An Experience-Feedback Algorithm of D-S Evidence Theory

Baowen Hu [1,a], Bo Shen [2,b] , Qing Liu[3,c]

[1]Key Laboratory of Communication & Information Systems, Beijing Municipal Commission of Education, Beijing Jiaotong University, Beijing, 100044, China

[2]Key Laboratory of Communication & Information Systems, Beijing Municipal Commission of Education, Beijing Jiaotong University, Beijing, 100044, China

[3]China Information Technology Security Evaluation Center

[a]09222034@bjtu.edu.cn, [b]bshen@bjtu.edu.cn [c]liuq@itsec.gov.cn

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Abstract. D-S evidence theory is a kind of important method of data fusion to get accurate prediction. In this paper, we propose an improved method in which we build an experience-feedback mechanism for reasoning process. Then prediction accuracy is fed backed to a new round of fusion process in the form of weights to improve new fusion results. We introduce two feedback algorithms and conduct an analysis through comparing some examples. Further, to solve the problem of cold start, we also suggest a method with the generation of random numbers. Simulation results show that the proposed algorithms can not only improve the performance of data fusion and the accuracy of forecast effectively, but also solve the problem of evidence conflict in D-S evidence theory. The information fusion technology is a kind of information process in order to make proper decision and credible predication through automatic analysis and optical synthesis of relevant observation data provided from various sensors utilizing computer technology. One of the main methods for information fusion is D-S evidential theory. The theory of evidence can fuse information provided by multiple sensors, thus reducing the uncertainty of the information.

Introduction

D-S evidence theory [1, 2] is an inexact reasoning theory. It belongs to the category of artificial intelligence, first used in the expert system, and possesses the ability to deal with uncertain information. As an inexact reasoning, it contents the weaker conditions than the Bayesian probability theory and has a direct expression of the “uncertain" and "do not know", which is also the main feature of the theory of evidence. As many fields such as medical diagnostics, target identification and military command need to take the uncertain information from multiple sources into account, we have seen important roles the evidence theory played in this regard.

The latest developments and applications of the evidence theory include that the rule-based evidential reasoning model and the decision-making model with the update of rule data base offline and online, the combination of evidence theory and support vector machine [3], the combination of evidence theory and rough set theory, the combination of evidence theory and fuzzy set theory[4], the combination of evidence theory and neural network[5].

For the D-S evidence theory, the prediction accuracy is an important issue. Moreover, cold start problem also affects prediction result. In this paper, random number will be used to solve cold-start problems, and prediction accuracy is fed backed to a new round of fusion process in the form of weights to improve new fusion results.

Theoretical Framework

D-S Evidence Theory

In the D-S evidence theory [2] model, the frame of discernment is a complete collection consisting of incompatible basic propositions (assumptions). It means all possible answers to a problem, but only one answer is correct. A subset of the framework is called proposition. The belief function *Belgium (A)* means the level of trust of the proposition. The likelihood function *Pl(A)* means the level of non-false trust in proposition *A*. *Pl(A)* is also a measurement of the uncertain thing if *A* is right. In fact, [*Bel(A)*, *Pl(A)*] indicates the uncertainty range of the proposition *A* . [0, *Bel(A)*] means the supporting evidence interval of the proposition *A*. [0, *Pl(A)*] means the intentional confidence interval of proposition *A*. [*Pl(A)*, 1] means the rejection of the range of evidence of proposition *A*.

If assuming that m_1 and m_2 is basic probability distribution function derived from two independent sources of evidence (sensor), then the combined action of the two pieces of evidence generates a new basic probability assignment function which reflects the integration of information. In this case, the Dempster joint rule [1] can calculate it.

Apparently, *Bel(A)* and *Pl(A)* summarize the relationship between the evidence and specific proposition *A* made up of a complete range of evidence, which is shown in Fig.1.

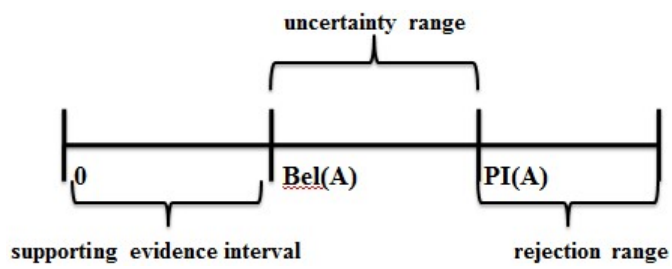

Fig.1 Schematic diagram of evidence interval

The rules of D-S evidence combination can be described as follows: there are two inference system whose basic probability assignment and trust function are respectively m_1, m_2 and Bel_1, Bel_2. We can use the following D-S rule to assign the probability of subset *A*.

$$m(A)=\frac{\sum_{A_1\cap A_2=A} m_1(A1)\ \times m_2(A_2)}{\sum_{A_1\cap A_2\neq\varnothing} m_1(A_1)\times m_2(A_2)}=m_1(A_1)\oplus m_2(A_2) \tag{1}$$

The *Bel* corresponding to m is denoted for $Bel = Bel_1 \oplus Bel_2$, which is called the synthesis or summation of Bel_1 and Bel_2.

In the equation (2) ,

$$\sum_{A_1\cap A_2\neq\varnothing} m_1(A_1)\times m_2(A_2)=1-\sum_{A_1\cap A_2=\varnothing} m_1(A_1)\times m_2(A_2)=1-k \tag{2}$$

1-*k* is the correction factor (normalized coefficient). In fact, the introduction of 1-*k* is actually to avoid non-zero probability being assigned to the empty set during the combination of evidence. As a result, the credit Assignment which is discarded by the empty set will be proportionally complemented to the non-empty set. *k* objectively reflects the degree of conflict between the evidences of the fusion process. . The greater *k* is, the more conflicts between evidences are the more obvious contradictions will be. If *k* is close to 1, result may be unreasonable which would lead to counterintuitive fusion. If *k* = 1, the D-S theory is not adaptive. D-S evidence combination rule provides a combination of two pieces of evidence rules. For a plurality of evidence, we can

repeatedly use formula for more evidences' combinations.

The most important feature of the structure of the D-S evidence theory is the introduction of uncertainty and the establishment of the basic probability assignment function (BPAF), trust function (BEL), the plausibility function (PL) and so on. It satisfies the weaker axiom than the probability theory. The D-S evidence theory will be more easily satisfied than the traditional Bayesian theory when it comes to the complete priori probability, the conditional probability and the uniform framework of discernment. The combination of evidence can deal with overlapping or non-mutually exclusive propositions.

Problem Statement and Assumptions.

In the wireless sensor model, what we want to do is to conclude our own judgment from the data obtained from various sensors. As shown in figure 2.

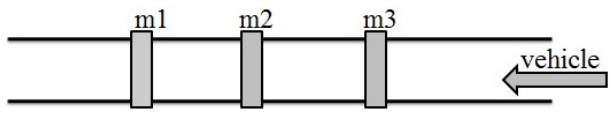

Fig.2 Model of sensor detection

The m_1, m_2, m_3 are three sensors mounted on a bridge. A vehicle which may be a car, a bus or a truck passes through the bridge. The m_1, m_2, m_3 respectively discriminate what type of the vehicle is according to their received signal, and output the predicted values. We integrate the predictive values with the methods of the theory of evidence. Then we draw our conclusions ultimately.

However, if there are serious conflicts between evidences, there will be defects showed as follows:

(1) 100% of the trust assigned to small proposition may cause counterintuitive results.

(2) The evidence can give a veto on the proposition, which may lead to the lack of robustness.

(3) It may be very sensitive to the basic belief assignment. During the actually data processing, the evidence conflicts often happen. So we should try to avoid the errors generated by the combination of conflict evidence. Otherwise it will cause erroneous conclusions.

This conflict of evidence makes the D-S evidence theory have a blind spot. In this paper, an empirical value feedback is used to improve it, and eventually plays a very good help to improve the performance of evidence theory fusion.

Feedback Method

In order to solve the issue of conflicts of evidence, we use the experience-feedback method. While we fuse the predictive value, we add this element of the experience to the process. For two inference systems, their basic probability assignment is m_1, m_2. We introduce $D(i)$($0 < D(i) < 1$) as experience weight for the subset A. First of all, we use the random number to assign the $D(i)$ an initial value which is greater than 0 and less than 1. Then the values of $D(i)$ is derived as the following two methods.

Method One

In the k_{th} fusion, when the $k\text{-}1_{th}$ predicted results of the inference system and the final fusion results are the same:

$$D(i) = D(i) + \partial * (1 - D(i)) \qquad 0 < \partial < 1 \tag{3}$$

Otherwise:

$$D(i) = D(i) - \partial * (1 - D(i)) \qquad 0 < \partial < 1 \tag{4}$$

Then we deal with the prediction of the initial data. If the predictive value is greater than the

average predictive value of all systems (sensor):

$m_i(A_j) = D(i) + m_i(A_j)$ $\quad 0 < D(i) < 1$ (5)

Otherwise:

$m_i(A_j) = m_i(A_j)$ (No treatment) $\quad 0 < D(i) < 1$ (6)

Finally, we use the following rule to fuse.

$$m(a) = \frac{\sum_{A_1 \cap A_2 = A} m_1(A_1) \times m_2(A_2)}{|1-k|} \tag{7}$$

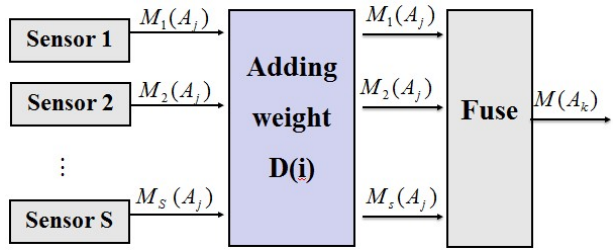

Fig.3 Calculation model

Method Two

We have another method to calculate *D(i)*. There are a total of *m* prediction systems and inference system *m(i)* has predicted accurately *n(i)* times before the k_{th} forecast. Then the weight coefficient *D(i)* can be characterized as follows:

$$D(i) = N(i) / \sum_1^m N(i) \tag{8}$$

Then we come to deal with the prediction of the initial data. If the predictive value is greater than the average predictive value of all systems (sensor), equation (5) is employed. Otherwise no treatment is needed, as implied by equation (6).

Finally, we use the rule of equation (7) to fuse.

Performance Evaluations

Now compare the above two methods through an example. Assuming that a vehicle passes a bridge and the bridge is equipped with two sensors, the previous prediction results of sensor m_1 and m_2 areas shown:

Table 1. Previous prediction results

m_1	×	√	√	√	√	√	×	√	√	√
m_2	×	×	×	×	√	×	×	×	√	×

Obviously, m_1 predicts more accurate than m_2. The prediction results are shown in the following table:

Table 2. Final prediction results

	car	truck	bus
m_1	0.9	0.09	0.01
m_2	0.01	0.09	0.9

Let's fusion the above data using traditional methods first:

k = 0.9×0.09 +0.9×0.9+0.09×0.01+0.09×0.9+0.01×0.01+0.01×0.09 = 0.9739

When it comes to the traditional D-S evidence theory, the value of k represents the conflict severity. So in this case, the evidence conflict is very serious. We continue to fusion data using the equation (1).

The result is: $m(a)$ = 0.345; $m(b)$ = 0.310; $m(c)$ = 0.345;

Obviously, m_1 and m_2 have great conflict on the propositions {car} and {buses}. However, the sensor m_1 has made a more accurate prediction in conventional prediction results. So the final result should be a car. But when we use the traditional DS evidence theory, the final result shows that the possibility of the bus is as much as the car. That is, we can't infer what the objects from the final fusion results lying in that the system does not take each prediction system in the past prediction accuracy into account. What's more, the k which reflects the degree of conflict among the evidences is ignored in the composition process.

In order to improve the performance of D-S evidence theory fusion when there are evidence conflicts, we fuse this data again using experience-feedback based evidence theory.

Method One: First calculate the trust weights $D(i)$. In the beginning of startup, we assign a random number to $D(i)$. Now we can assume $D(i)$ to be 0.5. For sensor m_1, m_2:

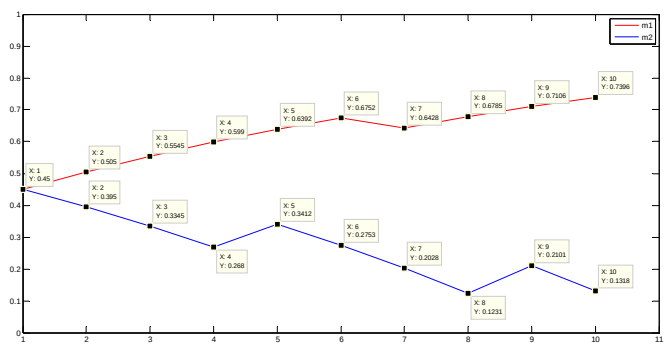

Fig.4 The value of trust weights $D(i)$.

For sensor m_1, we can see the final results of $D(i)$ is approximately 0.74. For sensor m_2, the final results of $D(i)$ is approximately 0.13.

Then we deal with the forecast data as follows: If the predictive value is greater than the average predictive value of all systems (sensor), equation (5) is also employed. Otherwise no treatment is needed, as implied by equation (6).

Result is as follows:

Table 3. Result of method one

	car	truck	bus
m_1	1.64	0.09	0.01
m_2	0.01	0.09	1.03

Table 4. Result of method two

	car	truck	bus
m_1	1.7	0.09	0.01
m_2	0.01	0.09	1.1

K=1.64*0.09+1.64*1.03+0.09*0.01+0.09*1.03+0.01*0.01+0.01*0.09=1.9314

$m(car)$ = 0.239; $m(truck)$ = 0.118; $m(bus)$ = 0.15. This result is more in line with the real situation. This method not only solves the problem of the evidence conflicts but also makes the prediction results more accurate.

Method 2: As the sensor m_1 has predicted accurately 8 times, and m_2 predicted accurately 2 times previously, $D(1) = 0.8$ and $D(2) = 0.2$.

k=1.7*0.09+1.7*1.1+0.09*0.01+0.09*1.1+0.01*0.01+0.01*0.09=2.1239

M (car) = 0.139; *M (truck)* = 0.065; *M (bus)* = 0.089. This result is also more in line with the real situation.

Summary and Conclusions

This paper presents a solution to the problem of evidence conflict in D-S evidence theory algorithm. Based on the problem, we designed two methods to assign the experience of every sensor a weight. After using this weight handling the former data, we carry the improved evidence theory out. This experience-feedback method is very effective for the prediction system. In addition, we improve the problem of evidence, and make predictive value closer to the real situation.

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