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ABSTRACT Decision fusion is an important issue in wireless sensor networks (WSN), and intuitionistic fuzzy set (IFS) is a novel method for dealing with uncertain data. We propose a multi-attribute decision fusion model based on IFS, which includes two aspects: data distribution-based IFS construction algorithm (DDBIFCA) and the category similarity weight-based TOPSIS intuitionistic fuzzy decision algorithm (CSWBT-IFS). The DDBIFCA is an IFS construction algorithm that transforms the original attribute values into intuitionistic fuzzy measures, and the CSWBT-IFS is an intuitionistic fuzzy aggregation algorithm improved by the traditional TOPSIS algorithm, which combines intuitionistic fuzzy values of different attributes and obtains a final decision for the monitoring target. Both algorithms have benefits, such as low energy consumption and low computational complexity, which make them suitable for implementation in energy-constrained WSNs. Simulation results show the efficiency of intuitionistic fuzzification for the DDBIFCA and a high classification accuracy, compared with traditional fuzzy fusion and other intuitionistic fuzzy aggregation algorithms, for the CSWBT-IFS.

INDEX TERMS Algorithm, intuitionistic fuzzy set, multi-attribute decision fusion, wireless sensor network.

I. INTRODUCTION

A wireless sensor network (WSN) is a typical distributed and highly self-organized ad hoc network that usually consists of a large number of low-cost sensor nodes, which collect data from around the environment and upload it to the Base Station (BS) directly or via a multi-hop route [1], [2]. WSN has many applications [3], [4], such as industrial control and monitoring, military surveillance, healthcare, and smart grid. One typical characteristic of WSN is that sensors are powered by batteries, thus the energy is limited. Moreover, sensor nodes are often deployed in hard-to-reach environments, without being recharged or replaced. Prolonging the network's lifetime, energy efficient in-network data processing is an effective alternative because it enables sensors to decrease data transmissions while improving reliability of results.

In WSN, sensor nodes collect regional data, which often has a lot of redundancy. For example, hundreds of sensor nodes are used to collect the temperature of an area and the maximum temperature should be recorded. So, it is not necessary to send all the temperature data, but simply a derivative (i.e., maximum temperature) to the relevant base station. Data fusion [5], [6] aims to aggregate redundant data at intermediate sensor nodes by applying a suitable fusion function on the received data. Data fusion reduces the amount of network traffic, which helps to reduce energy consumption on sensor nodes. The relationships among the input data is used to perform information fusion into different classes (cooperative, redundant, and complementary data). In addition, the abstraction level of the manipulated data (raw data/signal, feature, and decision) is used to distinguish among the fusion processes, which include raw fusion, feature fusion, and decision fusion.

In decision fusion algorithms for WSNs, each node of the network needs to obtain the raw data and process it locally, leading to a class that incorporates the original objective from the area where the data was collected. Most research efforts on local-decision algorithms have been based on the condition that the nodes know the local decision [7], [8]. However, the entire process of decision aggregation ranges from data collection to the final decision. The accuracy of the local decision would affect the accuracy of the final decision. Moreover, the local decision needs to be highly efficient because of the limited energy of the nodes. Therefore, an efficient and accurate local decision algorithm is essential for certain scenes.

The remainder of this paper is organized as follows. In Section 2, related works are summarized. In Section 3, an intuitionistic fuzzy-based local-decision model is proposed. Simulation results for the proposed model are presented in Section 4. Finally, Section 5 concludes the paper.

II. RELATED WORK AND CONTRIBUTIONS OF THIS WORK

A. RELATED WORK

A complete fuzzy set model includes two main parts, fuzzification and fuzzy logical operator. Fuzzification is used to change the original data into fuzzy data, and then it uses a certain operator to aggregate them. Therefore, a fusion result is created.

Most researches on intuitionistic fuzzy sets are concentrated in aggregation, namely the design or improvement of the fuzzy logical operator, seldom considering the actual fuzzification. Existing fuzzy methods are getting fuzzy data artificially or realize the transformation by evidence theory and traditional fuzzy sets.

Yu and Xu [9] gives an example of fuzzification using an artificial method for vehicle purchase scenes. In this scene, the intuitionistic fuzzy sets (IFS) are constructed using the consumer's subjective satisfaction for attributes as the membership function of some attributes like comfort level and security level. Yager [10] studied the transformation between the IFS and the confidence interval, presenting the IFS using evidence theory. The construction of basic probability assignment function in evidence theory has many completed methods; therefore, it's a new method to construct the IFS by basic probability assignment function. Finally, the intuitionistic fuzzy number is confirmed as long as the basic probability assignment function is known. Vlachos *et al.* [11] proposed the method of transforming traditional fuzzy sets to IFS using maximum entropy criteria in the image processing field. They study the impact of selecting different entropy measures in the framework of intuitionistic fuzzy image processing, especially in the process of intuitionistic fuzzification of images, and, according to the experiment, it is shown that the different notions of intuitionistic fuzzy entropy treat images in different ways, thus making the selection of the appropriate entropy measure application-dependent. There are some similarities between them, such as the theoretical framework, because IFS is an extension of fuzzy sets. However, the methods above have their respective limitations. Firstly, transforming the attribute to the IF value artificially is slow, especially when there are large amounts of data to be transformed. Secondly, this method is more subjective and uncertain, which may result in fuzzy set inconformity. In evidence theory-based transformation, the distribution of basic probability assignments in evidence theory is divided into much more detail than intuitionistic fuzzy sets, and the transforming process may result in the loss of information attributed to hesitation degree, which is a lack of rationality to some extent. In the third method, the construction of intuitionistic fuzzy entropy and optimization makes it too complex for a low-power demanding environment. Compared with these methods, the proposed data distribution-based IFS construction algorithm (DDBIFCA) in this paper has higher accuracy and less complexity. At the same time, the construction method is simple thus more suitable for wireless sensor networks.

The process of intuitionistic fuzzy information includes the design and improvement of fuzzy logical operators. The weighted geometric (WG) operator [12] and the ordered weighted geometric (OWG) operator are two common aggregation operators in the field of information fusion. Xu and Yager [12] introduced two operational laws of intuitionistic fuzzy values, and developed some new geometric aggregation operators, such as the intuitionistic fuzzy weighted geometric (IFWG) operator, the intuitionistic fuzzy ordered weighted geometric (IFOWG) operator, and the intuitionistic fuzzy hybrid geometric (IFHG) operator, which extend the WG operator and the OWG operator to accommodate situations where the given arguments are intuitionistic fuzzy sets. Xu [13] defined the intuitionistic fuzzy weighted averaging (IFWA) operator and the intuitionistic fuzzy ordered weighted averaging (IFOWA) operator, which extends two of the most common aggregation operators, which weighs both the given intuitionistic fuzzy value and its ordered position, and thus can reflect the importance degrees of both the given intuitionistic fuzzy argument and the ordered position of the argument. However, the operators above realize the aggregation under the assumption that the weight of each attribute value has been given. In contrast, our proposed algorithm, combined with the typical TOPSIS algorithm and IFA operator, focuses on how to get the corresponding attribute weight from the original training data, which can be applied into multiple attributes decision fusion with a higher accuracy.

The traditional aggregation method for fuzzy sets is to sum the weighted membership degree of each property using different operators, and then select the largest membership degree as the target category. Then, Boran *et al.* [14] combined the TOPSIS method and intuitionistic fuzzy set, which can be used in multiple attributes decision making environments. The IFWA operator is utilized to aggregate individual opinions of decision makers for rating the importance of criteria and alternatives. The improved intuitionistic fuzzy algorithm can get more accurate fusion results than traditional fuzzy decision, thanks to the flexibility. The proposed category similarity weighed-based TOPSIS intuitionistic fuzzy decision algorithm (CSWBT-IFS) put forward a novel attribute weight computing method according to the distance between different categories. The greater the IF value distance under the same attribute, the higher the attribute weight. On the contrary, the smaller the distance, the smaller the weight. At the same time, different from the traditional TOPSIS multi-attribute decision-making problems, this paper focuses on the multi-attribute classification problems. Therefore, it requires a unique ideal solution for each category rather than a shared ideal solution for all categories due to the difference between different categories' attributes. The proposed algorithm achieves higher classification accuracy compared to traditional intuitionistic fuzzy algorithms. A relatively complex computing task of attribute weights and ideal solutions are completed by the fusion center, satisfying the low power requirements in wireless sensor networks.

B. CONTRIBUTIONS OF THIS WORK

1) A multiple attributes decision fusion model based on the IFS (MADF-IFS model) is proposed.
2) We propose two algorithms, namely the data distribution-based IFS construction algorithm (DDBIFCA) and the category similarity weight-based TOPSIS intuitionistic fuzzy decision algorithm (CSWBT-IFS), in which we put forward a novel attribute weight computing method. Both consume low amounts of energy and are associated with low computational complexity.
3) Using extensive simulation tests, we evaluate the performance of the two proposed algorithms, namely DDBIFCA and CSWBT-IFS.

III. MADF-IFS MODEL

In this section, we introduce the specific application scenario, namely the target classification problems, based on multiple attribute decision making in WSN. We also establish the proposed MADF-IFS model and DDBIFCA and CSWBT-IFS algorithms.

First of all, in order to facilitate the research, several assumptions are made: 1) Sensor nodes are randomly and uniformly deployed over a flat area and there are no obstacles; 2) Each node gets its position from its GPS module and sends it to the fusion center for decision aggregation; 3) The target has many attributes and each sensor node consists of different modules to monitor different attributes, after which the proposed multiple attributes decision fusion algorithm is used to get the classification result.

The MADF-IFS model in WSN is shown in Fig. 1. There are a large number of sensors monitoring the target. After the data acquisition process, according to the proposed DDBIFCA algorithm, each sensor node transforms each attribute value into a group of IF values, which stands for the membership degree of the target for all possible categories in each attribute. Then, each node aggregates the IF values into one classification decision according to the CSWBT-IFS algorithm. Subsequently, the aggregated decisions are sent

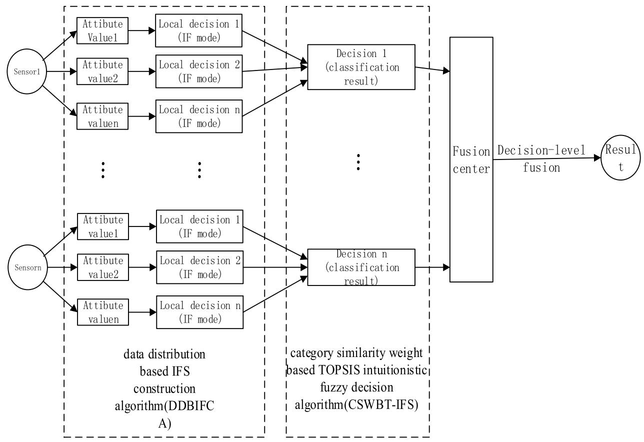

FIGURE 1. **The MADF-IFS model in WSN.**

to the FC. The FC aggregates the received local decisions to achieve a final result by fusion rules. In the following subsections, we describe the two algorithms in more detail.

A. DDBIFCA ALGORITHM

In this subsection, we describe the DDBIFCA algorithm in detail and have divided it into three parts: the calculation of membership function in TFS, transformation between the TFS and the IFS, and calculation of the hesitation degree. First of all, it's necessary to have a brief look at what the hesitate degree is. Intuitionistic fuzzy set A [14] in a finite set X can be written as: $A = \{(x, \mu_A(x), \nu_A(x))|x \in X\}$ where $\mu_A(x), \nu_A(x) : X \to [0, 1]$ are membership function and non-membership function, respectively, such that $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ while $\mu_A(x) + \nu_A(x) = 1$ in TFS. A third parameter of IFS is $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$, known as the intuitionistic fuzzy index or hesitation degree, which is a unique parameter in the intuitionistic fuzzy set. If $\pi_A(x)$ is small, then knowledge about x is more certain. If x is large, then knowledge about x is more uncertain.

1) CALCULATION OF MEMBERSHIP DEGREE IN TRADITIONAL FUZZY SETS (TFS)

In this subsection, we focus on how to get the membership function in TFS and, in the following parts, some transformations applied to convert from the traditional fuzzy sets (TFS) to the IFS are introduced. First, the original attribute information collected from the sensor nodes must be fuzzified into a set of membership functions, which is a number between 0 and 1. Each membership function respectively stands for the membership degree for every possible category in TFS.

It is assumed that the collected attribute values from the sensors are all scalar quantity and obey the Gaussian distribution. The Gaussian membership function is used for fuzzifying, transforming the attribute value into a membership function for every category. It has been proved that a variety of physical phenomena in nature are found to approximately obey the Gaussian distribution, which makes it a natural selection when the mean value and variance is known.

Therefore, the Gaussian distribution is one of the most widely used distributions in statistics and statistical tests.

If the sensor data follows a Gaussian distribution, the transformation membership function is defined as

$$f(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (1)$$

where c and σ denote the mean value and standard deviation, respectively.

2) FROM TFS TO IFS

Atanassov [15] presented a Kα operator that transforms the IFS to the TFS. If $A = \{(\mathrm{x}, \mu_{\mathrm{A}}(\mathrm{x}), \nu_{\mathrm{A}}(\mathrm{x}))|\mathrm{x} \in \mathrm{X}\}$ is an IFS and $\alpha \in [0, 1]$, then the operator Kα is shown as follows:

$$K_\alpha(A) = \{u, u_A(u) + \alpha\pi_A(u), \nu_A(u) + (1-\alpha)\pi_A(u)\} \quad (2)$$

In TFS, there is no hesitation degree and $\mu_A(x)+\nu_A(x) = 1$. Apparently, $K_\alpha(A)$ is a typical TFS, which assigns a part of the IFS's hesitation degree to the membership function and the rest to the non-membership function. Usually, the value of α is computed according to the proportion of the membership in IFS. That is,

$$\alpha = \frac{u_A(u)}{u_A(u) + \nu_A(u)} \quad (3)$$

Next, the TFS is transformed into IFS using the K_α operator. According to equation (2),

$$u = u_A(u) + \alpha\pi_A(u) \quad (4)$$

with

$$\pi_A(u) = 1 - u_A(u) - \nu_A(u) \quad (5)$$

Then, the membership of IFS expressed by the TFS is shown as follows:

$$u_A(u) = u(1 - \pi_A(u)) \quad (6)$$

According to equation (6), we can get u by the transformation membership function, namely equation (1), and thus the membership $u_A(u)$ and the non-membership $\nu_A(u)$ can be easily computed when the hesitation degree is given. The hesitation degree is the key point during transformation between the IFS and the TFS. Next, we present a data distribution based on the hesitation degree calculation method.

3) THE CALCULATION OF HESITATION DEGREE

In most cases, the wireless sensor data of the external environment obey the Gaussian distribution. In this paper, we assume that all the data samples are scalar values and obey the Gaussian distribution. Moreover, in the Gaussian distribution, the variance and the standard deviation determine the amplitude of the distribution. That is, the data distribution is more centralized when the variance is smaller and is more decentralized when the variance is larger. Usually, the more concentrated a set of data distribution is, the easier it is for us to judge whether an unknown data sample belongs to a set. Therefore, the variance, to a certain extent, on behalf of the degree of uncertainty or unknowns, is namely the hesitation degree in the intuitionistic fuzzy. We illustrate an example below.

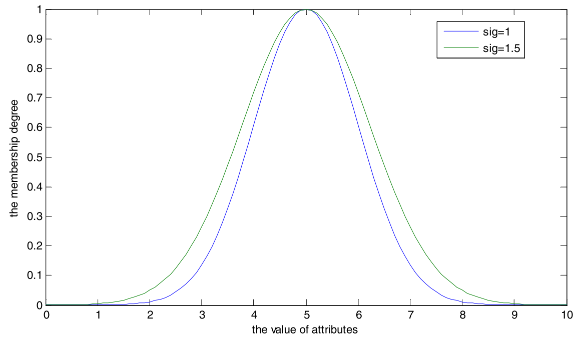

FIGURE 2. Example of two membership functions.

For example, set A = {3, 4, 5}, set B = {4, 4, 4}. From the frequency perspective, the possibility that element 4 belongs to set B is apparently higher than that for set A. Two curves of Gaussian distribution are shown in Fig. 2, in which the mean values of both are 5, and variances are 1 and 1.5. As we can see, the larger variance distribution achieves a larger membership degree when the attribute value is same. However, the larger the variance, the more unreliable the fuzzy membership degree value is. We can also arrive at the conclusion that the probability that element 5 belongs to these sets are both 1, according to the previous Gaussian membership function. However, the distribution of the data set is more centralized when variance is 1. Its membership should be larger while the hesitation degree should be smaller.

Assuming an extreme case, when the variance approaches infinity, the curve is close to a uniform distribution and the membership degree of each data point is 1, which is obviously inconsistent with the reality. Therefore, the greater the variance, the greater the uncertainty about the judgment of membership degree, that is, the greater the degree of hesitation. Therefore, the variance can be used to measure the hesitation degree in IFS.

The hesitation degree is calculated as follows:

We should define the threshold θ_j, which represents the maximum hesitation degree of attribute j in different classes, then the hesitation degree of the i-th sample in j-th attribute is:

$$\theta_{ij} = \frac{\sigma_{ij}}{\max(\sigma_{ij})}\theta_j, \quad (i = 1, 2, \ldots, n\, j = 1, 2, \ldots, k) \quad (7)$$

where σ_{ij} is the standard deviation of the i-th sample in the j-th attribute.

4) THE PSEUDOCODE OF THE DDBIFCA ALGORITHM

Fig. 3 shows the pseudocode of the DDBIFCA, which includes the following four main steps.

1) According to the assumptions, the data set of each attribute obeys the Gaussian distribution. Then, the mean values and standard deviations of the samples in each attribute are computed.

```
DDBIFCA
Input: 1. The training samples of data sets for n classes is
E={e1,e2,...,en}, ei is the test set of i-th sample where ei={ei1, ei2
, . . . , eik} and eij is the sample set of j-th attribute in the i-th
sample.
       2. The training samples of the data set for n samples:
C={c1,c2,...,cn}, ci={ci1, ci2, . . . , cik}
       3. The threshold of the hesitation degree is hesi_th.
Output: The results of IFS for each sample set of attribute
ifvConReasult.
Function IFVConstru(E, T, th)
  For each eij ∈ E
    mij=mean(eij)
    varij=var(eij)
  End For
  For j=1:k
    var_maxj=max(varij)
  End For
  For j=1
  For i=1:n:k
      gauss_memij=gaussmf(cij, [varij, mij])
      hesi_ij = hesi_th × var_ij / var_max_j
      μ_Aij ← gauss_mem_ij × (1 − hesi_ij)
      ν_Aij ← 1 − μ_Aij − hesi_ij
      ifvConReasult[i][j] ← [μAij, νAij]
    End For
  End for
  Return ifvConReasult
End IFVConstru
```

FIGURE 3. Pseudocode of DDBIFCA.

2) We fuzzify each attribute according to the Gaussian membership function to obtain a set of membership function μ of each attribute.
3) The threshold of hesitation degree θ_j is defined, and the computation of the hesitation degree $\pi_A(u) = \theta_{ij}$ is completed.

TFS is transformed to IFS according to equation (6).

B. CSWBT-IFS ALGORITHM

In this part, the intuitionistic fuzzy aggregation algorithm is discussed. According to the characteristics of wireless sensor networks, we combine the original TOPSIS algorithm and put forward a new method of determining attribute weight based on the similarity between categories. Finally, to solve the classification of multiple attribute decision, the CSWBT-IFS algorithm is proposed to complete the local decisions.

1) BRIEF INTRODUCTION TO TOPSIS

TOPSIS [16] was put forward by C.L. Hwang and K. Yoon in 1981, then widely used in multiple attributes decision making problems. There are two ideal solutions in TOPSIS, positive ideal solution (PIS) and negative ideal solution (NIS). We should rank the alternatives to evaluate them according to their distance to ideal solutions. TOPSIS is based on the method that the chosen alternative should have the farthest distance to the PIS and the shortest distance to the NIS. The process of TOPSIS is summarized as follows:

1) Assuming that the decision matrix is A, f_{ij} represents the evaluation of i-th alternatives on the j-th attribute. We should normalize the decision matrix using the follow formula to get $A' = f'_{ij} = f_{ij} / \sqrt{\sum_{i=1}^{n} f_{ij}^2}$

$$A = (f_{ij})_{n\times m} = \begin{bmatrix} f_{11}, & f_{12}, & \dots, & f_{1m} \\ f_{21}, & f_{22}, & \dots, & f_{2m} \\ \vdots & \vdots & & \vdots \\ f_{n1}, & f_{n2}, & \dots, & f_{nm} \end{bmatrix} \quad (8)$$

2) Calculate the weighted normalized decision matrix Z, $z_{ij} = \omega_j f'_{ij}\, \omega_j$ is the weight of the j-th attribute.
3) Determine the PIS Z^+ and NIS Z^-:

$$Z^+ = (z_1^+, z_2^+, \cdots, z_m^+) = \{\max_i z_{ij} \big| j = 1, 2, \cdots, m\} \quad (9)$$

$$Z^- = (z_1^-, z_2^-, \cdots, z_m^-) = \{\min_i z_{ij} \big| j = 1, 2, \cdots, m\} \quad (10)$$

4) Calculate the distance of each alternative to the PIS D_i^+ and NIS D_i^-:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} (z_{ij} - z_j^+)^2} \quad (11)$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} (z_{ij} - z_j^-)^2} \quad (12)$$

5) Calculate the relative closeness to the ideal solutions C_i and rank the alternatives according to the descending order of the relative closeness. The larger the C_i, the better the alternative.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}, \quad i = 1, 2, \dots, n \quad (13)$$

There are two key points to using TOPSIS in multi attributes decision making problems:

1) The method to get the weight of each attribute; and
2) The method to confirm the PIS and NIS.

In this paper, we combine the original TOPSIS and consider the WSN, proposing a unique method to get the weight of each attribute and the PIS and NIS.

2) THE CSWBT-IFS ALGORITHM

The intuitionistic fuzzy value of each class for all data can be computed according to the DDBIFCA proposed above. Then, we assume that there are n classes in the samples, k attributes in each sample, and a sense node collecting the

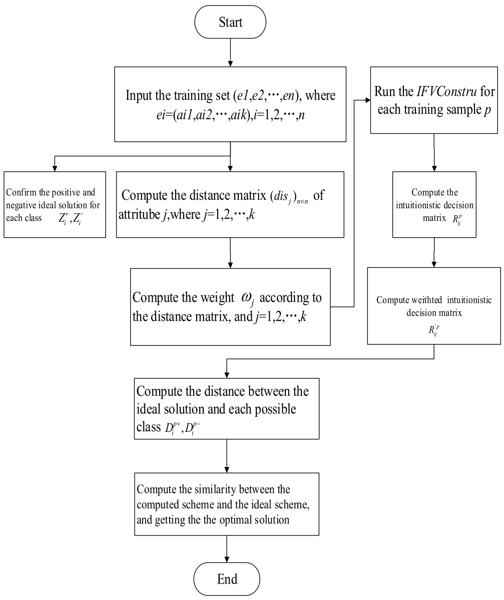

FIGURE 4. **CSWBT-IFS algorithm.**

data $c_i = \{c_{i1}, c_{i2}, \ldots, c_{ik}\}$. Therefore, according to the DDBIFCA, the intuitionistic fuzzy decision matrix is:

$$R_p = (r_{ij}^p)_{n\times k} = \begin{bmatrix} r_{11}^p, & r_{12}^p, & \ldots, & r_{1k}^p \\ r_{21}^p, & r_{22}^p, & \ldots, & r_{2k}^p \\ \vdots & \vdots & & \vdots \\ r_{n1}^p, & r_{n2}^p, & \ldots, & r_{nk}^p \end{bmatrix} \quad (14)$$

where $r_{ij}^p = (\mu_{ij}^p, \nu_{ij}^p)$ is the intuitionistic fuzzy value of the j-th attribute for the i-th class in the p-th node, and μ_{ij}^p is the membership of the j-th attribute for the i-th class in the p-th node. The CSWBT-IFS algorithm is used to make the local decision according to the matrix R_p.

The CSWBT-IFS algorithm uses three main steps. First, the weights and the positive-negative ideal solutions for each class are confirmed by the training set. Then, the intuitionistic fuzzy decision matrix R_p is determined according to the DDBIFCA. Finally, according to TOPSIS, the similarity between the computed scheme and the ideal scheme is calculated, and the optimal solution is obtained. Fig. 4 shows the algorithm.

Based on the steps of the algorithm above, some specific computations should be discussed. Then, how to calculate the weight in attributes and determine the positive-negative ideal solutions are presented.

3) CALCULATION OF WEIGHTS

In order to measure the similarity between IFS, Bustince *et al.* [17] gives the similarity measurement for IFS: assume that X is a non-empty set, $\Phi(X)$ is the IFS in X, and $A_j \in \Phi(X)(j = 1, 2, 3)$. Then, we use $\vartheta(A_1, A_2)$ to measure the similarity of IFS if it meets the following conditions:

1) $0 \leq \vartheta(A_1, A_2) \leq 1$
2) $\vartheta(A_1, A_2) = 1$ when $A_1 = A_2$
3) $\vartheta(A_1, A_2) = \vartheta(A_2, A_1)$
4) If $A_1 \subseteq A_2 \subseteq A_3$, $\vartheta(A_1, A_3) \leq \vartheta(A_1, A_2)$, $\vartheta(A_1, A_3) \leq \vartheta(A_2, A_3)$

On the contrary, the distance measurement between IFS is $d(A_1, A_1) = 1 - \vartheta(A_1, A_2)$.

Bustince *et al.* [17] give the Euclidean distance between IFS. Assuming that $X = \{x_1, x_2, \cdots, x_n\}$ is a finite set and A_1 and A_2 are both IFS, then the distance between them is:

$$d_2(A_1, A_2) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}(\mu_{A_1}(x_j) - \mu_{A_2}(x_j))^2 + (\nu_{A_1}(x_j) - \nu_{A_2}(x_j))^2} \quad (15)$$

In this paper, we assume that a sensor node consists of different modules to monitor attributes and the sample set collected by all the sensor nodes is $E = \{e_1, e_2, \ldots, e_n\}$, where e_i is the training set of the i-th sample set, and it consists of m data samples, $e_i = \{e_i^1, e_i^2, \cdots, e_i^m\}$. Each data sample consists of k attributes $e_i^p = \{e_{i1}^p, e_{i2}^p, \ldots, e_{ik}^p\}$, $p = 1, 2, \cdots, m$. The importance of each attribute is different, thus the calculation of weights for these attributes is as follows:

1) According to the DDBIFCA, we calculate the intuitionistic fuzzy matrix $(r_{ij}^{i_1 p})_{n\times k}$, where n is the number of the classes, and p is the p-th data sample of the i1-th sample set.
2) Recombine the intuitionistic fuzzy matrix:

$$(d_{ij}^{i_1})_{m\times 1} = \begin{bmatrix} r_{ij}^{i_1 1} \\ r_{ij}^{i_1 2} \\ \vdots \\ r_{ij}^{i_1 m} \end{bmatrix}, \quad (i, i_1 = 1, 2, \cdots, n\ j = 1, 2, \cdots, k) \quad (16)$$

Where $(d_{ij})_{m\times 1}$ is the membership of the data sample in the i1-th sample set to the i-th sample set in the j-th attribute, and $r_{ij}^{i_1 p} = (u_{ij}^{i_1 p}, v_{ij}^{i_1 p})$.
3) We calculate the distance matrix by Euclidean distance:

$$(dis_j^{i_1})_{n\times n} = \begin{bmatrix} 0, & dis(d_{1j}^{i_1}, d_{2j}^{i_1}), & \cdots, & dis(d_{1j}^{i_1}, d_{nj}^{i_1}) \\ dis(d_{2j}^{i_1}, d_{1j}^{i_1}), & 0, & \cdots, & dis(d_{2j}^{i_1}, d_{nj}^{i_1}) \\ \vdots & \vdots & & \vdots \\ dis(d_{nj}^{i_1}, d_{1j}^{i_1}), & dis(d_{nj}^{i_1}, d_{1j}^{i_1}), & \cdots, & 0 \end{bmatrix} \quad (17)$$

where the method of Euclidean distance [18] is.

$$d_2(A_1, A_2) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}(\mu_{A_1}(x_j) - \mu_{A_2}(x_j))^2 + (\nu_{A_1}(x_j) - \nu_{A_2}(x_j))^2}$$

4) Next, we calculate the distance matrix and the similarity matrix $(s_j^{i_1})_{n\times n}$ in the j-th attribute according to

$$dis_j = \frac{1}{n}(\sum(dis_j^1) + \sum(dis_j^2) + \cdots + \sum(dis_j^n)),\quad j = 1, 2, \cdots, n \quad (18)$$

5) We then normalize the vector dis, and obtain the weight vector w

$$w = (\frac{dis_1}{\sum_j dis_j}, \frac{dis_2}{\sum_j dis_j}, \cdots, \frac{dis_k}{\sum_j dis_j}) \quad (19)$$

4) DETERMINATION OF POSITIVE AND NEGATIVE IDEAL SOLUTIONS

The TOPSIS algorithm assumes that the positive ideal solution is the best scheme and the negative ideal solution is the worst scheme. In this paper, in contrast to the traditional multi-attributes decision, the positive ideal solution should be the most representative intuitionistic fuzzy number for each attribute. The ideal solution using a single data simply is not representative enough. Therefore, a comprehensive analysis of data samples is necessary to determine the ideal solution. Thus, there is not one ideal solution for all the classes, but rather one unique ideal solution for each class. The details of the ideal solution method are shown as follows.

First, according to equation [18] and equation [19], we confirm the positive ideal solution from the intuitionistic fuzzy average operator.

$$IFA(\alpha_1, \alpha_2, \ldots, \alpha_n) = \frac{1}{n}(\alpha_1 \oplus \alpha_2 \oplus \cdots \oplus \alpha_n) \quad (20)$$

$$Z_i^+ = \frac{1}{n}(r_i^1 \oplus r_i^2 \oplus \cdots \oplus r_i^m),\quad (i, = 1, 2, \cdots, n) \quad (21)$$

where $(r_i^p) = (r_{i1}^{ip}, r_{i2}^{ip}, \cdots, r_{ik}^{ip})$, $p = 1, 2, \cdots m$. And, if we assume that $\alpha_1 = (\mu_{\alpha 1}, \nu_{\alpha 1})$ and $\alpha_2 = (\mu_{\alpha 2}, \nu_{\alpha 2})$, then $\alpha_1 \oplus \alpha_2 = (\mu_{\alpha 1} + \mu_{\alpha 2} - \mu_{\alpha 1}\mu_{\alpha 2}, \nu_{\alpha 1}\nu_{\alpha 2})$.

Second, we confirm the negative ideal solution, which is the maximum distance to the positive ideal solution; that is:

$$dis(Z_i^-, Z_i^+)|_{Z_i^- = r_i^p} = \max_{r_i^p}(dis(r_i^1, Z_i^+), dis(r_i^2, Z_i^+), \cdots, dis(r_i^m, Z_i^+)),\quad (i = 1, 2, \cdots, n\ p = 1, 2, \cdots, m) \quad (22)$$

Third, we calculate the distance to the positive ideal solution and the negative ideal solution for each intuitionistic fuzzy value.

$$D_i^+ = \sqrt{\sum_{j=1}^{m}(z_{ij} - z_j^+)^2} \quad (23)$$

$$D_i^- = \sqrt{\sum_{j=1}^{m}(z_{ij} - z_j^-)^2} \quad (24)$$

TABLE 1. Part of Anderson's Iris data set.

NO.	Setosa				Versicolor				Virginica			
	Length of Calyx	Width of Calyx	Length of Petal	Width of Petal	Length of Calyx	Width of Calyx	Length of Petal	Width of Petal	Length of Calyx	Width of Calyx	Length of Petal	Width of Petal
1	5.1	3.5	1.4	0.2	7	3.2	4.7	1.4	6.3	3.3	6	2.5
2	4.9	3	1.4	0.2	6.4	3.2	4.5	1.5	5.8	2.7	5.1	1.9
3	4.7	3.2	1.3	0.2	6.9	3.1	4.9	1.5	7.1	3	5.9	2.1
4	4.6	3.1	1.5	0.2	5.5	2.3	4	1.3	6.3	2.9	5.6	1.8
5	5	3.6	1.4	0.2	6.5	2.8	4.6	1.5	6.5	3	5.8	2.2
6	5.4	3.9	1.7	0.4	5.7	2.8	4.5	1.3	7.6	3	6.6	2.1
7	4.6	3.4	1.4	0.3	6.3	3.3	4.7	1.6	4.9	2.5	4.5	1.7
8	5	3.4	1.5	0.2	4.9	2.4	3.3	1	7.3	2.9	6.3	1.8
9	4.4	2.9	1.4	0.2	6.6	2.9	4.6	1.3	6.7	2.5	5.8	1.8
10	4.9	3.1	1.5	0.1	5.2	2.7	3.9	1.4	7.2	3.6	6.1	2.5

Finally, we calculate each relative proximity C_i to the ideal solution, and sort C_i to obtain the optimal solution.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+},\quad i = 1, 2, \ldots, n \quad (25)$$

5) CASE STUDY

Table I shows part of Anderson's Iris data set [19].

First, retrieve the intuitionistic fuzzy set according to DDB-IFCA. Here, we only give the IF-represented results of the Setosa flower, in which three sets of intuitionistic fuzzy values under each attribute stand for the membership of each class. The results are shown in Table II.

Then, we compute the similarity matrix of Se, Ve, and Vi in the Length of Calyxas attribute, as follows:

$$s_1 = \begin{array}{c} \\ Se \\ Ve \\ Vi \end{array}\begin{array}{c} \begin{array}{ccc} Se & Ve & Vi \end{array} \\ \begin{bmatrix} 1 & 0.43 & 0.36 \\ 0.43 & 1 & 0.83 \\ 0.36 & 0.83 & 1 \end{bmatrix} \end{array}.$$

Similarly, the similarity matrix of the Width of Calyx, Length of Petal, and Width of Petal can be computed. The results are:

$$s_2 = \begin{array}{c} \\ Se \\ Ve \\ Vi \end{array}\begin{array}{c} \begin{array}{ccc} Se & Ve & Vi \end{array} \\ \begin{bmatrix} 1 & 0.63 & 0.67 \\ 0.63 & 1 & 0.94 \\ 0.67 & 0.94 & 1 \end{bmatrix} \end{array},$$

$$s_3 = \begin{array}{c} \\ Se \\ Ve \\ Vi \end{array}\begin{array}{c} \begin{array}{ccc} Se & Ve & Vi \end{array} \\ \begin{bmatrix} 1 & 0.43 & 0.44 \\ 0.43 & 1 & 0.62 \\ 0.44 & 0.62 & 1 \end{bmatrix} \end{array}$$

TABLE 2. IFV construction results of Setosa.

NO.	Setosa			
	Length of Calyx	Width of Calyx	Length of Petal	Width of Petal
1	(0.61, 0.28)	(0.59, 0.14)	(0.84, 0.11)	(0.89, 0.03)
	(0.25, 0.47)	(0.10, 0.60)	(0.00, 0.76)	(0.00, 0.83)
	(0.11 0.59)	(0.15, 0.55)	(0.00, 0.70)	(0.00, 0.70)
2	(0.88, 0.01)	(0.41, 0.32)	(0.84, 0.11)	(0.89, 0.03)
	(0.16, 0.57)	(0.65, 0.05)	(0.00, 0.76)	(0.00, 0.83)
	(0.06, 0.64)	(0.69, 0.01)	(0.00, 0.70)	(0.00, 0.70)
3	(0.75, 0.14)	(0.68, 0.05)	(0.32, 0.62)	(0.89, 0.03)
	(0.09, 0.64)	(0.41, 0.29)	(0.00, 0.76)	(0.00, 0.83)
	(0.03, 0.67)	(0.50, 0.20)	(0.00, 0.70)	(0.00, 0.70)
4	(0.57, 0.32)	(0.56, 0.17)	(0.84, 0.11)	(0.89, 0.03)
	(0.07, 0.66)	(0.54, 0.16)	(0.00, 0.76)	(0.00, 0.83)
	(0.02, 0.68)	(0.62, 0.08)	(0.00, 0.70)	(0.00, 0.70)
5	(0.78, 0.11)	(0.44, 0.28)	(0.84, 0.11)	(0.89, 0.03)
	(0.20, 0.52)	(0.05, 0.65)	(0.00, 0.76)	(0.00, 0.83)
	(0.08, 0.62)	(0.08, 0.62)	(0.00, 0.70)	(0.00, 0.70)
6	(0.13, 0.76)	(0.09, 0.64)	(0.05, 0.90)	(0.05, 0.87)
	(0.44, 0.29)	(0.00, 0.70)	(0.00, 0.76)	(0.00, 0.83)
	(0.22, 0.48)	(0.01, 0.69)	(0.00, 0.70)	(0.00, 0.70)
7	(0.57, 0.32)	(0.70, 0.03)	(0.84, 0.11)	(0.52, 0.40)
	(0.07, 0.66)	(0.18, 0.52)	(0.00, 0.76)	(0.00, 0.83)
	(0.02, 0.68)	(0.25, 0.45)	(0.00, 0.70)	(0.00, 0.70)
8	(0.78, 0.11)	(0.70, 0.03)	(0.84, 0.11)	(0.89, 0.03)
	(0.20, 0.52)	(0.18, 0.52)	(0.00, 0.76)	(0.00, 0.83)
	(0.08, 0.62)	(0.25, 0.45)	(0.00, 0.70)	(0.00, 0.70)
9	(0.22, 0.67)	(0.27, 0.46)	(0.84, 0.11)	(0.89, 0.03)
	(0.04, 0.69)	(0.70, 0.00)	(0.00, 0.76)	(0.00, 0.83)
	(0.01, 0.69)	(0.70, 0.01)	(0.00, 0.70)	(0.00, 0.70)
10	(0.88, 0.01)	(0.56, 0.17)	(0.84, 0.11)	(0.25, 0.66)
	(0.16, 0.57)	(0.54, 0.16)	(0.00, 0.76)	(0.00, 0.83)
	(0.06, 0.64)	(0.62, 0.08)	(0.00, 0.70)	(0.00, 0.70)

$$\text{and } s_4 = \begin{array}{c} \\ Se \\ Ve \\ Vi \end{array} \begin{array}{c} \begin{array}{ccc} Se & Ve & Vi \end{array} \\ \begin{bmatrix} 1 & 0.49 & 0.47 \\ 0.49 & 1 & 0.59 \\ 0.47 & 0.59 & 1 \end{bmatrix} \end{array}.$$

Then, the vector of the weight of attributes is $w = [0.27, 0.15, 0.30, 0.28]^{\mathrm{T}}$.

The positive ideal solution of Se is:

$$Z_1^+ = \begin{bmatrix} \frac{1}{10}[(0.61, 0.28) \oplus (0.88, 0.01) \oplus \cdots \oplus (0.88, 0.01)] \\ \frac{1}{10}[(0.59, 0.14) \oplus (0.41, 0.32) \oplus \cdots \oplus (0.56, 0.17)] \\ \frac{1}{10}[(0.84, 0.11) \oplus (0.84, 0.11) \oplus \cdots \oplus (0.84, 0.11)] \\ \frac{1}{10}[(0.89, 0.03) \oplus (0.89, 0.03) \oplus \cdots \oplus (0.25, 0.66)] \end{bmatrix}^T = \begin{bmatrix} (0.69, 0.13) \\ (0.53, 0.15) \\ (0.78, 0.16) \\ (0.80, 0.07) \end{bmatrix}^T.$$

In the same way, we have:

$$Z_2^+ = [(0.51, 0.18), (0.51, 0.10), (0.57, 0.14), (0.66, 0.10)],$$
$$Z_3^+ = [(0.53, 0.09), (0.54, 0.06), (0.55, 0.05), (0.50, 0.14)].$$

And the negative ideal solutions are:

$$Z_1^- = [(0.13, 0.76), (0.09, 0.64), (0.05, 0.90), (0.05, 0.87)],$$
$$Z_2^- = [(0.50, 0.23), (0.15, 0.55), (0.55, 0.21), (0.73, 0.10)],$$
$$Z_3^- = [(0.69, 0.01), (0.27, 0.43), (0.70, 0.00), (0.48, 0.22)].$$

Next, test data (5.1, 3.5, 1.4, 0.3) is given, and the class to which it belongs needs to be determined according to TOPSIS.

First, the intuitionistic fuzzy matrix of this data is:

$$d_{ij} = \begin{bmatrix} (0.61, 0.28) & (0.59, 0.14) & (0.84, 0.11) & (0.52, 0.40) \\ (0.25, 0.47) & (0.10, 0.60) & (0.00, 0.76) & (0.00, 0.83) \\ (0.11, 0.59) & (0.15, 0.55) & (0.00, 0.70) & (0.00, 0.70) \end{bmatrix}.$$

The new intuitionistic fuzzy matrix, which is weighted, is computed:

$$d'_{ij} = nwd_{ij} = \begin{bmatrix} (0.64, 0.25) & (0.41, 0.31) & (0.89, 0.07) & (0.56, 0.36) \\ (0.27, 0.44) & (0.06, 0.74) & (0.00, 0.72) & (0.00, 0.81) \\ (0.12, 0.57) & (0.09, 0.70) & (0.00, 0.65) & (0.00, 0.67) \end{bmatrix}$$

Next, the similarities of these three classes are $C_1 = 0.66$, $C_2 = 0.46$, $C_3 = 0.49$.

Thus, this data belongs to the first class, the Se class.

IV. PERFORMANCE EVALUATION

In this section, the performance of the proposed model in a real-world application is experimented. Anderson's iris data set, a classical data set in data mining and classification, is used, which includes 150 data samples divided into 3 classes, which are Setosa, Versicolour, and Virginica (short in Se, Ve, and Vi). There are 50 data samples in each class, and 4 attributes in each data sample: length of calyx, width of calyx, length of petal, and width of petal. As is shown in Table 1, classification of Anderson's iris data is already known. Thus, for each class, we use the 35 data samples ahead as the training set to compute the statistic information of attributes and the rest to test the performance of the DDB-IFCA algorithm. In this model, two algorithms are proposed: DDBIFCA and CSWBT-IFS. Therefore, the simulation is divided into two parts.

A. PERFORMANCE OF DDBIFCA

In our performance evaluation studies for the DDBIFCA algorithm, we use the following performance metrics:

Overall performance
Classification accuracy
Impact of the threshold in hesitation degree
Analysis of time complexity

1) OVERALL PERFORMANCE

Taking the Se data set as an example, the IFS construction result of length of calyx is shown in Fig. 5. Fig. 5 is the membership degree result, in which the three bar charts in each group respectively stand for the membership degree for Se, Ve, and Vi. Fig. 6 shows the non-membership. As we can

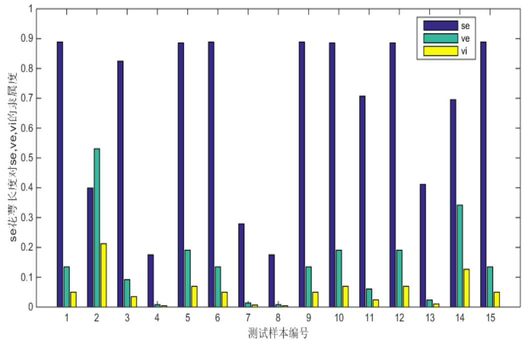

FIGURE 5. Membership degree.

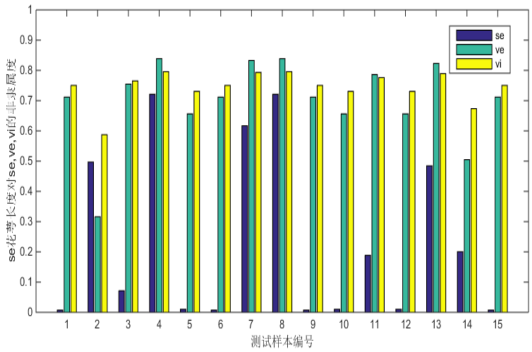

FIGURE 6. Non-membership degree.

see, the membership to Se is apparently greater than that of Ve and Vi, and the non-membership of Se is also less than the others. According to the meaning of IFS, the results show that the possibility that the data set belongs to Se is far greater than the Ve and Vi. Therefore, it is indicated that the DDBIFCA is reasonable.

For further analysis of the rationality of the algorithm, the concept of scoring function [20] is introduced to analyze the accuracy of IFS construction. For any IFS $\alpha = (\mu_\alpha, v_\alpha)$, we can use $s(\alpha)$ to evaluate:

$$s(\alpha) = \mu_\alpha - v_\alpha \tag{26}$$

$s(\alpha) \in [-1, 1]$ is the score of IFS α. The larger the $s(\alpha)$, the larger the IF value, which means the greater the probability that an element belongs to the set. Fig. 7 shows the score of Se, Ve, and Vi. As we can see, in addition to the second group of data, the Se score is greater than that of Ve and Vi, which indicates that, from the perspective of the length of the calyx, IFS construction achieves 93% accuracy. After 1,000 random tests, the average accuracy rate could reach 83%. Therefore, DDBIFCA can accurately represent the membership degree of the given attribute values for each category.

2) CLASSIFICATION ACCURACY

Fig. 8 shows the abnormal IFV construction numbers, namely the numbers of the inconsistent classification results between our algorithm and the original dataset for the 4 attributes presented earlier.

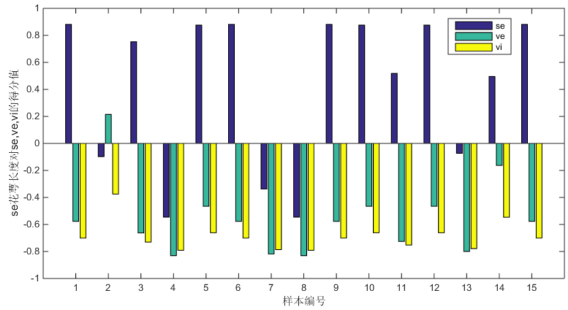

FIGURE 7. Score value.

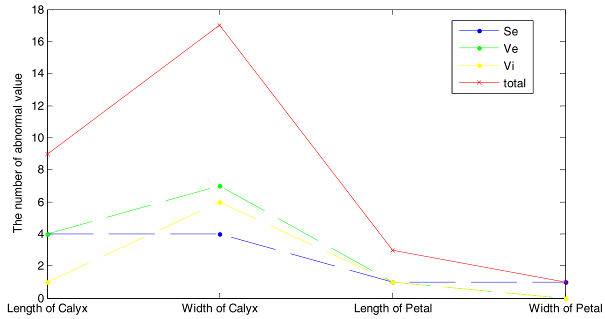

FIGURE 8. Abnormal IFV construction numbers ($\theta = 0.2$).

In order to analyze the reasons why we obtained those abnormal IFV construction numbers, the distribution of test samples for different attributes is observed. Fig. 9 shows the distributions of tests samples for Se, Ve, and Vi in different attributes. According to Fig. 9 (a) and Fig. 9 (b) below, the types of distributions are closed for the length of calyx and the width of calyx. In case of the width of calyx, the distribution of Ve and Vi is closer. Therefore, the classification accuracy of these two flowers is quite low. On the other hand, the distributions of the attribute set are more decentralized for the length of petal and the width of petal, which demonstrates higher accuracy.

3) IMPACT OF THE THRESHOLD IN HESITATION DEGREE

In DDBIFCA, the hesitation degree depends on the threshold θ, and different thresholds may lead to different IFS constructions. In this context, we investigate the impact of the threshold in hesitation degree. In the intuitionistic fuzzy set-based decision fusion, classification is not appropriate if the threshold is too large or too small. Therefore, in this paper, from our previous experiments, we assume that the value of the threshold ranges between 0.2 and 0.5.

Fig. 8, Fig. 10, and Fig. 11 are the abnormal IFV construction numbers, when $\theta = 0.2$, 0.3 and 0.5. From these figures, the total abnormal IFV construction numbers are basically unchanged for the different thresholds.

4) ANALYSIS OF TIME COMPLEXITY

In this part, the time complexity of DDBIFCA is discussed. We assume that there are n classes in the samples sets and

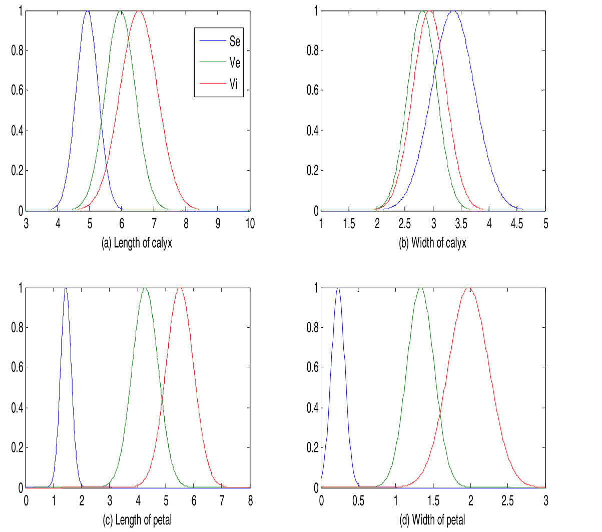

FIGURE 9. Distribution for tests with sample sets for Se, Ve, and Vifordifferent attributes.

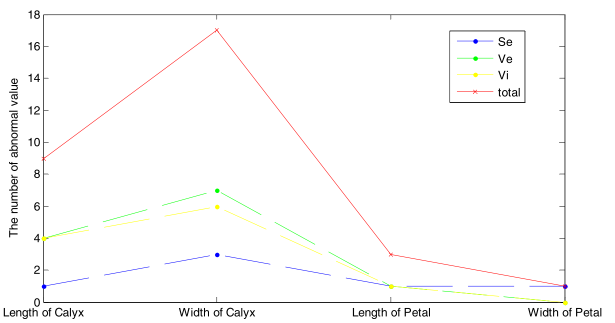

FIGURE 10. Abnormal IFV construction numbers ($\theta = 0.3$).

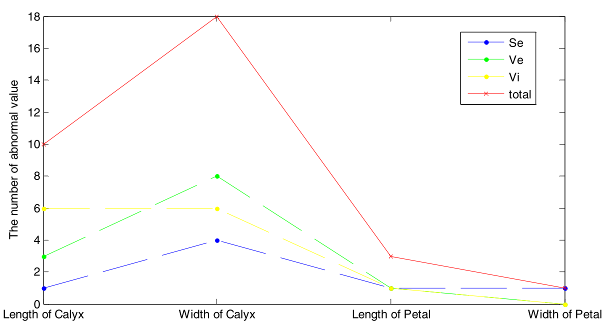

FIGURE 11. Abnormal IFV construction numbers ($\theta = 0.5$).

m data samples in each sample set (p training data samples and q test data sam*ples*, m = p + q), and k attributes in each data sample. Then, the time complexity in each process is as follows: The complexity in computing the mean value and variance is $2n \times O(p) = O(np)$. The complexity in computing the maximum variance in training data is $kn \times O(p) = O(nkp)$. The complexities of computing the Gaussian membership, hesitation degree, IFS-based membership, and non-membership in the test data are all $O(nkq)$. Therefore, the total time complexity of DDBIFCA is $O(nkp) + O(nkq) = O(nk(p+q)) = O(nkm)$.

TABLE 3. Classification accuracy of CSWBT-IFS compared with other fusion algorithms.

Algorithm	TFSBF	IFWA	CSWBT-IFS
Mean accuracy	92.3%	87.3%	94.7%

In WSN, the collection of training data and the computation of the mean value and the variance are done by the FC, and the results are transmitted to each node. Therefore, in local nodes, only the computation of intuitionistic fuzzification according to the attribute value is needed. Thus, the local time complexity is $O(nkp)$

The time complexity of DDBIFCA depends on the total number of all data samples, and the computation time has a linear relation with the total number of all data samples. Meanwhile, under the same experimental environment, the time complexity in evidence theory is $O(2^k np)$, which grows with an exponential trend when the attribute number grows. Finally, the DDBIFCA is simpler to compute, and efficient in terms of time complexity, and more suitable in energy-constrained WSNs.

B. PERFORMANCE OF CSWBT-IFS

In this section, the classification accuracy of CSWBT-IFS and the impact of the threshold on the accuracy are discussed. It is worth noting that the final result is the mean value of 1,000 repeated experiments. In each experiment, 35 data samples are chosen randomly from each data set to be used as the training data, and the remaining 15 data samples are used as the test data.

1) CLASSIFICATION ACCURACY

We compare the classification accuracy of CSWBT-IFS with two other fusion algorithms, namely, the traditional fuzzy set-based fusion algorithm (TFSBF) and the intuitionistic fuzzy weighted averaging algorithm (IFWA). The result is shown in Table III.

As shown in Table III, the classification accuracy in TFSBF is 92.3%, in IFWA it is 87.3%, and in CSWBT-IFS it is 94.7%. Therefore, the accuracy of IFWA is worse than that of TFSBF. In contrast, when compared with the accuracy of TFSBF and IFWA, the accuracy of the proposed algorithm, CSWBT-IFS, is higher than both by 2.4% and 7.4%, respectively.

Therefore, the IFS-based algorithm is much more flexible. In addition, the accuracy with the proposed algorithm also yields a better result.

2) IMPACT OF THRESHOLD ON THE ACCURACY

We also experimented with the IFS-based fusion algorithm in different hesitation degree thresholds and compared with a different operator-based aggregation algorithm. The algorithms include the single-attribute fusion algorithm (SAFA), IFA, IFWA, and CSWBT-IFS. The comparison results are shown in Fig. 12.

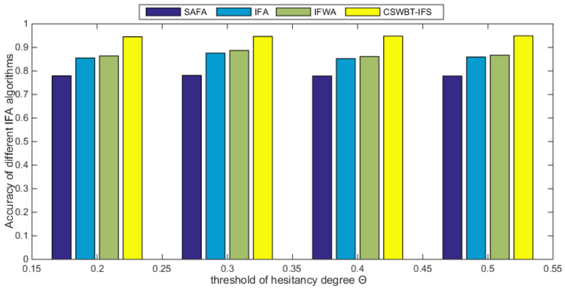

FIGURE 12. Comparison of different IFV aggregation algorithms.

As shown in Fig. 12, compared with the SAFA algorithm, using intuitionistic fuzzy fusion to combine the multi-attributes can yield a higher classification accuracy. In IFWA, the relative importance of different attributes is considered. The more important an attribute is, the higher weight value it has. Therefore, the accuracy of IFWA is 1% to 2% higher than that of IFA. Moreover, the CSWBT-IFS yields the highest accuracy among all the algorithms, and the accuracy is between 92% and 95%. The average accuracy, therefore, increases by 7% to 8%. This is a result of CSWBT-IFS not only considering the weight for the different attributes, but also using the positive-negative ideal solutions, which are confirmed by the IF value of sample sets.

Based on the above analysis, the proposed algorithm can increase accuracy more than the traditional intuitionistic fuzzy fusion algorithms. However, the weight allocation and the ideal solutions computation are computed at the fusion center. Then, the nodes locally fuzzify the collected data and compare it with the ideal solutions. Thus, the local decision is obtained. The process of computation is simple, which makes it suitable for minimizing the energy overhead in WSNs.

V. CONCLUSION

In this paper, we proposed the MADF-IFS model. First, based on the WSN characteristics, the DDBIFCA algorithm was proposed. This algorithm can transform raw data to the intuitionistic fuzzy values. The simulation results obtained show that the proposed algorithm is more accurate and reasonable than the existing algorithms we compared it against. Then, we proposed the CSWBT-IFS algorithm to address the problem of multi-attribute decision fusion. The simulation results show that, compared with the traditional fuzzy algorithms and the other intuitionistic fuzzy decision algorithms, our proposed algorithm increases the classification accuracy.

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