Classification of Uncertain Data Based on Evidence Theory in Wireless Sensor Networks

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Abstract. In wireless sensor networks, the classification of uncertain data reported by sensor nodes is an open issue because the given attribute information can be insufficient for making a correct specific classification of the objects. Although the traditional Evidential *k*-Nearest Neighbor (E*k*NN) algorithm can effectively model the uncertainty, it is easy to misjudge the target data to the incorrect class when the observed sample data is located in the feature overlapping region of training samples of different classes. In this paper, a novel Evidential *k*-Nearest Neighbor (NE*k*NN) algorithm is proposed based on the evidential editing method. The main idea of NE*k*NN algorithm is to consider the expected value and standard deviation of various training sample data sets, and use normalized Euclidean distance to assign class labels with basic belief assignment (BBA) structure to each training sample, so that training samples in overlapping region can offer more abundant and diverse class information. Further, E*k*NN classification of the observation sample data is carried out in the training sample sets of various classes, and mass functions of the target to be tested under this class are obtained, and Redistribute Conflicting Mass Proportionally Rule 5 (PCR5) combination rule is used to conduct global fusion, thus obtaining the global fusion results of the targets. The experimental results show that this algorithm has better performance than other classification methods based on *k*-nearest neighbor.

Keywords: Evidence theory · Uncertain data · Target classification · Combination rule

1 Introduction

When using the sensor's observation data to carry out the local classification of targets, the sensor's observation data contains a lot of imprecise information due to various interferences [1]. For example, some sample data comes from different categories of targets but they are very similar, that is, the sample data of different categories may

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partially overlap, which brings great challenges to traditional target classification tasks [2]. In the classification task with supervision, the sensor's observation data may be in the overlapping area of different categories of training samples, it is difficult for the traditional voting *k*NN classifier to accurately classify the target at this time. For this reason, many scholars have fully considered the distance relationship between the target and its neighbors, and proposed the fuzzy *k*NN (Fuzzy *k*NN, F*k*NN) classification algorithm [3]. This algorithm allows the target to belong to different categories with different fuzzy membership degrees, which obtains the better classification effect than voting *k*NN [4].

Dempster-Shafer evidence theory, also referred as evidential reasoning or belief functions theory, has been proved to be valuable as a solution for dealing with uncertain and inaccurate data [5], and it has been widely applied in sorts of applications, for example, state estimation [6], target recognition [7], data classification [2], and information fusion [8], and etc. As the extension of probability theory, evidence theory provides a series of functions and operations defined on the power set of the identification framework, which can effectively reason and model the uncertainty, and can provide more abundant category information than fuzzy membership [9]. Therefore, many scholars have combined evidence theory with traditional classification algorithms with supervision and developed a series of evidence classification algorithms. Among them, the most representative is the evidential *k*NN (Evidential *k*-Nearest Neighbor, E*k*NN) algorithm proposed by Scholars such as Denoeux, et al. [10, 11]. This algorithm is simple and direct with low error rate, so it is very suitable for the target classification task of sensor nodes. However, the E*k*NN algorithm only considers the factor of the distance between the target and the training samples, and does not treat all training samples differently [12]. It is assumed that the target sample is in the overlapping area of the training set, and the target data is far from the sample points of the same category, and closer to the sample points of other categories, if the E*k*NN algorithm is used at this time, the evidence formed by the sample points that are closer to the target will be given a large mass value, then when making the decision after the evidence is fused, it is easy to misjudge the target data into other categories. In [13], it is further pointed out that since the E*k*NN algorithm treats imprecise training samples from overlapping regions as training samples that truly represent the distribution of the target category, it will have a greater negative impact on the final classification effect. In order to solve this problem, it is necessary to preprocess the original training samples with the evidence editing method based on E*k*NN, and replace the category labels of the original training samples with basic belief assignment, it can better characterize the inaccuracy of the overlapping regions of categories. However, in [13], it is proposed that the evidence editing method will make the edited evidence have a higher correlation. When subsequently fusing the evidence constructed by the target's neighbors, it is necessary to evaluate the correlation between the evidences, and to search for the corresponding fusion rules according to the degree of correlation between the evidences. Therefore, this method has the problems of high algorithm complexity and excessive calculation, which is not suitable for sensor nodes with limited energy. In addition to the evidence editing method, in [14], it is pointed out that if a target falls in the overlapping area of the training set, to first consider using E*k*NN to classify the target in the training set of each category and then perform the evidence fusion of the classification results can also suppress the influence of other categories of training samples in the overlapping area on the fusion result. The improved E*k*NN algorithm (Improved Evidential k-Nearest Neighbor, IE*k*NN) was also proposed to improve the performance of the E*k*NN algorithm [15], however, IEkNN does not edit the samples, while directly uses the original training samples for classification [16].

In order to effectively model and reason about imprecise data, this paper proposes a NE*k*NN (New Evidential *k*-Nearest Neighbor, NE*k*NN) algorithm. The NE*k*NN algorithm proposes a simple evidence preprocessing method under the framework of evidence theory. This method only considers the expected value and standard deviation of the training sample sets of each category, thereby avoiding the evidence correlation that may be caused by the original evidence editing method. On this basis, by fusing the classification results of the target to be tested in the training sample set of each category, the E*k*NN obtain a more accurate identification and judgment of the target.

The other parts of this paper are arranged as follows. Section 2 fundamentally introduces the basis of evidence theory. Section 3 focuses on the original training data preprocessing method, and design the NE*k*NN classification algorithm after preprocessing. Section 4 comprehensively evaluates and analyzes the classification performance of the proposed NE*k*NN algorithm based on simulation data, and finally summarize the work of this paper in Sect. 5.

2 Basics of Belief Functions Theory

The Dempster–Shafer evidence theory introduced by Shafer is also known as belief functions theory [17]. In this theory, the frame of discernment Ω is a finite set, whose elements are exhaustive and mutually exclusive, and it is denoted as $\Omega = \{w_1, w_2, \ldots, w_i, \ldots, w_c\}$. 2^Ω is the power set of the frame of discernment, which represents the set of all possible subsets of Ω, indicated by $2^\Omega = \{\phi, \{w_1\}, \ldots \{w_n\}, \{w_1, w_2\}, \ldots, \{w_1, w_2, \ldots, w_i\}, \ldots, \Omega\}$. Given an object X, it can be classified as any singleton element and any sets of elements in 2^Ω with a basic belief assignment (BBA). The BBA is also known as the mass function, which is a mapping $m : 2^\Omega \to [0, 1]$ satisfying $\sum_{A \in 2^\Omega} m(A) = 1, m(\phi) = 0$. The function $m(A)$ is used to quantify the degree of belief that is exactly assigned to the subsets A of Ω. If $m(A) > 0$, the subset A can be called the focal elements of the mass function $m(\cdot)$. The mass values assigned to compound elements can reflect the imprecise observation of object X.

The mass function $m(\cdot)$ is always associated with three main functions, including the belief function $Bel(\cdot)$, the plausibility function $Pl(\cdot)$ and the pignistic probability function $BetP(\cdot)$, which are defined as follows, respectively:

$$Bel(B) = \sum\nolimits_{A \subseteq B} m(A) \tag{1}$$

$$Pl(B) = \sum\nolimits_{A \cap B \neq \emptyset} m(A) \tag{2}$$

$$BetP(w) = \sum\nolimits_{w \in A, A \subseteq \Omega} \frac{1}{|A|} m(A) \tag{3}$$

where $m(\cdot)$ is the focal elements on Ω, and $|A|$ denotes the cardinality of focal elements A. All three functions can be employed to make a decision on an unknown object according to a few rules, such as selecting the class with maximum *BetP*.

Assuming that there are two pieces of evidence denoted by m_1 and m_2, the popular Dempster's combination rule can be used to combine them as follows:

$$m_{\oplus}(A) = m_1(B) \oplus m_2(C) = \begin{cases} 0, & B \cap C = \phi \\ \frac{\sum B \cap C = A,\ \forall B,\ C \subseteq \Omega\, m_1(B) \times m_2(C)}{1 - \sum B \cap C = \phi,\ \forall B,\ C \subseteq \Omega\, m_1(B) \times m_2(C)} & B \cap C \neq \phi \end{cases} \quad (4)$$

where $\sum B \cap C = \phi,\ \forall B,\ C \subseteq \Omega\, m_1(B) \times m_2(C)$ represents the conflict between m_1 and m_2, which is used to redistribute the conflicting mass values. Dempster's combination rule is commutative and associative. It provides a simple and flexible solution for data fusion problems.

3 The New Evidential k-Nearest Neighbor Algorithm

In order to overcome the limitations of E*k*NN, a new E*k*NN classification algorithm is proposed in this section. The algorithm uses the method of preprocessing training samples to replace the category labels of the original samples with the basic belief assignment, so as to better describe the uncertainty of the training samples in the overlapping regions of the categories. In order to avoid the pre-processed evidence from generating greater correlation, the newly obtained category labels with the basic belief assignment structure for each sample are constructed based on the Mahalanobis distance from the evidence to the center of the corresponding category. In the subsequent classification of the target, it is first to find the k nearest neighbors of the input sample in each category of training sample set, construct k nearest neighbor evidence describing the respective classification information, and perform fusion to obtain the mass function under this category of condition, then the global fusion of evidence between categories is performed based on the mass function generated by each category, and the final classification result is obtained.

3.1 Preprocessing of Training Samples

In order to avoid evidence-related problems, this section focuses on the preprocessing method of training samples based on Mahalanobis distance. The concept of Mahalanobis distance belongs to the theory of multivariate statistical analysis [18]. It is a discriminant method that uses the distance between the sample to be judged and each population as the measurement scale to judge the attribution of the sample. When processing numerical data in wireless sensor networks, Mahalanobis distance comprehensively considers the two statistical characteristics of the expected value and standard deviation of each category in the true distribution. It avoids discussing the correlation caused by the specific distribution of sample data. At the same time, compared with Euclidean distance, Mahalanobis distance can also eliminate the interference of the correlation between attribute variables, which is more reasonable. The Mahalanobis distance used in this section can also be called the normalized Euclidean distance.

To consider a M-class problem, where the object may belong to M different classes, and $\Omega = \{w_1, \ldots, w_M\}$ is the set of all classes. It is supposed that the training sample set is $Y = \{y_1, \ldots, y_g\}$. First, the attribute information of each category of training sample can be used to calculate the center vector of the category. The center of $c_i (i = 1, \ldots, M)$ can be expressed as:

$$c_i = \frac{1}{s_i} \sum\nolimits_{y_j \in w_i} y_j \tag{5}$$

where s_i is the number of training samples of class w_i.

For each training sample $y_h (h = 1, \ldots, g)$, sample preprocessing is performed according to the distance from it to the center. The distance requires to fully consider the degree of dispersion of each category of sample distribution, that is, the size of the standard deviation. Therefore, the Mahalanobis distance is used as the measurement scale of distance here, which is:

$$d_h^{w_i} = \sqrt{\sum_{k=1}^{p} \left(\frac{y_h(k) - c_i(k)}{\delta_i(k)} \right)^2} \tag{6}$$

where $\delta_i(k)$ is the standard deviation of the training data set of class w_i, $y_h(k)$ and $c_i(k)$ are the values of the attribute vector y_h and center c_i on the k-th dimension respectively, and p is the number of dimensions.

The smaller the distance $d_h^{w_i}$ is, the more likely the training sample y_h belongs to the category w_i. If y_h is farther from the center c_i, the less likely it is that y_h belongs to category w_i. Therefore, the support of y_h belonging to category w_i is:

$$s_h(W_i) = e^{-d_h w_i} \tag{7}$$

The BBA m_h should correspond to the normalized $s_h(w_i)$, formally defined by:

$$m_h = \frac{s_h(w_i)}{\sum_{l=1}^{M} s_h(w_l)} \tag{8}$$

The above mass function m_h provides more powerful information to characterize the uncertainty for training sample y_h than the original class label $w_i \in \Omega$, and it can be consider as a new soft class label of the sample y_h. As a consequence, the new training sample set with soft class labels $Y' = \{y_1, \ldots, y_g\}$ is adopted for the target classification task in this paper.

3.2 Classification with Preprocessed Training Samples

After preprocessing, the next problem to be solved is how to classify the newly observed unknown target $x \in R^P$ based on the preprocessed training samples. Different from the general classification problem, the category of training sample used here is represented by the structure of basic trust distribution, so it is necessary to improve the original evidence kNN classification algorithm accordingly to enable it to classify x reasonably using the category label of this structure. For the target $\Omega = \{w_1, \ldots, w_M\}$ of categories

M, it is to first establish training sample sets for each category based on the total training samples, and then refer to the EkNN classification algorithm to generate evidence that can be combined in various training sets based on the training samples and the feature data of the target to be tested. The entire classification process can be divided into the construction and fusion of mass functions under each category, and the global fusion of the fusion results between categories, which will be introduced separately below.

The Construction and Fusion of Mass Functions

To consider the k nearest neighbor samples of the target x to be tested in the training samples of category $w_i(i = 1, \ldots, M)$, if one of the training samples is very close to the sample x to be tested, the training sample provides a more reliable evidence for the classification of the sample to be tested. Conversely, if the distance is far, the reliability of the evidence provided by the training sample is relatively small. According to the evidence kNN algorithm, it is to choose Euclidean distance as the measurement scale to calculate the distance between the target and the training sample. It is assumed that the set of k nearest neighbor samples of target x in category w_i is, $\Gamma_i = \{(y_1, d_1), \ldots, (y_k, d_k)\}$, $d_j(j = 1, \ldots, k)$ is the Euclidean distance between neighbor y_j and target x, m_j is the category label of y_j, β_j is the reliability of classifying x based on sample y_j, then the evidential mass function $m_j^{'}$ provided by y_j for the classification of target x can be expressed as:

$$\begin{cases} m_j^{'}(w_i) = \beta_j m_j(w_i), i = 1, \ldots, M \\ m_j^{'}(\Omega) = \beta_j m_j(\Omega) + \left(1 - \beta_j\right) \end{cases} \tag{9}$$

where the reliability β_j is determined by the Euclidean distance d_j between y_j and the target x. The greater the distance between the two, the lower the corresponding reliability, that is, the reliability β_j and d_j show a decreasing relationship, which can be expressed as:

$$\beta_j = e^{-\left(d_j / \overline{d}^i\right)} \tag{10}$$

where $\overline{d}^i$ is the average distance between all training samples in category w_i.

In order to classify the unknown target x, the k mass functions constructed by the k nearest neighbor samples $y_j(j = 1, \ldots, k)$ in the category w_i need to be fused to obtain the classification result of the target by the training samples of the category w_i. In the fusion process, considering that the mass functions provided by the same category of training samples have high consistency, the Dempster combination rule can be used directly for the fusion operation, it an be expressed as:

$$m_i = m_1^{'} \oplus m_2^{'} \oplus \cdots \oplus m_j^{'} \tag{11}$$

where $\oplus$ is Dempster combination operation.

Considering that there are a total of M categories of targets, a set of M nearest neighbor samples of the target can be generated, namely. According to Eq. (11), the mass function set $\Gamma = m_1, \ldots, m_M$ under categories M can be obtained.

The Global Fusion of the Fusion Results Between Classes
For the mass function set of categories M targets, the mass value constructed by the samples of category w_i is mainly assigned to the corresponding focal element, that is $m_i(w_i)$. Therefore, it can be considered that the distribution of mass values of different categories is different, and there will be certain conflicts between the mass functions obtained by Eq. (11). At this time, if the Dempster combination rule is used for global fusion, a fusion result that contradicts the facts may be obtained. Therefore, when fusing between categories, this paper uses PCR5 (Redistribute Conflicting Mass Proportionally Rule 5, PCR5) combination rules to accurately and reasonably allocate conflict information. The PCR5 rule is an evidence fusion rule proposed by Desert and Smarandache for conflicting data. This rule can accurately distribute the conflict information proportionally according to the mass values of the two parties in the conflict, which is very suitable for combining high conflict evidence. While compared with the Dempster rule, it is a more conservative combination method, and the convergence speed of the fusion result is relatively slow. Assuming that B and C are two independent evidences to be combined, the corresponding focal elements are B_j and C_j, and the mass functions are m_1 and m_2 respectively, then the PCR5 rule can be expressed as [19]:

$$m(x) = \sum_{\substack{B_i, C_j \in 2^{\Omega} \\ B_i \cap C_j = x}} m_1(B_i)m_2(C_j) + \sum_{\substack{y \in 2^{\Omega} \\ x \cap y = \emptyset}} \left[\frac{m_1(x)^2\, m_2(y)}{m_1(x)\, m_2(y)} + \frac{m_2(x)^2\, m_1(y)}{m_2(x)\, m_1(y)} \right] \tag{12}$$

where x and y are two focal elements of evidence body B and C with conflicting information.

Example 1: The evidence body m_1 confirms that the mass value of that the target belongs to category w_1 is 0.9, and the mass value of that the target belongs to category w_3 is 0.1. The evidence body m_2 confirms that the mass value of that the target belongs to category w_2 is 0.9, and the mass value of that the target belongs to category w_3 is 0.1.

After combining m_1 and m_2 by the Dempster combination rule, it can be obtained that:

$$m_{Dempster}(w_1) = 0,\ m_{Dempster}(w_2) = 0,\ m_{Dempster}(w_3) = 1.$$

After combining m_1 and m_2 by the PCR5 combination rule, it can be obtained that:

$$m_{PCR5}(w_1) = 0.486,\ m_{PCR5}(w_2) = 0.486,\ m_{PCR5}(w_3) = 0.028.$$

It can be seen that the original two evidences respectively believe that the target belongs to w_1 and w_2, And the reliability values provided are all 0.9. The Dempster rule offers a fusion result contrary to m_1 and m_2, which is obviously not reasonable. While PCR5 believes that the mass values of that the target belongs to m_1 and m_2 are still the same and are much higher than the mass value of that the target belongs to w_3. The fusion result is more reasonable and credible than the result of Dempster's rule.

Therefore, considering the inconsistency of evidence between categories, for the mass function set of the categories M observation target, it is necessary to use the PCR5 combination rule for fusion, and it can be obtained that:

$$m = m_1 \overset{PCR5}{\oplus} m_2 \overset{PCR5}{\oplus} \cdots \overset{PCR5}{\oplus} m_M \tag{13}$$

where $\overset{PCR5}{\oplus}$ represents PCR5 combination operation.

The final fusion result m can be calculated according to Eq. (13). According to the mass value of each category assigned to it, the final recognition result can be made on the target x, that is, the unknown target x is assigned to the category with the maximum mass value.

4 Experimental Results

This section is to use simulation analysis to compare the NEkNN classification algorithm mentioned in this paper with voting kNN, EkNN, IEkNN, and to illustrate the effectiveness of NEkNN. In the experiment, the parameters in EkNN are optimized according to the existing method [20]. The experiment utilizes simulation data to compare and analyze the misclassification rate of the proposed method and other classification methods based on k-nearest neighbors.

In this target recognition simulation experiment, a classification problem of 3-class target $\Omega = \{w_1, w_2, w_3\}$ is considered. After the sensor's observation data is preprocessed by data association and feature extraction, the training database is used to classify the feature data containing these three categories of targets. Assuming that the feature data is a three-dimensional vector, and the observation data and training data are generated from three three-dimensional data sets that obey the Gaussian distribution, then its mean and standard deviation have the following characteristics:

Table 1. 3-class data set with 3D Gaussian distributions.

Label	μ_1	μ_2	μ_3	Standard deviation
w_1	1	1	1	1
w_2	-1	1	0	1
w_3	0	-1	1	2

In Table 1, the three characteristics of each category of data have the same standard deviation. For example, the probability density functions of the three attribute data of category w_2 are: $x_1|w_2 \sim N(-1, 1), x_2|w_2 \sim N(1, 1), x_3|w_2 \sim N(0, 1)$, their standard deviation is the same as 1, and it randomly generates 3×100 test samples and 3×200 training samples. It is to select kNN, EkNN, IEkNN to compare and analyze with NEkNN proposed in this paper, take the value of the adjacent number k from 5 to 15, and take the average of 10 simulation results as the error rate of the test data set. The classification results are shown in Table 2.

It can be seen from Table 2 that the EkNN and IEkNN methods are better than the traditional voting kNN and can effectively improve the classification accuracy. The NEkNN algorithm proposed in this paper can better characterize the imprecision of the sample data in the overlapping area of the category and improve the classification accuracy of the data by using the basic belief assignment to replace the original category

Table 2. 3-class data set with 3D Gaussian distributions.

k	kNN	EkNN	IEkNN	NEkNN
$k = 5$	32.73	29.12	25.12	23.60
$k = 6$	32.68	28.33	25.19	23.97
$k = 7$	31.19	27.87	25.38	24.06
$k = 8$	33.62	27.61	24.67	24.11
$k = 9$	31.44	27.59	24.71	23.86
$k = 10$	32.25	27.55	25.09	24.03
$k = 11$	31.28	27.43	25.02	23.79
$k = 12$	31.42	26.96	24.91	23.45
$k = 13$	30.99	26.93	24.47	23.52
$k = 14$	32.94	26.86	24.52	23.35
$k = 15$	32.17	26.98	24.59	23.35
$k = 16$	32.73	29.12	25.12	23.60

label. Therefore, compared with the EkNN and IEkNN algorithms, it has a smaller classification error rate, especially when the number of neighbors is small, the performance improvement is more significant. In addition, it can be found that compared with other classification methods based on k-nearest neighbors, NEkNN method is less sensitive to the value of k-nearest neighbor.

5 Conclusion

In order to effectively express and reason about imprecise data, this paper proposes an evidence editing classification method based on EkNN. Before identifying and classifying the sample to be tested, this method uses a class label with a basic belief assignment structure to replace the original numerical category of the training sample, so that the training sample in the class overlapping area can provide more abundant and more diverse category information. And lay a better foundation for the follow-up kNN classification process. From the comparative analysis of related experiments, it can be found that for imprecise sample data, the NEkNN algorithm can obtain better classification performance than other classification algorithms based on k-nearest neighbors. Our future work mainly involves the following two aspects: (1) finding a more efficient strategy to estimate the mass values to improve the classification accuracy; (2) designing more credible combination rules to deal with the uncertain data in IOT environment.

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