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RESEARCHING AND DEVELOPING A SPATIAL COMPLEX FUZZY INFERENCE SYSTEM AND APPLICATION FOR NOWCASTING SATELLITE IMAGES

Major: Information Systems

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SUMMARY OF COMPUTER DOCTORAL THESIS

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Introduction

1. Rationale

Changes in the earth's surface occur due to natural disasters, deforestation, changes due to erosion, urbanization, or natural variability such as weather, climate, etc. are issues of particular concern today. Timely and accurate forecasting of changes makes the interaction between nature and humans appropriate, helps manage and use resources better, and helps orient production and business activities more appropriately. [1, 2] .

With the development of remote sensing image systems, remote sensing image change detection has been attracting widespread attention as one of the most critical applications in remote sensing. Remote sensing images have several types, such as Landsat, Sentinel, SPOT, etc. In particular, the Landsat 7 ETM+ image includes eight channels: indigo, green, red, near-infrared, mid-infrared (shortwave), thermal infrared, and panchromatic. SPOT 5 image includes five channels: green, red, near-infrared, mid-infrared (short wave), and panchromatic channel [3].

A short-term forecast of a series of satellite images (Landsat images) is a forecast that uses a finite number of images (from 6 to 10 images) at a previous time as the basis for forecasting a finite number of images at the next time with data including spatial and temporal factors. The spatial-temporal factor is the image of a specified place at different times. [4, 5].

This thesis is focused on the problem of predicting the next change in a sequence of satellite images using spatiotemporal data. In essence, this problem involves predicting the next state of an object or phenomenon by analyzing satellite images of the same location captured at different times, in order to discern patterns of change and make accurate predictions [6, 7].

More specifically, the problem of predicting changes in a sequence of satellite images can be framed as follows: given a set of satellite images captured at different times $T(1), T(2), ..., T(k)$ of the same spatial area, the aim is to predict the image of that spatial area at the next time step $(k + 1)$ based on an analysis of the changes observed in the input sequence.

This thesis adopts a rigorous academic methodology to conduct an in-depth investigation of this problem.

One of the most popular research directions for this problem can be attributed to the use of inference systems such as Mamdani [8–14] or the use of adaptive neuro-fuzzy inference systems [15–19] (ANFIS). ANFIS is a combination of ANN and a traditional fuzzy inference system through the learning mechanism of ANN via IF-THEN rules with defined fuzzy functions. This overcomes the limitations of both methods and has the ability to learn noisy data from this set of IF-THEN rules, as well as the ability to retain information from the neural network. In addition to using neural networks [2, 20–23], many researchers are interested in their ability to maximize data usage, high efficiency, and automatic identification of important input features. In addition to the traditional fuzzy inference system, complex fuzzy inference systems [24–28] have received more attention lately, with their complex value adding additional information to the fuzzy model to determine image features more clearly. In addition to model-related factors, rule systems also play a very important role [29–32]. A good rule system is one that ensures both the quality and quantity of rules, therefore mechanisms for rule generation, rule selection, and appropriate rule reduction are needed [33–35, 35–37]. In addition to rule-related factors and inference systems, high-performing models today often have very large and diverse parameter sets, so selecting a suitable training method [37–40] is also critical. Different methods of adjusting rules will lead to different rule systems, requiring a toolkit to evaluate the effectiveness of these rule systems.

Based on related publications, most proposed methods for predicting changes in satellite image sequences involve combining different approaches from deep learning, supervised and unsupervised learning, and various classification methods during the sample training, difference detection, etc., to obtain the predicted results of the next image. However, there are still some limitations as follows:

- Machine learning methods usually yield good results for small data, but these models often perform poorly for large or incomplete data.

- With deep learning approaches, the models have high accuracy, but they require a large amount of input data and slow processing time, making them unsuitable for short-term forecasting problems.

- Due to the characteristics of short-term satellite image sequence forecasting, which require quick prediction time and contain spatial and temporal elements, the approach of building a complex fuzzy inference system without time may be more suitable, as demonstrated in some studies. However, some new inference methods focus only on the real part and neglect the phase or separate the real and phase parts of the input values, reducing the significance of the fuzzy inference system on complex domains.

These practical issues indicate that researching and developing a Spatial complex fuzzy inference system and applying it to short-term satellite image sequence forecasting is a critical theoretical requirement (such as improving studies on complex fuzzy inference systems without time, determining good parameter sets in models, optimizing rule methods in inference systems) and applying the proposed model to practical prediction processes.

2. Research objectives of the thesis

2.1. General objective of the thesis

The general objective of this thesis is to study the development of Spatial Complex fuzzy inference system and its application in short-term prediction of satellite image sequences. Subsequently, the proposed method will be implemented, compared, and evaluated against other methods using various metrics to demonstrate its effectiveness.

2.2. Specific Objectives

Based on the existing limitations and drawbacks of publications on fuzzy sets, fuzzy inference systems and short-term prediction methods for satellite imagery, as well as the general objective, the thesis focuses on proposing the construction of a complex fuzzy inference system that is spatial and applying it to short-term prediction of satellite imagery with the following specific objectives:

- *Objective 1*: To propose a Spatial complex fuzzy inference system for short-term prediction of satellite imagery.
- *Objective 2*: To propose a method for simultaneous determination of parameters in the spatial complex fuzzy inference system.
- *Objective 3*: To propose a method for optimizing rules in the spatial complex fuzzy inference system.

- *Objective 4*: To propose a model for applying the spatial complex fuzzy inference system to short-term prediction of satellite imagery.

3. Object and Scope of the Thesis

3.1. Object of Study

The object of study in this thesis is the inference systems based on the complex fuzzy sets approach, the methods for simultaneously determining the parameters of complex fuzzy rule systems, and the techniques for enhancing fuzzy rule systems.

3.2. Scope of Study

Based on the research objectives and content, the scope of this thesis is proposed as follows:

- ***Theory:*** Theoretical study on complex fuzzy sets, fuzzy logic inference systems, methods for simultaneously determining the parameters of fuzzy rule systems, and techniques for optimizing rules.
- ***Experiment:*** The thesis focuses on studying and testing short-term prediction problems of remote sensing image sequences with spatial factors.
- ***Data:*** Research conducted on Landsat remote sensing images of the United States Navy and PRISMA data.

4. Methodology and Research Content

4.1. Research Methodology

The research methodology of this thesis includes both theoretical and experimental methods.

4.2. Research Content

With the aforementioned research objectives, the thesis focuses on investigating the following main contents:

- Studying satellite image databases and models/methods for short-term prediction of satellite image sequences.
- Reviewing related publications on fuzzy sets, fuzzy reasoning systems, and their applications in short-term prediction of satellite image sequences. Understanding the advantages and limitations of each method and proposing an improved approach.
- Developing and improving the proposed fuzzy reasoning system with spatial reasoning, developing a spatial rule consistency measure and a method for simultaneous determination of parameters for the spatial fuzzy reasoning system.

5. Contribution of the Thesis

The main contributions of this thesis are as follows, in accordance with the formal style of a doctoral dissertation in the field of Information Technology:

- **Proposal of a spatial complex inference system for short-term prediction of satellite image**.

  The proposed model processes input data to obtain a set of real and phase components (the difference between pixel values of two consecutive images).

  After preprocessing, the input data is clustered using the Fuzzy C-Means algorithm [41].

  Based on the clustering results, complex fuzzy rules are generated in a triangular-shaped space.

  The parameters for the fuzzy inference function are trained using the ADAM algorithm [42] to find suitable values. The resulting complex fuzzy rules in the triangular-shaped space are then defuzzified by the parameters obtained from the training process.

  The predicted results of the real and phase components are further trained using the ADAM algorithm [42] to determine the dependency coefficients for better image synthesis.

- **Proposal of a method for simultaneous determination of parameters in Spatial complex fuzzy inference systems**.

  This thesis extends the spatial complex fuzzy-nonlinear-time inference system for short-term prediction of satellite image sequences introduced in Chapter 2 by adding four sets of parameters to the model.

  A method for simultaneously determining these parameters is proposed using the FWADAM+ algorithm.

- **Proposal of a method for optimizing rules in spatial complex fuzzy inference systems**.

  The thesis introduces an adaptive spatial complex fuzzy inference model based on the complex fuzzy inconsistency measure for detecting changes in Remote Sensing Images (RSI).

  The proposed model generates rules directly from newly acquired images in the test set and compares the resulting complex fuzzy inconsistency measures with those of the old rule set generated by the Spatial CFIS. The system decides whether to add, remove, or aggregate rules based on the comparison results.
  Finally, a new rule set is obtained to adjust and adapt to the new image set, improving both the accuracy and speed of the model.

6. Novelty of the thesis

Compared to the studies on fuzzy reasoning such as Lan et al.'s work on fuzzy inference systems with uncertain premises ([25]), this thesis contributes to the development of complex fuzzy inference systems for spatio-temporal reasoning (Spatial CFIS) and related improvements in simultaneous parameter learning.
In contrast to the classical fuzzy inference systems like Mamdani, Takagi-Sugeno, and Tsukamoto, which are commonly used in research, the thesis provides a complex fuzzy inference system capable of processing data with both spatial and temporal factors, which classical fuzzy inference systems cannot handle.
Moreover, compared to the studies on machine learning and deep learning models, the proposed solutions in this thesis can handle short-term data with high accuracy and require small input data.

7. The layout of thesis

The thesis **"Research and Development of Spatial Complex Fuzzy Inference System for Short-term Prediction of Satellite Image"** consists of an introduction, 4 chapters, a conclusion, and a list of references with the following main contents:

- **Introduction**
- **Chapter 1**: Presents the fundamental knowledge for the research topic.
- **Chapter 2**: Presents the proposal for constructing the spatial complex fuzzy inference system for short-term prediction of satellite image time series (Spatial CFIS), experimental results, and analysis of the proposed model.
- **Chapter 3**: Presents the proposed method for determining the parameters simultaneously in the spatial complex fuzzy inference system for short-term prediction of satellite image time series, experimental results, and analysis of the proposed method.
- **Chapter 4**: Presents the proposed method for optimizing the rules in the spatial complex fuzzy inference system for short-term prediction of satellite image time series, experimental results, and analysis of the proposed method.
- **Conclusion and Future Work**

Chapter 1

OVERVIEW OF RESEARCH AND THEORETICAL BASIC

1.1 Theoretical basic

1.1.1 A fuzzy set

The concept of fuzzy sets was introduced by Lotfi A.Zadel [43] in 1965 with the aim of describing the concepts of "unclear sets" in the study of uncertain factors

Definition 1.1. *[43] If X is a base set (or a topological space) and its elements are denoted by x, then a fuzzy set A in X is determined by a pair of values as the formula (1.1) below.*

$$A = \{(x, \mu_A(x))|x \in X\} \tag{1.1}$$

Where $\mu_A(x)$ is called the membership function of x in the fuzzy set A, abbreviated as MF. That is, the membership function is a mapping of each element of X to a degree of membership in the range $[0, 1]$.

1.1.2 Complex Fuzzy Set

Definition 1.2. *Complex Fuzzy Set [44] is characterized by a membership function $\mu_S(x)$ that lies within the unit circle in the complex plane and has the form:1.2 as follows:*

$$\mu_S(x) = r_S(x).e^{j\omega_S(x)}, j = \sqrt{-1} \tag{1.2}$$

Where the amplitude $r_S(x)$ and phase $\omega_S(x)$ are both real-valued with condition $r_S(x) \in [0, 1]$.

According to Ramot [44, 45], complex fuzzy sets are considered an effective modeling tool for problems, time-varying meaningful objects, or problems with periodic factors

1.1.3 Fuzzy Inference System (FIS

Fuzzy Inference System (FIS) [46] is a popular computational framework based on fuzzy theory. It is commonly applied when constructing decision support models. There are three types of FIS: Mamdani FIS, Sugeno FIS(or Takagi – Sugeno), and Tsukamoto FIS.

1.1.4 Complex fuzzy logic system (CFLS)

Ramot [45] proposed a complex fuzzy logic system (CFLS) that consists of three stages: The fuzzification module, The fuzzy inference stage, and The defuzzification process. The three stages of the CFLS are summarized below:
The fuzzification module: the process of converting the crisp inputs into complex fuzzy inputs
The fuzzy inference stage: the process of using CFLs to map the complex fuzzy inputs into complex fuzzy outputs through the complex fuzzy implication.
The fuzzy inference stage: the process of using CFLs to map the complex fuzzy inputs into complex fuzzy outputs through the complex fuzzy implication.
In CFLS, Ramot et al. did not outline any specific method of defuzzification to reduce the complex fuzzy outputs into crisp outputs.

1.1.5 Mamdani Complex Fuzzy Inference System (M-CFIS)[47]

The general structure of Mamdani CFIS consists of six following steps:
Step 1: Create a set of complex fuzzy rule
Step 2: Fuzzify of the inputs
Step 3: Find the rule's firing strength
Step 4: Define the consequence of the complex fuzzy rules
Step 5: Aggregation
Step 6: Defuzzification

1.1.6 Some basic operations of CFS

Complement of a Complex Fuzzy Set
Let A be a complex fuzzy sets, and let: $\mu_A(x) = r_A(x)e^{j\omega_A(x)}$.

Definition 1.3 ([44])**.** *The complement of A (denoted as $\overline{A}$) and is specified by the function:*

$$\overline{A} = \{(x, \mu_{\overline{A}}(x))|x \in U\} = \left\{(x, r_{\overline{A}}(x)e^{j\omega_{\overline{A}}(x)})|x \in U\right\} \quad (1.3)$$

Where $r_{\overline{A}}(x) = 1 - r_A(x)$ $\omega_{\overline{A}}(x) = 2\pi - \omega_A(x)$.

In [44], Complement of a Complex Fuzzy Set has some forms as follows:

$$\overline{A} = (1 - r_A(x)) .e^{j(-\omega_A(x))} \quad (1.4)$$

$$\overline{A} = (1 - r_A(x)) .e^{j(\omega_A(x))} \quad (1.5)$$

$$\overline{A} = (1 - r_A(x)) .e^{j(\omega_A(x)+\pi)} \quad (1.6)$$

Union and intersection of two Complex Fuzzy Sets

Consider two CFSs, A and B , in a universe of discourse X with membership degrees of $\mu_A(x) = r_A(x)e^{j\omega_A(x)}$ and $\mu_B(x) = r_B(x)e^{j\omega_B(x)}$, , respectively. The operations of these two CFSs are defined as follows:

Definition 1.4 ([44]). *The union of A and B (denoted as $A \cup B$) :*

$$\begin{aligned} A \cup B &= \{(x, \mu_{A\cup B}(x))|x \in U\} \\ &= \left\{(x, r_{A\cup B}(x)e^{j\omega_{A\cup B}(x)})|x \in U\right\} \\ &= \left\{(x, [r_A(x) \oplus r_B(x)]\, e^{j\omega_{A\cup B}(x)})|x \in U\right\} \end{aligned} \tag{1.7}$$

where $\oplus$ is t-conorm, example $r_{A\cup B}(x) = \max\{r_A(x), r_B(x)\}$.

Definition 1.5 ([44]). *Intersection of two Complex Fuzzy Sets, A and$B$ (denoted as $A \cap B$):*

$$\begin{aligned} A \cap B &= \{(x, \mu_{A\cap B}(x))|x \in U\} \\ &= \left\{(x, r_{A\cap B}(x)e^{j\omega_{A\cap B}(x)})|x \in U\right\} \\ &= \left\{(x, [r_A(x) \otimes r_B(x)]\, e^{j\omega_{A\cap B}(x)})|x \in U\right\} \end{aligned} \tag{1.8}$$

Where $r_{A\cap B}(x) = \min\{r_A(x), r_B(x)\}$ and $\omega_{A\cap B}(x) = \min(\omega_A(x), \omega_B(x))$. Where $\otimes$ is t-norm, for example, Min-operator.

1.1.7 Complex Fuzzy Measures

Definition 1.6. *A distance of complex fuzzy sets [48] is $\rho : (F^*(U) \times F^*(U)) \to [0, 1]$ for any A, B and $C \in F^*(U)$ if satisfies:*

1. $\rho(A, B) \geq 0, \rho(A, B) = 0$ *if and only if* $A = B$
2. $\rho(A, B) = \rho(B, A)$
3. $\rho(A, B) \leq \rho(A, C) + \rho(C, B)$

where $F^*(U)$ lis the set of all complex fuzzy sets in U

1.1.7.1. Complex Fuzzy Cosine Similarity Measure (CFCSM) [49]

Definition 1.7. *Assume that there are two complex fuzzy sets, namely $S_1 = r_{S_1}(x)\, e^{j\omega_{S_1}(x)}$ and $S_2 = r_{S_2}(x)\, e^{j\omega_{S_2}(x)}$, $x \in X$.*
A Complex Fuzzy Cosine Similarity Measure (CFCSM) between S_1 and S_2 is:

$$C_{CFS} = \frac{1}{n}\sum_{k=1}^{n} \frac{a_1a_2 + b_1b_2}{\sqrt{(a_1)^2 + (b_1)^2}.\sqrt{(a_2)^2 + (b_2)^2}} \tag{1.9}$$

Where $a_1 = \mathrm{Re}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $b_1 = \mathrm{Im}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $a_2 = \mathrm{Re}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$; $b_2 = \mathrm{Im}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$

1.1.7.2. Complex Fuzzy Dice Similarity Measure (CFDSM) [49]

Definition 1.8. *Assume that there are two complex fuzzys ets, namely$S_1 = r_{S_1}(x)\, e^{j\omega_{S_1}(x)}$ and $S_2 = r_{S_2}(x)\, e^{j\omega_{S_2}(x)}$, $x \in X$. A Complex Fuzzy Dice Similarity Measure (CFCSM) between S_1 and S_2 is:*

$$D_{CFS} = \frac{1}{n}\sum_{k=1}^{n}\frac{2\sqrt{a_1b_1a_2b_2}}{a_1b_1 + a_2b_2} \tag{1.10}$$

Where $a_1 = \operatorname{Re}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $b_1 = \operatorname{Im}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $a_2 = \operatorname{Re}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$; $b_2 = \operatorname{Im}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$

1.1.7.3. Complex Fuzzy Jaccard Similarity Measure (CFJSM) [49]

Definition 1.9. *Assume that there are two complex fuzzy sets, namely* $S_1 = r_{S_1}(x)\, e^{j\omega_{S_1}(x)}$ *and* $S_2 = r_{S_2}(x)\, e^{j\omega_{S_2}(x)}$, $x \in X$.

A Complex Fuzzy Jaccard Similarity Measure (CFJSM) between S_1 *and* S_2 *is:*

$$J_{CFS} = \frac{1}{n}\sum_{k=1}^{n}\frac{\sqrt{a_1b_1a_2b_2}}{(a_1b_1 + a_2b_2) - \left(\sqrt{a_1b_1}.\sqrt{a_2b_2}\right)} \tag{1.11}$$

Where $a_1 = \operatorname{Re}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $b_1 = \operatorname{Im}\left(r_{S_1}(x)\, e^{j\omega_{S_1}(x)}\right)$; $a_2 = \operatorname{Re}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$; $b_2 = \operatorname{Im}\left(r_{S_2}(x)\, e^{j\omega_{S_2}(x)}\right)$

1.1.8 Remote Sensing

Remote sensing is a scientific field that collects information about the Earth's surface without actually making physical contact with it. This is achieved by recording reflected or emitted energy and then processing, analyzing, and applying that information [50].

Remote sensing imagery has various characteristics, including spectral bands, spatial resolution, spectral resolution, radiometric resolution, and temporal resolution. There are many types of remote sensing images/satellites available, such as Landsat, SPOT, MOS, IRS, IKONOS, WORLD VIEW – 2, COSMOS [50], and so on.

With outstanding advantages compared to traditional methods, remote sensing technology has been widely used and has brought tremendous benefits in agriculture, forestry, natural resource management, environmental monitoring, etc.

1.2 Data, environment, and measure Used in the experiment

The first dataset is a series of consecutive satellite images extracted from the US Navy's weather image database [51].

The second dataset is from the PRISMA project [52] of the Italian Space Agency.

To evaluate the effectiveness of proposed methods, the thesis uses two metrics: R Squared (R^2) [53] and Root Mean Squared Error (RMSE) [54], and then uses two-way ANOVA to analyze the results.

Chapter 2

SPATIAL COMPLEX FUZZY INFERENCE SYSTEM

2.1 Introduction

In this chapter, the thesis focuses on presenting the new contribution of the proposed **Spatial Complex Fuzzy Inference System** applied in the short-term prediction of the satellite image.

The main idea of this proposal is that from the input image sequences, first, we processed to obtain the input dataset consisting of real and phase parts (the difference between pixels of two consecutive images). These matrices are then processed by the FCM algorithm [41] to be divided into appropriate clusters. From the clustering results, spatial complex fuzzy inference rules will be generated in time. The parameters for the fuzzy solver in this method are trained by the Adam algorithm [42] to find appropriate parameters.

2.2 Proposed Model

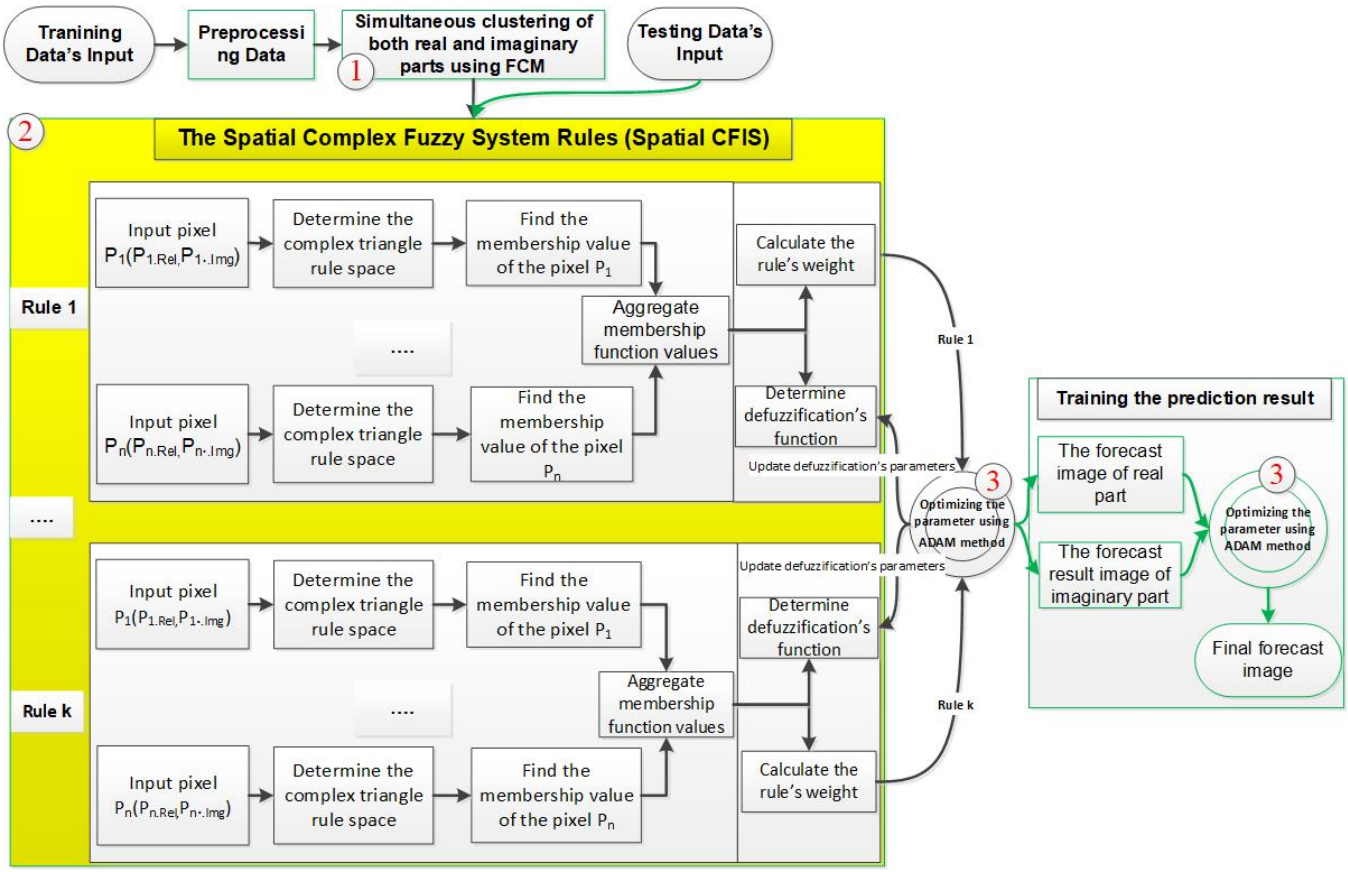


Figure 2.1: Proposed Model Spatial CFIS

2.3 Algorithm details

1. **Step 1: Data pre-processing**

(a) ***Step 1.1. Convert color images from satellite images (RGB color image) to gray images***
The obtained remote sensing color image is grayed [55] out according to formula (2.1) for calculation

$$Y = 0.2126R + 0.7152G + 0.0722B \tag{2.1}$$

(b) ***Step 1.2. Determine the difference matrix***
Each value in the difference matrix is computed by using equation (2.2) based on the difference $HoD_k(i), i = 1, .., N$ between the corresponding regions of the remote sensing image $X^{(t)}$ at time t, where $k = 1, 2, ..., d$.

$$HoD_k(i) = X^{(t)} - X^{(t-1)} \tag{2.2}$$

The difference set $\{HoD_1(i), HoD_2(i), HoD_3(i), ..., HoD_d(i)\}$ of the time series input at time t is determined by equation (2.2).

2. **Step 2: Clustering the input data using Fuzzy C-means at the same time in both the real part and the imaginary part**

The data dependency of $X_k(X^{(t)}, HoD^{(t)})$ on cluster j is denoted by U_{kj} and incorporated into the objective function using the formula 2.3

$$J = \sum_{k=1}^{N} \sum_{j=1}^{C} U_{kj}^{m} \|X_k - V_j\|^2 \rightarrow min \tag{2.3}$$

3. **Step 3: Generating rules according to the spatial fuzzy triangle**

Triangular fuzzy rules created on clusters $\{P_1, P_2, P_3, ..., P_c\}$ in which the j^{th} rule corresponding to P_j represented as follows:

Rule j: if $x_1 = A_{1j}$ and $x_2 = A_{2j}$ and ... and $x_k = A_{dj}$ then $y = B_j$ The values of (a, b, c, a', b', c') computed by following formulas

$$b_{kj} = V_j \tag{2.4}$$

$$a_{kj} = \frac{\sum_{i=1,2,\ ...n\ and\ I_i^{(k)} \le b_{kj}} U_{\mathrm{i,j}} \times I_i^{(k)}}{\sum_{i=1,2,\ ...n\ and\ I_i^{(k)} \le b_{kj}} U_{\mathrm{i,j}}} \tag{2.5}$$

$$c_{kj} = \frac{\sum_{i=1,2,\ ...n\ and\ I_i^{(k)} \ge b_{kj}} U_{\mathrm{i,j}} \times I_i^{(k)}}{\sum_{i=1,2,\ ...n\ and\ I_i^{(k)} \ge b_{kj}} U_{\mathrm{i,j}}} \tag{2.6}$$

$$b'_{kj} = V_j \tag{2.7}$$

$$a'_{kj} = \frac{\sum_{i=1,2,\ ...n\ and\ HoD_i^{(k)} \le b_{kj}} U_{\mathrm{i,j}} \times HoD_i^{(k)}}{\sum_{i=1,2,\ ...n\ and\ HoD_i^{(k)} \le b_{kj}} U_{\mathrm{i,j}}} \tag{2.8}$$

$$c'_{kj} = \frac{\sum\limits_{i=1,2,\ ...n\ and\ HoD_i^{(k)} \geq b_{kj}} U_{\mathrm{i,j}} \times HoD_i^{(k)}}{\sum\limits_{i=1,2,\ ...n\ and\ HoD_i^{(k)} \geq b_{kj}} U_{\mathrm{i,j}}} \tag{2.9}$$

where $I_i^{(k)}, HoD_i^{(k)}$ is the real and imaginary path value k^{th} input of the training X_i.

Based on the equations (2.4) – (2.9), the triangles of the fuzzy rules are built from which to determine the Spatial Complex Fuzzy System Rules (Spatial CFIS).

4. **Step 4: Output interpolating**
   (a) ***Step 4.1. Move pixels to the area of the complex fuzzy rule of the triangle.***
   Move pixels to the complex fuzzy space of the law of the triangle by determining a α coefficient so that after dividing the value of the point outside the triangle fuzzy space by α we obtain all the points in the solution region.
   (b) ***Step 4.2. Interpolate values***
   Interpolate value $O_i^* = (O_{i.\,\mathrm{Re}\,l}^*, O_{i.\,\mathrm{Im}\,g}^*)$ according to the following formula

$$O_{i.\,\mathrm{Re}\,l}^* = \frac{\sum\limits_{j=1}^{q} \min_{1\leq k\leq d} U_{A_{kj}}(X_i^{(k)}) \times DEF(X_i)}{\sum\limits_{j=1}^{q} \min_{1\leq k\leq d} U_{A_{kj}}(X_i^{(k)})} \tag{2.10}$$

$$O_{i.\,\mathrm{Im}\,g}^* = \frac{\sum\limits_{j=1}^{q} \min_{1\leq k\leq d} U_{A_{kj}}(X_i^{(k)}) \times DEF(HoD_i)}{\sum\limits_{j=1}^{q} \min_{1\leq k\leq d} U_{A_{kj}}(X_i^{(k)})} \tag{2.11}$$

5. **Step 5: Train the weights of the defuzzification**
   Defuzzification values are calculated below

$$DEF(X_i) = \frac{h_1 a + h_2 b + h_3 c}{\sum\limits_{i=1}^{3} h_i} \tag{2.12}$$

$$DEF(HOD_i) = \frac{h'_1 a' + h'_2 b' + h'_3 c'}{\sum\limits_{i=1}^{3} h'_i} \tag{2.13}$$

To get a good prediction, it is necessary to determine appropriate defuzzified weights $(h_1, h_2, h_3, h'_1, h'_2, h'_3)$. Using the ADAM algorithm [42], the optimal defuzzified parameters are determined and the mean of variance (RMSE) is the objective function.

$$RMSE = \sqrt{\sum_{i=1}^{n} \left(X_i^{(t)} - \hat{X}_i^{(t)} \right)^2} \tag{2.14}$$

where $\hat{X}_i^{(t)}$ is the predicted value determined by the formula (2.10, 2.11).

6. **Step 6. Predict the output image**
   The output pixel value of the real part forecast image is taken directly from the result $O^*_{i.\,\mathrm{Re}\,l}$ (calculated in **Step 4.2**), and the phase is calculated based on the conversion ratio of the phase $O^*_{i.\,\mathrm{Im}\,g}$ (2.15), where $X_i^{(t-1)}$ is the actual value at the time $t-1$:

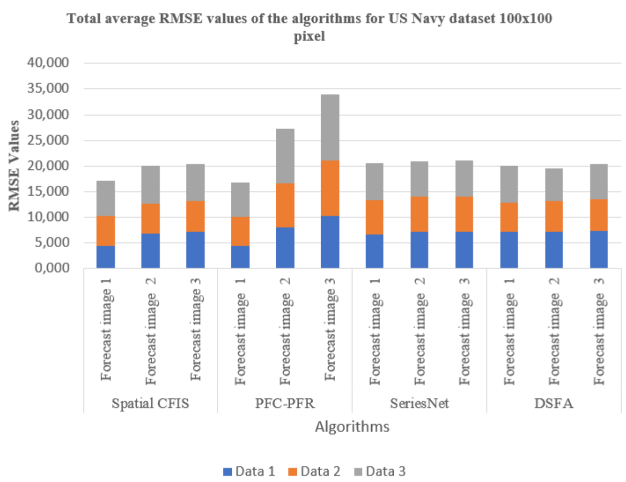
$$O^{*'}_{i.\,\mathrm{Img}} = X_i^{(t-1)} * (1 + O^*_{i.\,\mathrm{Img}}) \tag{2.15}$$

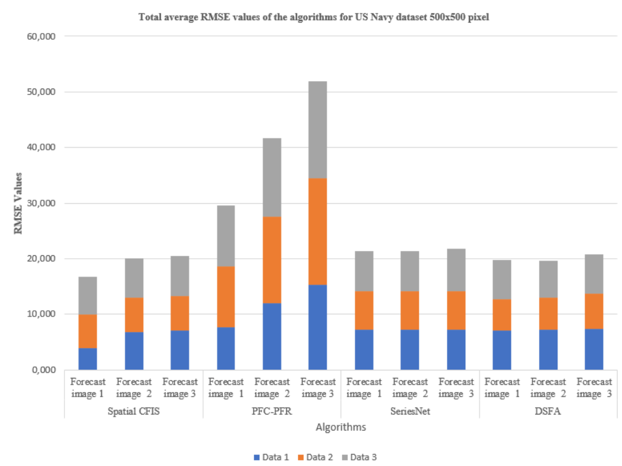
   Finally, the next forecast image results O_i^* can be calculated based on the combined results of the pixel real and imaginary part according to the formula (2.16) follow:

$$O_i^* = \gamma \times O^*_{i.\,\mathrm{Re}\,l} + (1-\gamma) \times O^{*'}_{i.\,\mathrm{Img}} \tag{2.16}$$

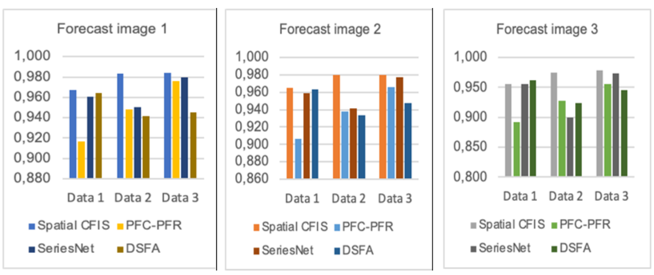
2.4 Experimental Results

The figure below showcases the outcomes of the RMSE analysis conducted on Spatial CFIS using the dataset of the United States Navy. The images under examination have dimensions of 100x100 and 500x500 pixels. The graphical representation of the RMSE analysis is of utmost importance in evaluating the efficiency of the implemented system. Through this analysis, the deviation between the predicted values and the actual values can be assessed, thus providing a measure of the system's precision.

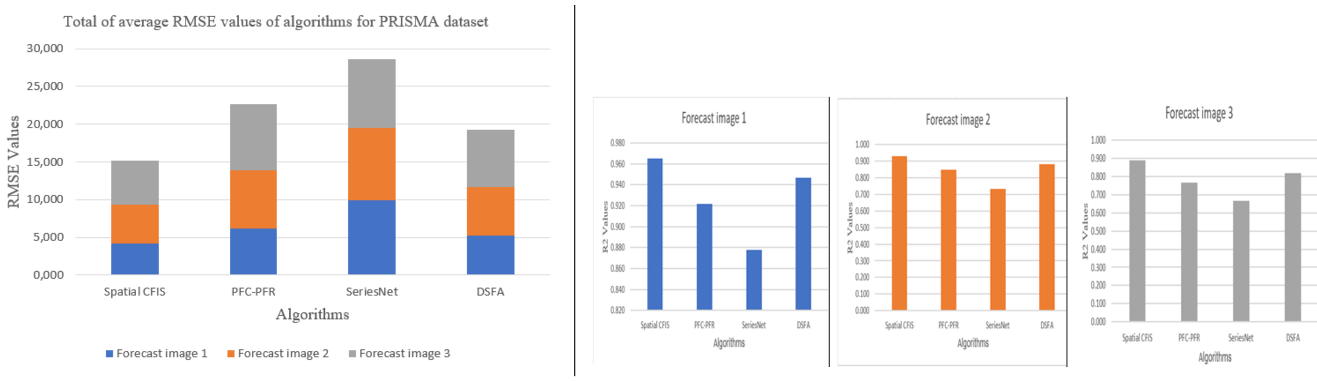




The figure below illustrates the results of R^2 analysis on Spatial CFIS with respect to the dataset of the United States Navy. The images in consideration possess dimensions of both 100x100 and 500x500 pixels. The visualization of said analysis serves as a fundamental aspect of evaluating the effectiveness of the implemented system. Through this analysis, the degree of correlation between predicted and actual values can be assessed, thus providing a measure of the system's accuracy.



The figure below displays the outcomes of the RMSE and R^2 analyses carried out on Spatial CFIS using the Prisma dataset. The graphical representation of said analyses serves as a crucial aspect in evaluating the effectiveness of the implemented system. By utilizing both RMSE and R^2 analyses, the accuracy and precision of the system can be comprehensively assessed. Therefore, the graphical representation of the results of these analyses is crucial in evaluating the performance of the system in a real-world scenario.



Chapter 3

THE METHOD FOR CONCURRENT PARAMETER IDENTIFICATION IN SPATIAL COMPLEX FUZZY INFERENCE SYSTEMS

3.1 Introduction

In this paper, a new method is proposed to determine the inference process parameters of boundary point, rule coefficient, defuzzification coefficient, and dependency coefficient and present a new FWADAM+ method to train that set of parameters simultaneously. The initial data is clustered simultaneously according to each data group. This result will be the basis for determining a suitable set of parameters using the FWADAM+ concurrent training algorithm.

3.2 Proposed Model Co-Spatial CFIS+

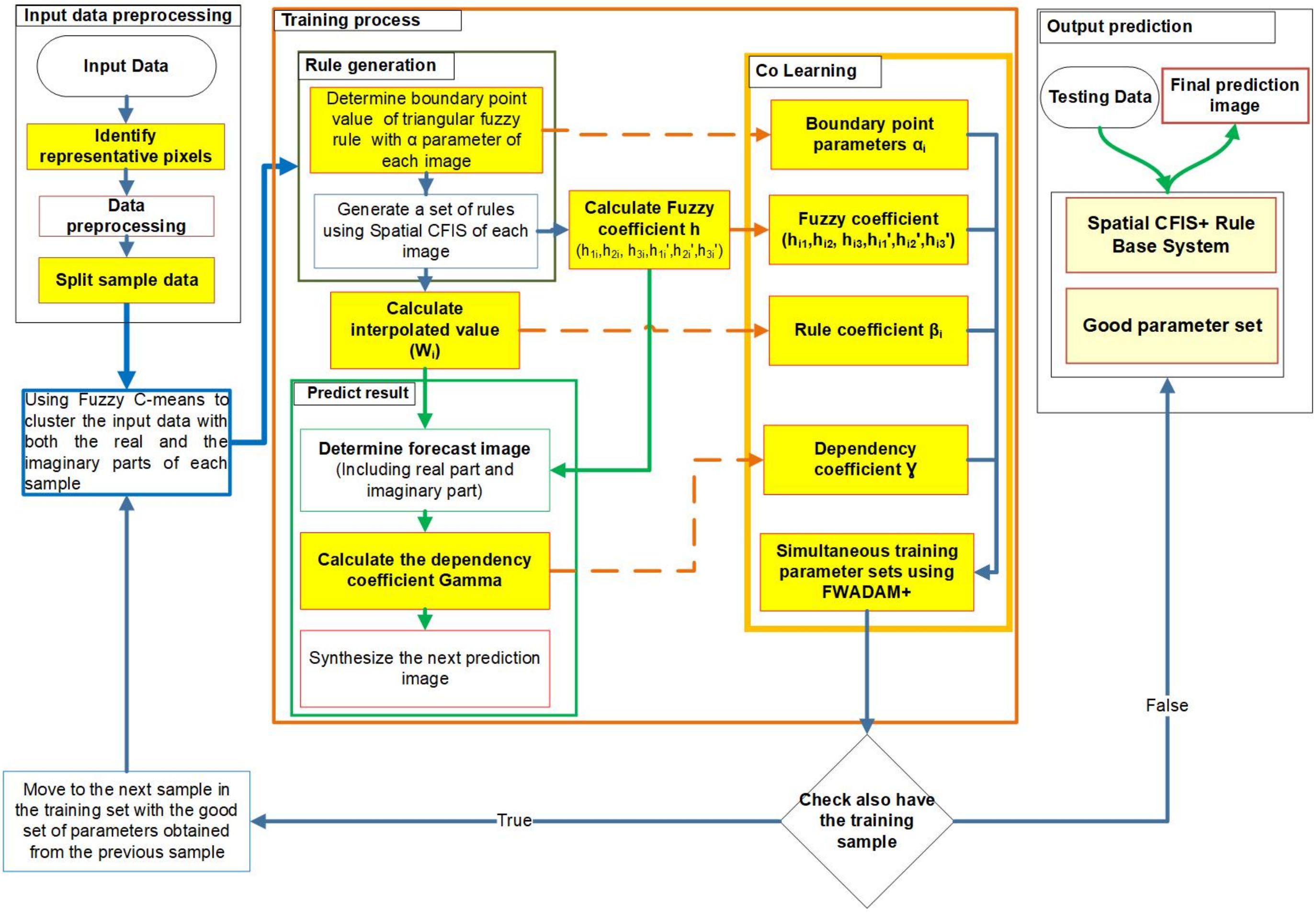


Figure 3.1: The implementation process

3.3 Details of the proposed algorithm

- **Step 1: Input data preprocessing**

  - The satellite images are converted from color images to gray images.

  - Reduce image size by representative pixels; the original input image is divided into small images of size $c \times c$, with each image will find the representative image according to the (3.1) following formula:

$$\mathrm{I}\bar{m} = \sum_{i=1}^{c^2} \kappa_i \mathrm{Im}_i \tag{3.1}$$

where κ_i and Im_i are calculated using the formula (3.2)

$$\begin{cases} \kappa_i = \frac{1}{\|\mathrm{Im}_{tb} - \mathrm{Im}_i\| \times d_i} & \kappa_i \text{ tha mãn } \sum_{i=1}^{c^2} \kappa_{ij} = 1 \\ \mathrm{Im}_{tb} = \frac{\sum_{i=1}^{c^2} \mathrm{Im}_i}{c^2} \end{cases} \tag{3.2}$$

  - Then, the difference matrix (imaginary part) is determined by directly subtracting the difference between the respective regions of the representative image of the corresponding remote sensing image using the formula (3.3).

$$HOD = \mathrm{Im}_{tb}^{(t)} - \mathrm{Im}_{tb}^{(t-1)} \tag{3.3}$$

Get the input method is: $X(Im_{tb}^{t}, HoD)$

- Finally, the input data is divided into the number of samples according to the following (3.4) formula:

$$M = \frac{N-Z}{Z(1-dr)} + 1 \tag{3.4}$$

- **Step 2: Data clustering**

  After preprocessing data, we apply Fuzzy C-means [41] to cluster the input data, simultaneously the real and the imaginary part of each image in each data sample. The result of the clustering process is the set of degree matrix U and the cluster center vector V of each corresponding image.

- **Step 3: Generate and aggregate Spatial CFIS+ rules from clustering results**

  At first, we determine the boundary point value a, b, c, a', b', c' of input data X^t boundary point parameters α_j of each rule. We use the center V_j represented to b and b' , where:

$$b_{ij} = \alpha_j^b \times V_j^{rel} \tag{3.5}$$

$$b'_{ij} = \alpha_j^{b'} \times V_j^{img} \tag{3.6}$$

$$a_{ij} = \alpha_j^a \times \left(\frac{\sum_{i=1,2,\ ...n \ and \ X_i^{(k)} \le b_{ij}} U_{\mathrm{i,j}} \times X_i^{(k)}}{\sum_{i=1,2,\ ...n \ and \ X_i^{(k)} \le b_{ij}} U_{\mathrm{i,j}}} \right) \tag{3.7}$$

$$a'_{ij} = \alpha_j^{a'} \times \left(\frac{\sum_{i=1,2,\ ...n \ and \ HOD_i^{(k)} \le b_{ij}} U_{\mathrm{i,j}} \times HOD_i^{(k)}}{\sum_{i=1,2,\ ...n \ and \ HOD_i^{(k)} \le b_{ij}} U_{\mathrm{i,j}}} \right) \tag{3.8}$$

$$c_{ij} = \alpha_j^c \times \left(\frac{\sum_{i=1,2,\ ...n \ and \ X_i^{(k)} \ge b_{ij}} U_{\mathrm{i,j}} \times X_i^{(k)}}{\sum_{i=1,2,\ ...n \ and \ X_i^{(k)} \ge b_{ij}} U_{\mathrm{i,j}}} \right) \tag{3.9}$$

$$c'_{ij} = \alpha_j^{c'} \times \left(\frac{\sum_{i=1,2,\ ...n \ and \ HOD_i^{(k)} \ge b_{ij}} U_{\mathrm{i,j}} \times HOD_i^{(k)}}{\sum_{i=1,2,\ ...n \ and \ HOD_i^{(k)} \ge b_{ij}} U_{\mathrm{i,j}}} \right) \tag{3.10}$$

- **Step 4: Calculate inference value and predict the next image**

  Determine rule coefficient β_i by the (3.11) following formula:

$$\mathrm{W}_i = \frac{\beta_{i1} \times \mathrm{w}_{i1} + \beta_{i2} \times \mathrm{w}_{i2} + \ldots + \beta_{iR} \times \mathrm{w}_{iR} + \beta_{iR+1}}{\beta_{i1} + \beta_{i2} + \ldots + \beta_{iR+1}} \tag{3.11}$$

Then, we calculate the defuzzification coefficient $h_{1j},\ h_{2j},\ h_{3j},\ h'_{ij},\ h'_{2j},\ h'_{3j}$ by formula (3.12-3.13):

$$DEF_j(X^{(t)}) = \frac{h_{1j}a + h_{2j}b + h_{3j}c}{h_{1j} + h_{2j} + h_{3j}} \tag{3.12}$$

$$DEF_j(HOD^{(t)}) = \frac{h'_{1j}a' + h'_{2j}b' + h'_{3j}c'}{h'_{1j} + h'_{2j} + h'_{3j}} \tag{3.13}$$

The dependence coefficient $\gamma \in [0,1]$ is determined to control real and imaginary parts of the prediction result as follows:

$$O_i^* = \gamma \times O_{i.\,\mathrm{Re}\,l}^* + (1-\gamma) \times O_{i.\,\mathrm{Im}\,g}^{*'} \tag{3.14}$$

(*) Prediction result of the next image $O_{i.Rel}^*$ belong to real part calculated (3.15) below fomula.

$$O_{i.\,\mathrm{Re}\,l}^* = \frac{\sum\limits_{j=1}^{R} \mathrm{W}_i(X_i^{(k)}) \times DEF_j(X^{(t)})}{R} \tag{3.15}$$

(**) Prediction result of the next image belonging to the imaginary part $O_{i.Img}^{*'}$ calculated by the (3.16) formula:

$$O_{i.\,\mathrm{Im}\,g}^{*'} = X_i^{(t)} \times (1 + O_{i.\,\mathrm{Im}\,g}^*) \tag{3.16}$$

$$O_{i.\,\mathrm{Im}\,g}^* = \frac{\sum\limits_{j=1}^{R} \mathrm{W}_i(X_i^{(k)}) \times DEF_j(HOD^{(t)})}{R} \tag{3.17}$$

The next predicted image X^{db} is the result from the inference of all of the pixels from center image O^*.

$$X_i^{db} = abs\left(\frac{1}{\kappa_i \times d_i} - O^*_{\lceil \frac{i}{c^2} \rceil}\right) \tag{3.18}$$

- **Step 5: Simultaneous training of the parameters in the model (Co-Learning)**

  From this set of parameters α_j, β_i, h_i, and γ, we also propose a new method for training simultaneously a set of parameters above by the FWADAM+ optimization method so that the objective function (3.1) reaches the minimum value:

Input: $Params_i$, $\omega_{min}, \omega_{max}$

Parameter: $\rho_1^t, \rho_2 \in [0,1)$, $\rho_1^1 = \rho_1$, $\rho_1^t = \rho_1 \lambda^{t-1}, \lambda \in (0,1)$

$\phi_t = \frac{1}{\sqrt{t}}, t = 1,2,...,T$

Initially Set: $m^1 = 0$, $v^1 = 0$, $\omega_{max} = 1$, $\omega_{min} = 0.5$ and $L^1 = Params_i$

Output: $Params_{i+1}$

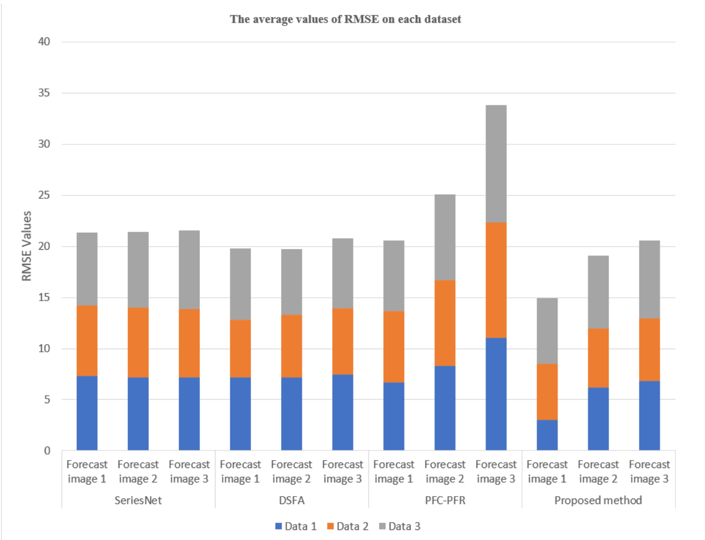
1	**for** $t = 1,2,3, \ldots$ **do**
2	$t = t + 1$
3	Calculate similarity $Similarity_k = Cosine\left(Params_{ik}^t, Params_{ik}^{t-1}\right)$, $t > 1, \forall Params_{ik}^{t-1} \in L^{t-1}, Params_{ik}^{t-1} \neq \gamma$
4	Updated L^t $L^t = (\gamma)$ *Initial* $L^t = \gamma$ *after every time t* $Choose \begin{cases} L^t = L^t \cup Params_{ik}^t & \omega_{min} \leq Similarity_k \leq \omega_{max}, t > 1 \\ L^t = Params_{ik}^t & Similarity_k \leq \omega_{min}, t > 1 \end{cases}$
5	$g^t = \nabla f(L^t)$
6	$m^t = \rho_1^t m^{t-1} + (1 - \rho_1^t) \times g^t$
7	$v^t = \rho_2 v^{t-1} + (1 - \rho_2) \times (g^t)^2$
8	Determine $F^t(L^t) = \eta \left\langle \sum_{\tau=1}^{t} m_\tau, L^t \right\rangle + \left\| \sum_{k=1}^{4} (P_k^t \times L^t) \right\|^2$
9	$V^t = diag\{v^t\}$
10	Find $s^t = \arg\min_L \in \left\langle \nabla F^t(L^t), L^t \right\rangle$
11	Every certain number of times: Update $\omega_{min} = \omega_{min} \times 110\% \quad \forall \omega_{min} < \omega_{max}$
12	$Params_i^{t+1} = Params_i^t + \phi^t \times (V^t)^{-1/2} (s^t - Params_i^t)$
13	**end for**
14	**return** $Params_{i+1} = Params_i^T$

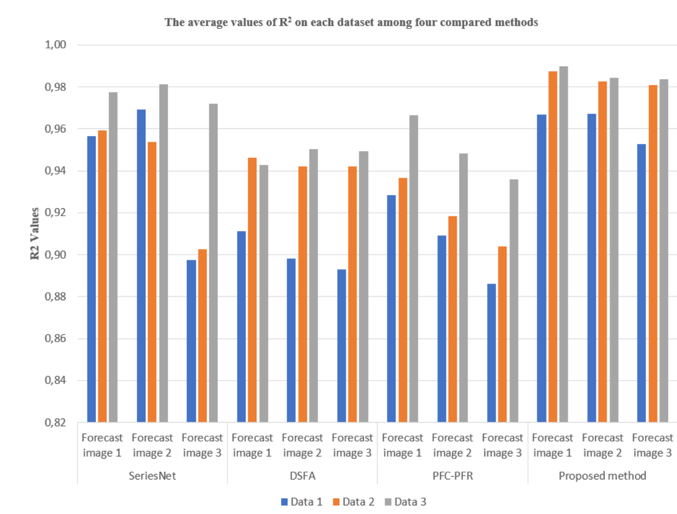
(Highlighted:) **Contributions of the proposed method**

Table 3.1: FWADAM+ Algorithm

3.4 Experimental results of the proposed model

The average results of RMSE and R^2 when applying SeriesNet, DSFA, PFC-PFR, and the proposed method are presented as follows:





The results show that the proposed method outperforms the other three methods. Specifically, the runtime of the proposed method is equivalent to about 90.6%, 93.4%, and 38.1% of the runtime of SeriesNet, DSFA, and PFC-PFR methods, respectively.

Chapter 4

THE OPTIMAL METHOD FOR COMPLEX RULE-BASED FUZZY INFERENCE SYSTEMS

4.1 Introduction

In Chapter 2 and Chapter 3, the thesis proposed a model of Spatial Complex fuzzy inference systems (Spatial CFIS) and a method for concurrent parameter identification in Spatial Complex fuzzy inference systems (Co-Spatial CFIS+). The proposed model is built based on rule generation and training at time t, followed by forecasting future images $(t + 1, t + 2, ...)$.

However, in practical applications, forecasting future images $t + 1, t + 2, ...$ will introduce errors that accumulate over time, making the model less effective.

To reduce the accumulation of errors in the forecasting process, the thesis proposes an adaptive Spatial Complex fuzzy inference system using fuzzy measures called Spatial CFIS++. The main features of this approach include:

- Introducing an adaptive Spatial Complex fuzzy inference systems model based on fuzzy measures to detect changes in remote sensing image (RSI) sequences. This model takes into account the spatial and temporal characteristics of RSI images using CFS theory.

- Proposing a method to directly generate rules from new images obtained in the test set.

- Introducing fuzzy measures for comparing two rule sets to determine which rules should be added, removed, or combined based on the comparison results. Finally, a new rule set is obtained to adjust and adapt to the new image set, improving both the accuracy and time efficiency of the model.

4.2 Proposed Model Spatial CFIS++

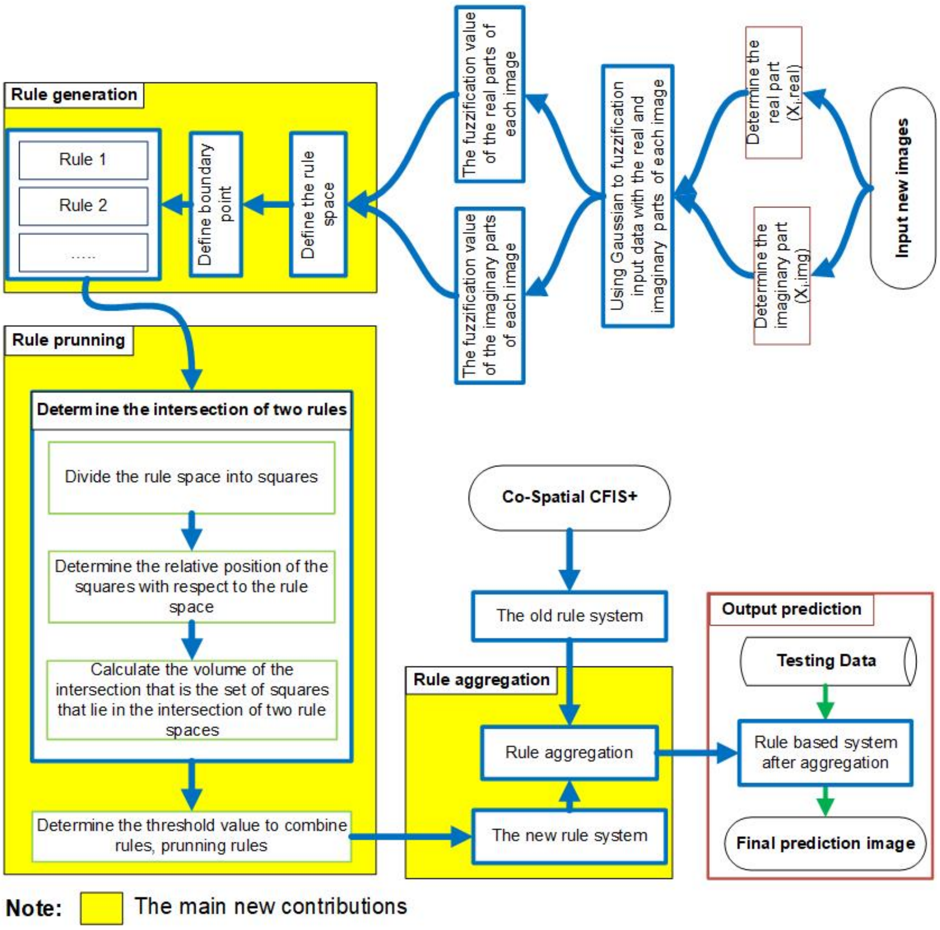


Figure 4.1: The implementation process

4.3 Details of the proposed algorithm

- **Step 1. Preprocessing input data**
- ***Step 1.1 Convert color images into gray images***
- ***Step 1.2 Determine the imaginary part (HOD)***

  The phase part is specified by the different points between the first image in the forecast set (the picture has just been obtained) and the last image in the previously trained. The phase value is obtained using the following formula (4.1).

$$HoD_i = (I_i - I_{(i-1)}) \tag{4.1}$$

- ***Step 1.3 Transform the amplitude and phase part of the grayscale image into the form [0,1]***
- **Step 2. Fuzzification**

  To perform the fuzzification of both the real and imaginary parts of the input image, we make use of the Gaussian fuzzification function, as described by Kreinovich [56]. Formula (4.2) is employed to achieve this purpose.

$$\mu_{gaussian}(x; m, \sigma) = e^{-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2} \tag{4.2}$$

- **Step 3. Determine the rule space**

Definition 4.1. *The rule space [57] is the space that is calculated by the formula (4.3) as follows:*

$$\Omega = \{(x, y, z) \,|x_{min} \le x \le x_{max}, y_{min} \le y \le y_{max}, z_{min} \le z \le z_{max}\} \quad (4.3)$$

- **Step 4. Rule generation**

Step 4.1 Define regions (groups of pixels)

In the case of RSI with a vast number of pixels, processing each pixel will consume a lot of computational time and system resources. Therefore, reducing the data dimension to minimize computation time and system resources is necessary. This study suggests using a histogram [58] to group pixels, then divide pixels into specific regions.

Step 4.2 Determine the boundary parameters of a rule (a, b, c, a', b', c')

Because of using complex fuzzy rulebase of Co-Spatial CFIS+, this step needs to determine the rule parameters such as (a, b, c, a', b', c'):

Step 4.2.1. Determine value (b, b')

The values b and b'' have been established via the Ternary search algorithm [59].

Step 4.2.2. Determine the value (a, a', c, c')

The values (a, a', c, c') are the boundary parameters and calculate by the following formulas (4.4-4.7) [?]:

$$a_j = \frac{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ X_{ij}^{(k)} \le b_{ij}} U_{\text{i,j}} \times X_{i,j}^{(k)}}{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ X_{ij}^{(k)} \le b_{ij}} U_{\text{i,j}}} \quad (4.4)$$

$$a'_j = \frac{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ HOD_{ij}^{(k)} \le b_{ij}} U_{\text{i,j}} \times HOD_{i,j}^{(k)}}{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ HOD_{ij}^{(k)} \le b_{ij}} U_{\text{i,j}}} \quad (4.5)$$

$$c_j = \frac{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ X_{ij}^{(k)} \ge b_{ij}} U_{\text{i,j}} \times X_{i,j}^{(k)}}{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ X_{ij}^{(k)} \ge b_{ij}} U_{\text{i,j}}} \quad (4.6)$$

$$c'_j = \frac{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ HOD_{ij}^{(k)} \ge b_{ij}} U_{\text{i,j}} \times HOD_{i,j}^{(k)}}{\sum\limits_{i=1,2,\ ...,|NP_j|\ and\ HOD_{ij}^{(k)} \ge b_{ij}} U_{\text{i,j}}} \quad (4.7)$$

- **Step 5: Rule review**

Let D be the solution coverage region, V be the domain of the rule space, and D is bounded by:

$$V = \iiint_D dV \quad (4.8)$$

$$\Leftrightarrow V = \int_a^b \int_{g_1(x)}^{g_2(x)} \int_{f_1(x,y)}^{f_2(x,y)} dz dy dx = \int_a^b \int_{g_1(x)}^{g_2(x)} \left(\int_{f_1(x,y)}^{f_2(x,y)} dz \right) dy dx. \tag{4.9}$$

Steps 5.1: Determine the intersection between two rule space domains p, q

The rule space domain of two rules p, q is specified by the formula (4.10 - 4.11) as follows:

$$V_p = \int_{a^p}^{b^p} \int_{g_2^p(x)}^{g_2^p(x)} \left(\int_{f_2^p(x,y)}^{f_2^p(x,y)} dz \right) dy dx \tag{4.10}$$

$$V_q = \int_{a^q}^{b^q} \int_{g_2^q(x)}^{g_2^q(x)} \left(\int_{f_2^q(x,y)}^{f_2^q(x,y)} dz \right) dy dx \tag{4.11}$$

The author determines the measure of two complex fuzzy rules in the triangular space as the intersection space part between the two rules p, q due to formula (4.12) below:

$$V_{pq} = V_p \cap V_q \tag{4.12}$$

To determine the value V_{pq} of the intersection domain between two rules, the solution space Ω divided into square blocks according to formula (4.13) as follows:

$$\Omega_{ijk} = [x_{i-1}, x_i] \times [y_{j-1}, y_j] \times [z_{k-1}, z_k] \tag{4.13}$$

After being divided into square blocks of size θ as shown above, the solution domain Ω needs to satisfy the following expression (4.14):

$$\begin{cases} V_{actual} = S_{base\ area} \times h \\ \left| 1 - \frac{V_{actual}}{V_\theta} \right| \leq \varepsilon \end{cases} \tag{4.14}$$

Steps 5.1.1: Determine the relative position of the square block with the rule space

Consider the first side of the rule space V

Suppose points' coordinates $A(x_A, y_A, z_A)$, $B(x_B, y_B, z_B)$, $C(x_C, y_C, z_C)$ are on the first side of the rule space. The equation of the first side is determined by equation (4.15)

$$N_a x + N_b y + N_c z + d = 0 \tag{4.15}$$

The coefficients (N_a, N_b, N_c) satisfy the following set of equations (4.16):

$$\vec{N} \cdot G_{ijk} = N_a \times x_i + N_b \times y_j + N_c \times z_k \tag{4.16}$$

Repeat with all the remaining sides of the solution space domain V and determine the point's relative position G_{ijk} with the rule space V as formula (4.17). After that, we can specify the square block v in the rule space V.

$$\begin{cases} If \quad \vec{N} \cdot G_{ijk} < 0, G_{ijk} \notin V \\ \quad elsewise, G_{ijk} \in V \end{cases} \tag{4.17}$$

Steps 5.1.2: Determine the intersection of two rule spaces

The intersection of two rule spaces (denote V_{pq}) is the set of square blocks Ω_{ijk} in the rule spaces p and q. Therefore, V_{pq} is determined by the following formula:

$$V_{pq} = \sum V_{\Omega_{ikj}} \quad (4.18)$$

$$V_{\Omega_{ijk}} = |x_{i-1}, x_i| \times |y_{j-1}, y_j| \times |z_{k-1}, z_k| \quad (4.19)$$

Steps 5.2. Optimizing rule

At this step, we process to optimize the rule, including combining rules, removing rules, or adding rules to obtain a better rule system as follows:

- If $\frac{V_{pq}}{V_p} \geq \varepsilon_v$ and $\frac{V_{pq}}{V_q} \geq \varepsilon_v$ and $\frac{a_p}{a_p} + \frac{c_p}{c_p} + \frac{a'_p}{a'_p} + \frac{c'_p}{c'_p} < \varepsilon_R$ then combining the rules:

$$a_{new} = \frac{a_p + a_q}{2}; b_{new} = \frac{b_p + b_q}{2}; b_{new} = \frac{c_p + c_q}{2}$$

$$a'_{new} = \frac{a'_p + a'_q}{2}; b'_{new} = \frac{b'_p + b'_q}{2}; b'_{new} = \frac{c'_p + c'_q}{2}$$

- If $\frac{V_{pq}}{V_q} \geq \varepsilon_v$ and $\frac{V_{pq}}{V_p} < \varepsilon_v$ and $\frac{a_p}{a_p} + \frac{c_p}{c_p} < \varepsilon_R \, or \, \frac{a'_p}{a'_p} + \frac{c'_p}{c'_p} < \varepsilon_R$ Then remove the rule q.
- If $\frac{V_{pq}}{V_q} < \varepsilon_v$ and $\frac{V_{pq}}{V_p} \geq \varepsilon_v$ and $\frac{a_p}{a_p} + \frac{c_p}{c_p} < \varepsilon_R \, or \, \frac{a'_p}{a'_p} + \frac{c'_p}{c'_p} < \varepsilon_R$ Then remove the rule p.
- If $\frac{V_{pq}}{V_q} < \varepsilon_v$ and $\frac{V_{pq}}{V_p} < \varepsilon_v$ Then use both rules p and q.

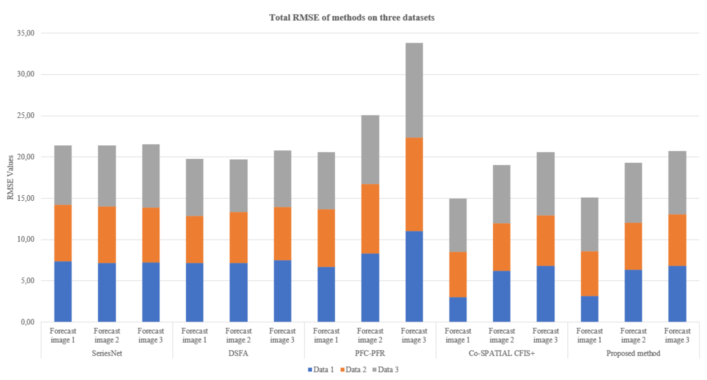
After evaluating all pairs of rules, we obtain the rule base generated from the new image R'.

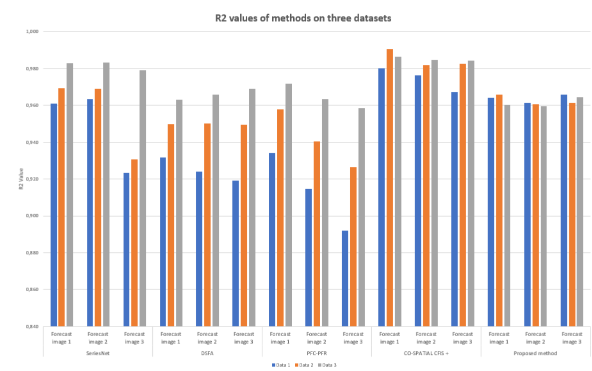
- **Step 6: Synthesize the old rulebase R and new rulebase R'**

  In this step, we will compare each rule of the new rulebase with the rules of the old rulebase using the intersection of the rulebase in step 5.

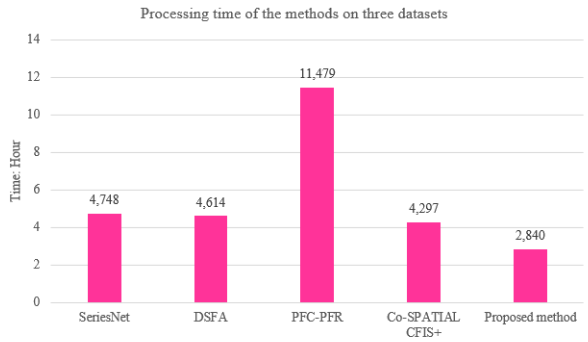
4.3.1 Experimental results of the proposed model

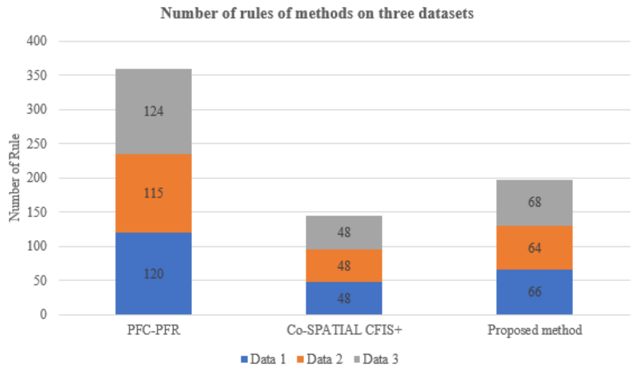
Based on the average RMSE results of the methods on three datasets, the RMSE value of the proposed method is equivalent to that of the Co-Spatial CFIS+ method (the average total RMSE value of the proposed method is about 1% higher than that of Co-Spatial CFIS+), but it performs better than the seriesNet, DSFA, and PFC-PFR methods. These results are visually presented below.





The computation time and the total number of processed rules of the proposed method and the SeriesNet, DSFA, PFC-PFR, and Co-Spatial CFIS+ methods on all 3 datasets





From the results, we have the total processing time of the proposed method is lower than that of Co-Spatial CFIS+ (34%), SeriesNet (40%), DSFA (38%) and notably lower than that of PFC-PFR (60%).

CONCLUSION

The main key contributions

With the research focus on developing a complex fuzzy inference system without time applied to the short-term prediction of satellite image sequences, the thesis has the following main contributions:

- **Firstly**, the thesis proposed a spatial complex fuzzy inference system without time (Spatial CFIS) to detect changes in satellite images.

  - The proposed method generates complex fuzzy rules using fuzzy clustering (FCM) and predicts images through complex fuzzy rules in a triangular space.

  - To improve the effectiveness of the method, Spatial CFIS uses the ADAM algorithm to optimize the weights of the fuzzy coefficient and the dependence coefficient between the real part and the imaginary part.

- **Secondly**, the thesis proposed a method to simultaneously determine the parameters for the spatial complex fuzzy inference system without time (Co-Spatial CFIS+), including:

  - Proposed an improved complex fuzzy rules without time by adding parameters for the rule system for each rule.

  - Proposed a method for simultaneously training FWADAM+ to find better parameters to serve the image prediction process.

- **Thirdly**, the thesis proposed an adaptive spatial complex fuzzy inference system based on complex fuzzy measures called Spatial CFIS++ with the following features:

  - Introduce a complex fuzzy inference model without time based on complex fuzzy measures to detect changes in Remote Sensing Image (RSI) sequences. This model relates to the spatial and temporal characteristics of RSI images through the theory of CFS.

  - Propose a method for generating rules directly from newly obtained images in the test set.
  - Propose complex fuzzy measures for comparing two rule systems: the old rule system generated based on Spatial CFIS and the new rule system generated directly from the image. The system will decide to add, subtract or aggregate rules based on the comparison results. Finally, a new rule set is obtained to adjust and adapt to the new image set, improving both the accuracy and time of the model.

Some limitations

Along with the research results achieved, the dissertation still has some limitations such as:

The complex fuzzy clustering algorithm is an iterative algorithm that requires a lot of computational time. Some input values are initialized randomly, so the number of algorithm iterations depends on the quality of the initial data.

Clustering using groups of pixels can reduce processing time, but still uses the FCM algorithm for clustering, so the speed has not been significantly improved.

The determination of the intersection domain of the rule system still has a lot of errors, which will directly affect the model's results.

The mechanism of dividing groups of pixels is still simple, leading to the occurrence of fragmented, discrete pixel groups.

The MapReduce method and distributed processing in the proposed model are only used at the clustering step to replace the FCM algorithm, so the processing speed of the model has not been significantly improved.

The rule reduction and optimization mechanism in the model is still quite simple, so there is still room for improvement in the rules.

Future works

In the future, the next development direction of the thesis can be carried out according to the following research directions:

– Improve the algorithm to increase computational efficiency and reduce memory resource utilization.

– Improve the model by further reducing processing time while ensuring the stability and accuracy of the model;

– Continue to research and propose learning algorithms such as transfer learning, collaborative learning, etc., in the process of training parameter sets, and further reduce the Spatial CFIS rule system to optimize the rule system.

– Test the proposed models in the dissertation with more complex datasets in various fields of life such as healthcare, economics, geography, etc.

– Apply, deploy, and integrate the proposed research into real-world systems such as weather forecasting, natural disasters, hurricane forecasting, etc.

THE LIST OF WORKS OF THE AUTHOR RELATED TO THE THESIS

1. Published

[CT1] **Le Truong Giang**, Trieu Thu Huong, Nguyen Long Giang, Le Hoang Son, Tran Manh Tuan, Luong Thi Hong Lan. (2020) "A novel spatial complex fuzzy inference system applied in changing detection of remote sensing images". *Conference Proceedings Fundamental and Applied Information Technology (FAIR)*, 267-275, DOI: 10.15625/vap.2020.00178

[CT2] **Le Truong Giang**, Le Hoang Son, Nguyen Truong Thanh, Nguyen Long Giang, Tran Manh Tuan, Nguyen Van Luong, Phung The Huan, Pham Ba Tuan Chung, (2022). "Co Learning for Spatial Complex Fuzzy Inference System for Change Detection from Satellite Images". *The Proceedings of the* $24^{t}h$ *National Conference on Information and Communication Technology - VNICT 2022*, 192-198.

[CT3] **Le Truong Giang**, Le Hoang Son, Nguyen Long Giang, Tran Manh Tuan, Nguyen Van Luong, Mai Dinh Sinh, Ganeshsree Selvachandran, Vassilis C. Gerogiannis. (2022) "A New Co-Learning Method in Spatial Complex Fuzzy Inference Systems for Change Detection from Satellite Images", *Neural Computing and Applications.* https://doi.org/10.1007/s00521-022-07928-5 **(SCIE, Springer, 2021 IF=5.102)**

[CT4]**Le Truong Giang**, Le Hoang Son, Tran Manh Tuan, Pham Ba Tuan Chung.(2020) "Cloud satellite image prediction with complex fuzzy inference Systems". *The Proceedings of the* $22^{t}h$ *National Conference on Information and Communication Technology - VNICT 2020.*

[CT5] Trung Tuan, N., **Le Truong Giang**, Pham Huy Thong, Nguyen Van Luong, Le Minh Tuan, Nguyen Quoc Uy, & Le Minh Hoang. (2023). "A novel method for weather nowcasting based on spatial complex fuzzy inference with multiple band input data". *Journal of Computer Science and Cybernetics.* https://doi.org/10.15625/1813-9663/18028

2.Under review

[CT6] Nguyen Truong Thang, **Le Truong Giang**, Le Hoang Son, Nguyen Long Giang, Tran Manh Tuan, David Taniar, Nguyen Van Thien. "A Novel Spatial Complex Fuzzy Inference System for Detection of Changes in Remote Sensing Images", *Applied Intelligence*, **(SCIE, Springer, 2021 IF=5.019)** Under review.

[CT7] **Le Truong Giang**, Le Hoang Son, Nguyen Long Giang, Tran Manh Tuan, Nguyen Van Luong, Luong Thi Hong Lan, Nguyen Truong Thang "Adaptive Spatial Complex Fuzzy Inference Systems with Compex Fuzzy Measures", *IEEE Access*, **(SCIE, IEEE, 2021 IF=3.476)** Under review.