmatrix} \quad \begin{Bmatrix} 0, x \leq 36 \\ \dfrac{x-36}{87-36}, 36 \leq x \leq 87 \\ \dfrac{125-x}{125-87}, 202 \leq x \leq 125 \\ 0,125 \leq x \end{Bmatrix} \quad \begin{Bmatrix} 0, x \leq 145 \\ \dfrac{x-145}{149-145}, 145 \leq x \leq 149 \\ \dfrac{203-x}{203-149}, 149 \leq x \leq 203 \\ 0,203 \leq x \end{Bmatrix} \quad \begin{Bmatrix} 0, x \leq 175 \\ \dfrac{x-175}{250-175}, 175 \leq x \leq 250 \\ 0,250 \leq x \end{Bmatrix} \tag{3}$$

***The fourth input (Mean distribution)***

Average distribution in cloud dispersion: the more the mean average of cloud dispersion is, the brighter the cloud will be given. The range of integers in this input, *i.e.* 0 to 4.5, the functions placement and their values in this input are as follows: the further we move from 0 to 4.5, the cloud brightness will increase. That is, in the interval of 0 to 1.5, the cloud dispersion is low and hence, the cloud is dark. The range of 1 to 3.5 belongs to the uniform or gray clouds and finally, the range of 3 to 4.5 is dedicated to the light clouds with more dispersion than the gray and dark clouds. Considering the input characteristics, it can be used as one of the most important factors affecting the cloud type prediction. Fig. 4 indicates the quality of fuzzifying this input.

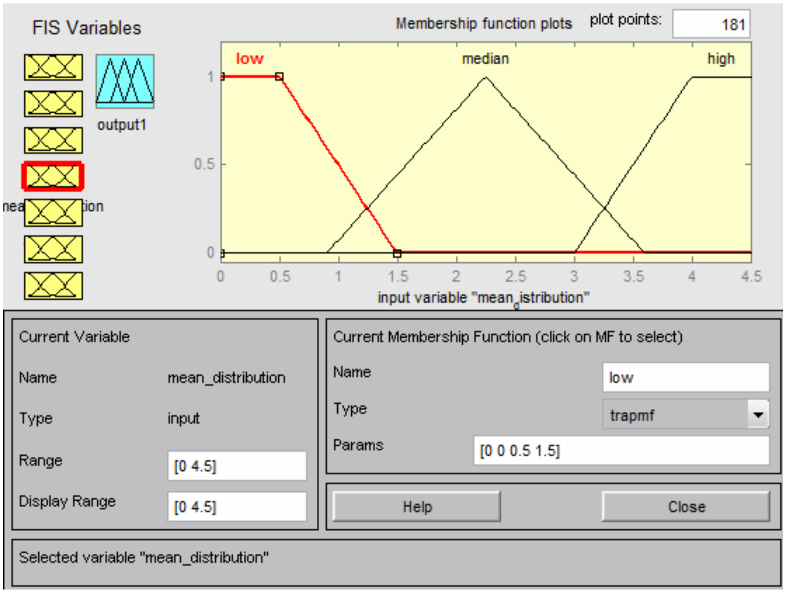


**Fig. 4.** The input fuzzy membership function of the mean distribution variable.

Eq. 4 illustrates the fuzzification of the Mean Distribution variable which are consisted of two trapezoid fuzzy membership functions and one triangular fuzzy membership function (median).

***Fifth input (Contrast)***

This field is the difference between the lowest and highest brightness levels in the image. A high contrast picture is not necessarily a clear image but is a high-quality one, and we use it as an auxiliary field to better identify the cloud type. Fig. 5 and Eq. 5 show the fuzzification steps of contrast variable which are divided four different fuzzy membership functions including very low, low, median, and high.

***The sixth input (Entropy)***

Cloud entropy: Obtaining the amount of could dislocation or disorder with the use of physical laws is called entropy. High entropy indicates a low level of correlation coefficient among pixels. The lower the entropy is, the easier it will be to distinguish the dark or light cloud, and high entropy is probably indicative of gray cloud (Fig. 6). Eq. 6 illustrates the fuzzification of entropy variable which are included of two trapezoid fuzzy membership functions and two triangular fuzzy membership functions (low, median).

$$\begin{Bmatrix} 0, x \leq 0 \\ 1, 0 \leq x \leq 0.5 \\ \frac{1.5-x}{1.5-0.5}, 0.5 \leq x \leq 1.5 \\ 0, 1.5 \leq x \end{Bmatrix}$$
$$\begin{Bmatrix} 0, x \leq 0.9 \\ \frac{x-0.9}{2.25-0.9}, 0.9 \leq x \leq 2.25 \\ \frac{3.6-x}{3.6-2.25}, 2.25 \leq x \leq 3.6 \\ 0, 3.6 \leq x \end{Bmatrix}$$
$$\begin{Bmatrix} 0, x \leq 3 \\ \frac{x-3}{4-3}, 3 \leq x \leq 4 \\ 1, 4 \leq x \leq 4.5 \\ 0, 4.5 \leq x \end{Bmatrix} \quad (4)$$

$$\begin{Bmatrix} 0, x \leq 0.0145 \\ 1, 0.0145 \leq x \leq 0.12 \\ \frac{0.25-x}{0.25-0.12}, 12 \leq x \leq 0.25 \\ 0, 0.25 \leq x \end{Bmatrix}$$
$$\begin{Bmatrix} 0, x \leq 0.15 \\ \frac{x-0.15}{0.32-0.15}, 0.15 \leq x \leq 0.32 \\ \frac{0.5-x}{0.5-0.32}, 0.32 \leq x \leq 0.5 \\ 0, 0.5 \leq x \end{Bmatrix}$$
$$\begin{Bmatrix} 0, x \leq 0.4 \\ \frac{x-0.4}{0.58-0.4}, 0.4 \leq x \leq 0.58 \\ \frac{0.76-x}{0.76-0.58}, 0.58 \leq x \leq 0.76 \\ 0, 0.76 \leq x \end{Bmatrix}$$
$$\begin{Bmatrix} 0, x \leq 0.65 \\ \frac{x-0.65}{0.85-0.65}, 0.65 \leq x \leq 0.85 \\ 1, 0.85 \leq x \leq 1 \\ 0, 1 \leq x \end{Bmatrix} \quad (5)$$

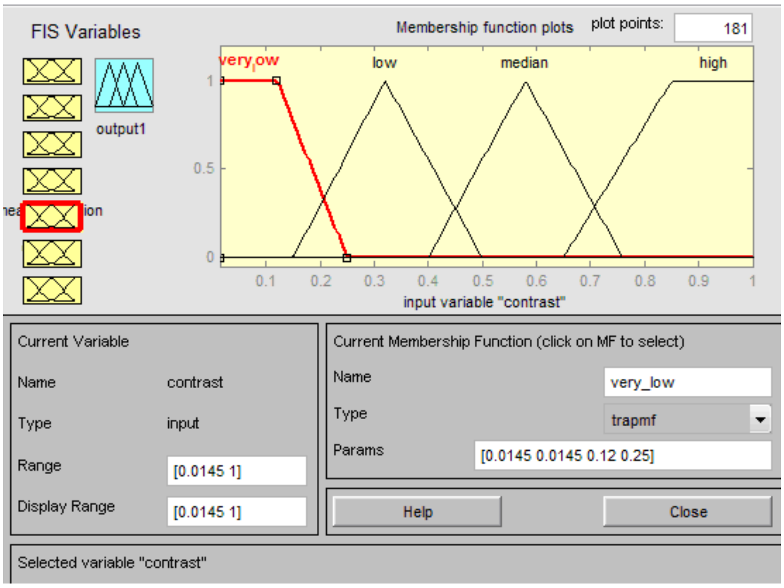


**Fig. 5.** The input fuzzy membership function of the contrast variable.

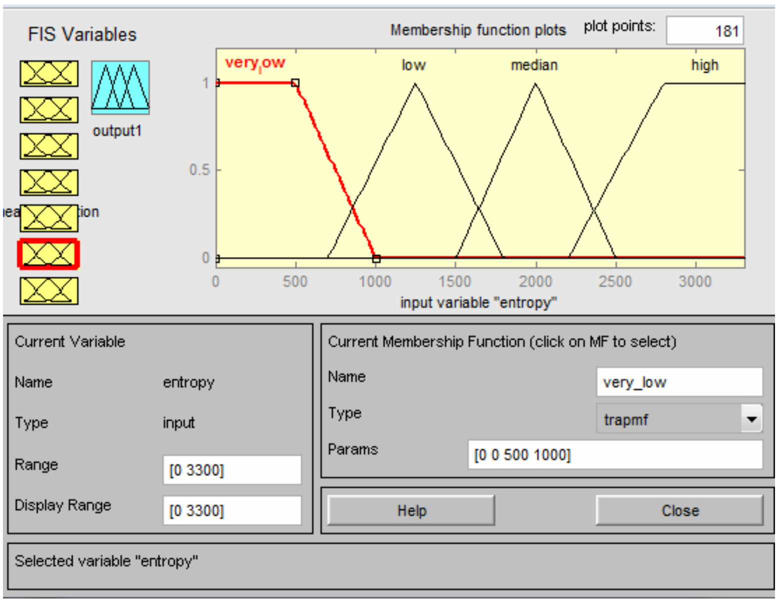


**Fig. 6.** The input fuzzy membership function of entropy variable.

***The seventh input (Second angular momentum)***

The second angular momentum: It is the amount of cloud movement from one angle to the other one. We know that the dark clouds have a lower velocity and displacement; and the greater the angle, the brighter the image. This parameter plays an important role in determining the cloud velocity and so, it can be very helpful in diagnosing the cloud type. The fuzzification levels of the second angular momentum variable are shown in Fig. 7 and Eq. 7.

$$\begin{cases} 0, x \leq 700 \\ \frac{x-700}{1250-700}, 700 \leq x \leq 1250 \\ \frac{1800-x}{1800-1250}, 1250 \leq x \leq 1800 \\ 0, 1800 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 0 \\ 1, 0 \leq x \leq 500 \\ \frac{1000-x}{1000-500}, 500 \leq x \leq 1000 \\ 0, 1000 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 2200 \\ \frac{x-2200}{2800-2200}, 2200 \leq x \leq 2800 \\ 1, 2800 \leq x \leq 3300 \\ 0, 3300 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 1500 \\ \frac{x-1500}{2000-1500}, 1500 \leq x \leq 2000 \\ \frac{2500-x}{2500-2000}, 2000 \leq x \leq 2500 \\ 0, 2500 \leq x \end{cases} \tag{6}$$

$$\begin{cases} 0, x \leq 0.03 \\ \frac{x-0.03}{0.062-0.03}, 0.03 \leq x \leq 0.062 \\ \frac{0.093-x}{0.093-0.062}, 0.062 \leq x \leq 0.093 \\ 0, 0.093 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 0. \\ 1, 0 \leq x \leq 0.021 \\ \frac{0.047-x}{0.047-0.021}, 0.021 \leq x \leq 0.047 \\ 0, 0.047 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 0.072 \\ \frac{x-0.072}{0.11-0.072}, 0.072 \leq x \leq 0.11 \\ \frac{0.143-x}{0.143-0.11}, 0.11 \leq x \leq 0.143 \\ 0, 0.143 \leq x \end{cases}$$

$$\begin{cases} 0, x \leq 0.122 \\ \frac{x-0.122}{0.16-0.122}, 0.122 \leq x \leq 0.16 \\ 1, 0.16 \leq x \leq 0.18 \\ 0, 0.18 \leq x \end{cases} \tag{7}$$

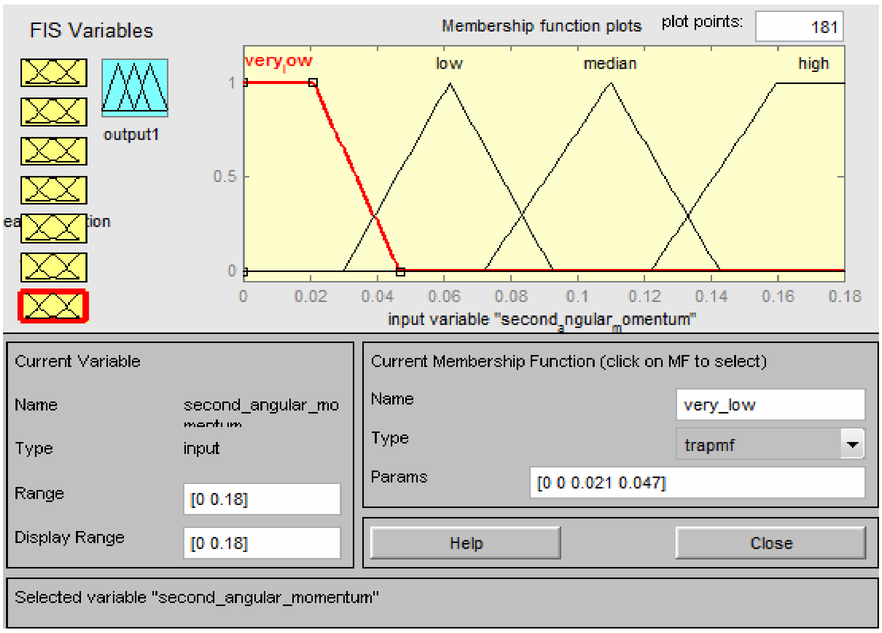


**Fig. 7.** The input fuzzy membership function of the second angular momentum variable.

***The output of the proposed system (Cloud)***

The system output will detect the cloud type after deduction and analysis of the input data. These clouds are sorted on the degree of brightness and are placed in the range of 0 to 250. The system is able to detect seven different types of clouds which are shown clearly in Fig. 8.

### 3.2.2. Fuzzy rules in the proposed system

Fuzzy rules are a set of fuzzy variables interacting with the above operators and form conditions, and the conditions' response leads to some decisions. In a fuzzy rule, only the membership value of the conditions section is attributed to the decision. The proposed system takes advantage of 14 rules for identifying seven different types of clouds, and each rule is set by the 'and' among the input variables. There were 24 rules at the beginning of system design. But after several tests and the experts' supervision, they were again designed and developed until reaching 14 principal rules (Fig. 9). The rules must be carefully designed to eliminate any conflict among them; they should also be independent of each other as far as possible.

Table 2 reviews three instances of rules showing three different types of clouds in the output, *i.e.* light, opaque (gray) and dark.

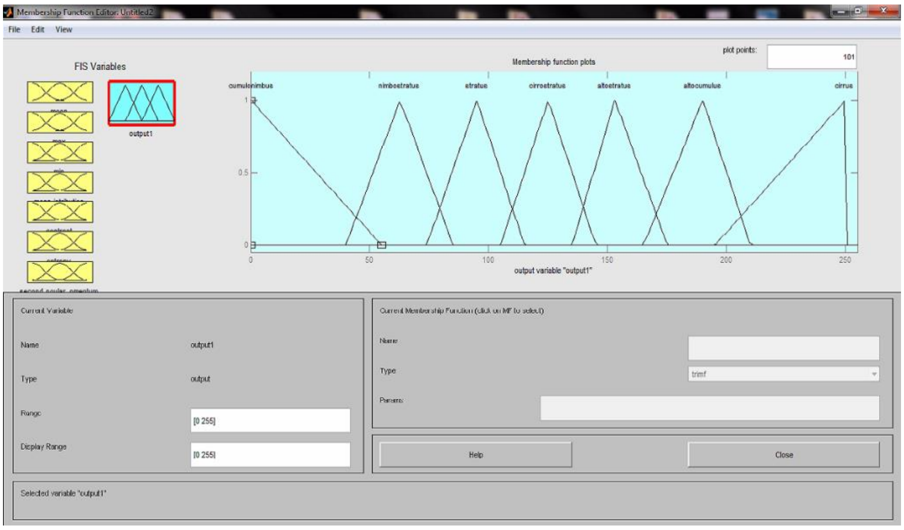


**Fig. 8.** The output fuzzy membership function of second angular momentum.

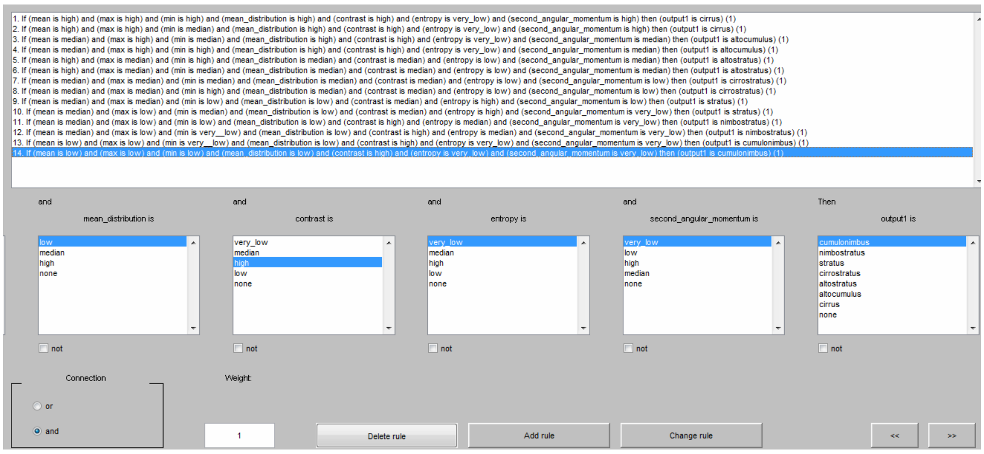

**Fig. 9.** The fuzzy rules of the proposed system.

**Table 2**
The analyzing of fuzzy rules for three different kinds of clouds.

| Second angular momentum | Entropy | Contrast | Mean distribution | Min | Max | Mean | Cloud type |
|---|---|---|---|---|---|---|---|
| high | Very low | High | High | High | High | High | Cirrus |
| low | Low | median | median | High | median | median | Cirrostratus |
| Very low | Very low | High | Low | Very low | Low | Low | Cumulonimbus |

### 3.2.3. Evaluating of the mean distribution

This input shows cloud dispersion. As we know, the brighter clouds have less correlation and more dispersion compared to the darker clouds. In the above example, various values are given to different clouds in the rules as follows:

- The "high" value for the Cirrus bright clouds,
- The "low" value for the Cumulonimbus dark clouds,
- The "median" value for the Cirrostratus opaque clouds.

### 3.2.4. Description of entropy

The membership function for the entropy input is set as follows:

The lower its value is, the better the recognition of cloud brightness or darkness will be. Nevertheless, two values of "very low" and "low" are respectively considered for the two cloud types of Cirrus and Cumulonimbus. The entropy value of the Cirrostratus is "low".

### 3.2.5. Second angular momentum

One way to distinguish the light cloud from a dark one is this input value, *i.e.* the higher its value is, the cloud will be brighter. Hence, the values considered in the rules for the Cirrus, Cirrostratus and Cumulonimbus clouds are respectively high, low and very low.

## 4. Experimental results

Two methods were used for testing the proposed system and determining its accuracy:

First method: The system was evaluated according to the data bank of the cloud and was checked in more than 100 different modes. In this mode, the system accuracy was equal to $88.25 \pm 0.5$ %. In the second method, the system was tested under the supervision of specialists and their selected data, and its degree of accuracy was equal to $82.62 \pm 0.34$ %. In Table 3, some part of the system test results are shown according to the first method, and the correctness or incorrectness is shown by T / F in the last column.

Fig. 10 shows a proposed system test in the case that the system should have detected the Cirrus cloud. As Fig. 10 shows, rule number 1 is fired and shows the output value of 229 which is an authentic expression of the test in question.

One important point about a fuzzy expert system is the semantic relationship among the input data. Data covariance can be of great help in improving the design of an expert system because it helps us remove any heterogeneous data in the design. Fig. 11 shows the relationship between three various inputs, which is shown in 3-D graphics.

**Table 3**
The evaluation of the proposed system.

| mean | max | min | Mean distribution | contrast | entropy | Second angular momentum | True or false |
|---|---|---|---|---|---|---|---|
| 213.3555 | 240 | 163 | 3.8890 | 0.0254 | 862.8417 | 0.0833 | T |
| 186.0195 | 236 | 150 | 3.9318 | 0.0223 | 810.1126 | 0.0884 | T |
| 220.0352 | 240 | 159 | 2.8862 | 0.1251 | 234.3500 | 0.0359 | F |
| 194.8008 | 234 | 152 | 4.0206 | 0.0217 | 1046.5958 | 0.0972 | T |
| 229.9531 | 235 | 193 | 2.5383 | 0.1449 | 107.8208 | 0.0215 | F |
| 210.7266 | 237 | 165 | 3.8960 | 0.0236 | 789.9916 | 0.0864 | T |
| 218.4648 | 234 | 184 | 3.4987 | 0.0377 | 326.4500 | 0.0530 | T |
| 179.5859 | 236 | 152 | 3.9730 | 0.0233 | 950.5250 | 0.0938 | T |
| 172.6563 | 227 | 59 | 3.2430 | 0.0509 | 230.2292 | 0.0398 | F |
| 193.3711 | 236 | 151 | 3.8339 | 0.0255 | 740.1833 | 0.0800 | T |

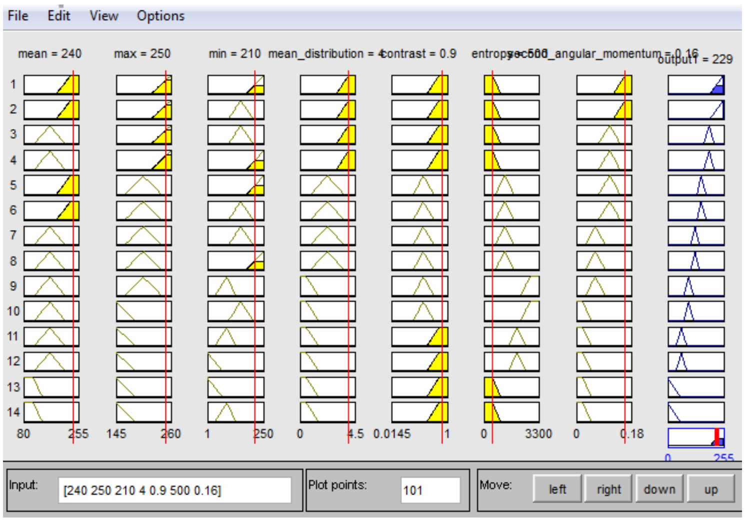

**Fig. 10.** The test sample of the proposed system for the cirrus cloud.

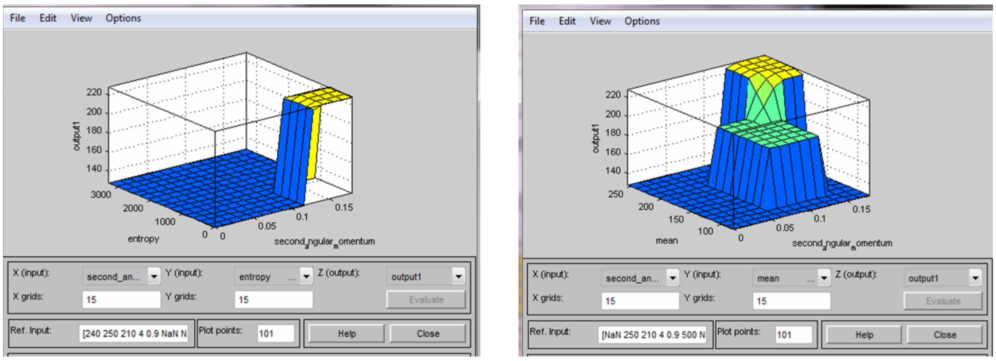
**Fig. 11.** It is divided two parts, the 3D picture on the right shows a correlation between a mean variable and second angular momentum variable and the 3D picture on the left presents a correlation between entropy variable and second angular momentum variable

The following section discusses another sample of system test in Fig. 12. In this test, the data indicate the cloud type of Cumulonimbus which is a relatively dark cloud, and the system managed well to estimate the condition.

**Fig. 12.** The test sample of the proposed system for a stratus cloud.

## 5. Conclusion

It can be seen obviously, that meteorology is tied to the daily life of human societies. Coordinating organizations and individuals with atmospheric phenomena play a strong role in advancing the work and progress of human societies. In this regard, it is important to identify cloud types. We used the data of the visible values in the Cloud Data Set, loaded on the UCI website in 1989 by Philip Collard. This way, we can use satellite imagery to discover cloud types. According to the results, the system predicted cloud types with an accuracy level of $88.25 \pm 0.5$ %. Considering the performed tests, the system authenticity is approved. Fuzzy neural networks are proposed to improve the system performance.

## References


Aha DW, Bankert RL (1997). Cloud classification using error-correcting output codes. Artificial Intelligence Applications: Natural Resources, Agriculture, and Environmental Science, 11: 13-28.

Arthur D and Vassilvitskii S (2007). K-means++: The advantages of careful seeding. In the SODA '07 Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms, Society for Industrial and Applied Mathematics Philadelphia, USA: 1027-1035.

Bay SD (1999). Nearest neighbor classification from multiple feature subsets. Intelligent Data Analysis, 3(3): 191–209. https://doi.org/10.1016/S1088-467X(99)00018-9

Bocaniala CD, Bumbaru S, and Palade V (2005). Experimental validation of a novel fuzzy classifier performance. Studies in Informatics and Control, 14(3): 167-180.

Chen S, Guerra-Salcedo C, and Smith SF (1999). Non-standard crossover for a standard representation commonality-based feature subset selection. In the 1st Annual Conference on Genetic and Evolutionary Computation, Morgan Kaufmann Publishers Inc., Massachusetts, USA: 129-134.

Collard P (1989). Cloud cover database. UCI Repository of Machine Learning Databases, University of California at Irvine, USA. Available online at: https://bit.ly/36ueA9W

Dehuri S and Cho SB (2008). Multi-objective classification rule mining using gene expression programming. In the Third International Conference on Convergence and Hybrid Information Technology, IEEE, Busan, South Korea. https://doi.org/10.1109/ICCIT.2008.27

Devaney M and Ram A (1997). Efficient feature selection in conceptual clustering. Machine Learning: Proceedings of the Fourteenth International Conference, Nashville, USA.

Drobics M and Botzheim J (2008). Optimization of fuzzy rule sets using a bacterial evolutionary algorithm. Mathware and Soft Computing, 15(1): 21-40.

Frossyniotis D, Likas A, and Stafylopatis A (2004). A clustering method based on boosting. Pattern Recognition Letters, 25(6): 641–654. https://doi.org/10.1016/j.patrec.2003.12.018

Guerra-Salcedo C and Whitley D (1998). Genetic Search for feature subset selection: A comparison between CHC and GENESIS. In the Third Annual Genetic Programming Conference, 3-12.

Lim L, Lee DS, Ismail R, Grainger RG, Gierens K, and Ponater M (1999). Comparison of cirrus cloud coverage calculated from reanalysis meteorological data with satellite data. In the TAC-Conference, Oxford, UK.

Pang S (2004). Data approximation for bayesian network modelling. International Journal of Computers, Systems and Signals, 5(2): 53-61.

Reif M, Shafait F, and Dengel A (2011). Prediction of classifier training time including parameter optimization. In the Annual Conference on Artificial Intelligence, Springer, Berlin, Heidelberg, Germany, 7006: 260-271. https://doi.org/10.1007/978-3-642-24455-1_25

Sun Y, Tang Y, Ding S, Lv S, and Cui Y (2011). Diagnose the mild cognitive impairment by constructing Bayesian network with missing data. Expert Systems with Applications 38: 442-449. https://doi.org/10.1016/j.eswa.2010.06.084

Wanas NM and Kamel MS (2001). Decision fusion in neural network ensembles. In the IJCNN'01 International Joint Conference on Neural Networks, IEEE, Washington, USA, 4: 2952-2957. https://doi.org/10.1109/IJCNN.2001.938847

Zadeh LA (1965). Fuzzy sets. Information and control, 8(3): 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X