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# Research on Dynamic Trust Computing Method Based on Multi-Dimensional Evidence

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***Abstract***

*From the perspective of the credibility of evaluating network main body, first consider to improving of evidence source on which trust computing is based, and propose the concept of multi-dimensional evidence. The multi-dimension refers to involvement of multiple types of evidence, and the multi-dimensional evidence, in this paper, involves mainly e-commerce business feedback evidence, online community business feedback evidence and network operation behavior evidence. On this basis, the evidence features can be incorporated into combination rule of evidence, design a new method to calculate the dynamic trust, and propose an improved D-S combination rule to synthesize multi-dimensional evidence, better to solve the problem of uncertainty of evidence. Experiments show it can effectively resist network fraud.*

***Keywords:*** *Evidence theory; Multi-dimensional evidence; Dynamic trust computing; Network security*

## 1. Introduction

The emergence of concepts and ideas of trust management and trust negotiation provides a new solution to the security and trust issues for all network environment based on open, distributed and dynamic characteristics. In recent years, many scholars have made a lot of beneficial research in the field, and put forward many dynamic trust computing methods. But overall, these methods are generally to the trading feedback information that the network main body participate in transactions as the original data source of trusted computing. For instance, credit feedback accumulation algorithm in TaoBao and eBay. These algorithms that simply rely on trading business feedback as original evidences and cumulative credit index are difficult to prevent online fraud. According to the report of the Internet fraud complaint center, online auction fraud was ranked first on the Internet fraud [1]. Obviously evidence source has obvious limitations, the evidences have not considered network operating behavior implemented by main body through technical means, which make the evidence source on which trust computing is based is not complete. Network main body, for example, by some means, (such as collusion and malicious evaluation) changes the reputation of his own or another's in the electronic commerce system, the behavior itself embodies that the main body is not credible, but the information on network operation subject cannot be reflected in the business feedback evidences.

In view of the above-mentioned limitations, from the perspective of the credibility of evaluating network main body, we propose a new trust computing method suited to multi-

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dimensional evidence, based on the idea of trust management method. It overcomes the defect when trust is assessed only according to a single type of evidence source. On this basis, an improved D-S combination rule is proposed, using it to synthesis multi-dimensional evidence [2-5], these methods effectively solves the problems that the source of evidence is incomplete and uncertainty.

## 2. D-S Evidence Theory

D-S evidence theory provides flexible algorithm for the synthesis and expression of uncertain data by introducing belief function and plausibility function, not only can be used to deal with random uncertainty problem, but also can be used to deal with epistemic uncertainty problem. It is an important part of D-S theory to synthesize evidences from multiple sources, and the conflict between evidences can be modeled. D-S evidence theory particularly stresses the coordination of multiple evidences, so it discards all conflicting evidences. When D-S formula is adopted to synthesize highly conflict evidences, the result often is perverse.

Definition 1 two evidence combination

Suppose $m_1$ and $m_2$ are basic probability assignment function of two evidences E1 and E2 under the discernment frame Θ, the focal elements are $A_{1i}$ , $A_{2j}$ , then D-S combination rule is :

$$m(A)=\begin{cases}\dfrac{\sum\limits_{A_{1i}\cap A_{2j}=A} m_1(A_{1i})m_2(A_{2j})}{1-K}, & A\neq\phi\\ 0 & A=\phi\end{cases} \tag{1}$$

Where, $K=\sum\limits_{A_{1i}\cap A_{2j}=\phi} m_1(A_{1i})m_2(A_{2j})$ represents intensity of conflict between the evidences $E_1$, $E_2$, called conflict coefficient. When $k$=1, the 2 evidences are total conflict, There is a zero denominator in the combination rule (1), so it cannot synthetic. The closer K approximates to 1, the higher the conflict is.

Definition 2 multiple evidence combination

To synthesize the basic belief assignment function $m_1$, $m_2$,…,$m_n$ for $E_1$,$E_2$, …,$E_n$ under the discernment frame Θ, the combination rule is:

$$m(A)=\frac{\sum\limits_{\cap A_{nj}=A}\prod\limits_{\substack{1\le i\le n\\ 1\le j\le q}} m_i(A_{ij})}{1-K} \tag{2}$$

Where $A\neq\varnothing$ , $n$ is the number of evidences, $q$ is the number of focal elements, and $K$ is calculated as follow:

$$K=\sum_{\cap A_{nj}=\varnothing}\prod_{\substack{1\le i\le n\\ 1\le j\le q}} m_i(A_{ij}) \tag{3}$$

## 3. Improvement of D-S Combination Rule

Improvement to the D-S evidence theory is mainly on improvement of combination rule, because D-S combination rule may appear problem in the process of practical application, which it cannot be used or its conclusion doesn't meet human reasoning. Literature [6] summarized that D-S combination rule could produce six paradoxes, namely total conflict paradox , 0 trust paradox,1 trust paradox, evidence invalidation paradox, trust excursion paradox, and focal element fuzzy paradox, it is mainly because of conflicting evidence existed. There are a lot of research achievements about conflicting evidence combination, Such as Smets's combination rule [7], Yager's combination rule [8], Lefever's combination rule [9] and Murphy's combination rule [10].

 

Murphy proposed an improved combination rule, which could solve the problem of high conflicting evidences, but the simple average method ignored conflicting specific case between evidence, in the actual application it may lead to deviation from the actual results.

Based on the idea of Murphy, and consider avoiding the disadvantages of simple average method, we put forward a new combination rule based on conflicting intensity $G$ and effective conflicting intensity $G_e$, short for "G-$G_e$ combination rule. The synthesis steps are as follows:

(1) Base on conflicting intensity G, take weighted average for trust assignment number of all evidences.

(2) Use effective conflicting combination rule to synthesize n-1 times to n $m\left(A_i^a\right)$.

$G$-$G_e$ combination rule is as follows.

Suppose $m_1, m_2, \cdots, m_n$ are the basic belief assignment function of evidences $E_1, E_2, \cdots, E_n$ under the discernment frame Θ, $A_1, A_2, \cdots, A_n$ are total focal elements involved in all evidences.

### 3.1. Conflicting Intensity G

Literature [6] gives the definition of conflicting intensity G, that is:

Definition 3 Suppose $m_1$,$m_2$ are the basic belief assignment function of two evidences E1, E2 under the discernment frame Θ, the focal elements are $A_{1i}$, $A_{2j}$, then:

(1)Consistent degree of evidences $E_1$ and $E_2$

$$H(E_1, E_2) = \sum_{A_{1i}=A_{2j}} m(A_{1i}) m(A_{2j}) \tag{4}$$

(2)Conflicting degree of $E_1$、$E_2$

$$C(E_1, E_2) = \sum_{A_{1i}\cap A_{2j}=\phi} m(A_{1i}) m(A_{2j}) \tag{5}$$

(3)Conflicting intensity G of $E_1$、$E_2$

$$G(E_1, E_2) = \frac{C(E_1, E_2)}{H(E_1, E_2) + C(E_1, E_2)} \tag{6}$$

### 3.2. Weighted Average to Belief Assignment Number

For two evidence $E_i$, $E_j$, define $d_{ij}=1-G_{ij}=d_{ji}$ is similarity of evidence $E_1$, $E_j$, and $d_{ij}=d_{ji}=1$, thus can obtain similar matrix of all n evidences.

$$S = \begin{Bmatrix} d_{11}\cdots d_{1j}\cdots & d_{1n} \\ \vdots \quad \ddots \vdots & \ddots \vdots \\ d_{i1}\cdots d_{ij}\cdots & d_{in} \\ \vdots \quad \ddots \vdots & \ddots \vdots \\ d_{n1}\cdots d_{nj}\cdots & d_{nn} \end{Bmatrix} = \begin{Bmatrix} 1\cdots d_{1j}\cdots & d_{1n} \\ \vdots \quad \ddots \vdots & \ddots \vdots \\ d_{i1}\cdots 1\cdots & d_{in} \\ \vdots \quad \ddots \vdots & \ddots \vdots \\ d_{n1}\cdots d_{nj}\cdots & 1 \end{Bmatrix} \tag{7}$$

The smaller conflicting intensity between evidences is, the more evidences support each other, so to add the each row for the matrix S can get the support of all other evidence for $E_j$, that is

$$Sup(m_i)=\sum_{j=1}^{n} d_{ij}\ , \quad i,j=1,2,\ldots,n \tag{8}$$

The weights of weighted average can be obtained by the support normalized.

 

$$Weit(m_i)=Sup(m_i)/\sum_{i=1}^{n}\sup(m_i),\ i\ ,j=1,2,\ldots,n \tag{9}$$

At this point, take weighted average for the basic belief assignment number of n group evidences.

$$m(A_l^a)=\sum_{i=1}^{n}\text{Weit}(m_i)m_i(A_l) \tag{10}$$

After the above steps, we can obtain basic belief assignment function after weighted average.

$$M^a(A)=m^a(\{A_1\},\{A_2\},\ldots,\{A_l\})=(m^a(A_1),\ m^a(A_1),\ldots,\ m^a(A_n)) \tag{11}$$

Murphy used D-S combination rule (that is Eq. (1)) to synthesize evidences after averaging, the method used normalized factor *1 / (1 - k)*, and a part of the conflict is completely allocated to non-$\Theta$ focal elements. This thought is not entirely reasonable, because conflict coefficient $k$ is not fully effective information, if invalid information is assigned to non-$\Theta$ focal elements, then combination result stray actually from the true.

In order to solve above problems, we divide the conflict into two parts: effective conflict and invalid conflict, the effective conflict refers to the effective part for proposition discrimination, the invalid conflict refers to the invalid part for proposition discrimination. Based on literature [6] gives the definition of consistent degree and conflicting degree on evidences, this paper gives the definition of effective conflict [11-15].

Definition 4 effective conflict

For two evidences $E_i$, $E_j$, the basic belief assignment are $m_1$,$m_2$, the focal elements are $A_{1i}$,$A_{2j}$, $A_1$,$A_2$,…, $A_i$ are total focal elements involved in all evidences. Then:

Effective part of the conflict with $E_1$、$E_2$

$$G_e(E_1,E_2)=\frac{H(E_1,E_2)}{H(E_1,E_2)+C(E_1,E_2)} \tag{12}$$

Based on the definition above, this paper gives a new synthesis method on effective conflict. Suppose $m_1$ and $m_2$ are the basic belief assignment function of two evidences E1 and E2 under the discernment frame Θ, the focal elements are $A_{1i}$,$A_{2j}$, $A_1$,$A_2$,…, $A_i$ are total focal elements involved in all evidences. Then

$$m(A_i)=\begin{cases}\sum\limits_{A_{1i}\cap A_{2j}=A_l} m_1(A_{1i})m_2(A_{2j})+\Delta\varphi\times G_e\times K, A\neq\Theta\\ \sum\limits_{A_{1i}\cap A_{2j}=A_l} m_1(A_{1i})m_2(A_{2j})+(1-G_e)\times K, A=\Theta\end{cases} \tag{13}$$

$$\text{Where, } \Delta\varphi=\frac{m_1(A_l)+m_2(A_l)}{\sum m_1(A_{1i})m_2(A_{2j})} \tag{14}$$

### 3.3. Synthesize n-1 Times to n $m^a(A)$

*G-G_e* combination rule keeps commutative law and associative law in D-S combination rule, so a new algorithm is designed in this paper, which synthesize n-1 times to n $m^a(A)$. This algorithm can greatly reduce computational complexity, as follows.

Algorithm 1

$m_0^a(A)\leftarrow m^a(A)$

$m(A)\leftarrow m_0^a(A)$

l←n

m←n←-1

$Flag_{m-1}$←0

While l>1

 

do $m_m^a\ (A) \leftarrow m_{m-1}^a(A) \oplus m_{m-1}^a(A)$
$Flag_m \leftarrow l\%2$
$l \leftarrow int(l/2)$
if $Flag_{m-1}=1$
then $m(A) \leftarrow m(A) \oplus m_{m-1}^a(A)$
end
$m(A) \leftarrow m(A) \oplus m_{m-1}^a(A)$

### 3.4. Analyze the Effectiveness of *G-G_e* Combination Rule

Suppose discernment frame $\Theta=\{A, B\}$, 4 basic belief assignment function $m_1,m_2,m_3,m_4$, are shown in table 1.

**Table . Basic Belief Assignment Function**

| evidence # | $m_1$ | $m_2$ | $m_3$ | $m_4$ |
|---|---|---|---|---|
| *m(A)* | 0.9 | 0 | 1 | 0.7 |
| *m(B)* | 0 | 1 | 0 | 0.3 |
| *m(Θ)* | 1.0 | 0 | 0 | 0 |

**Table 2. The Combination Results**

| rules | Ⅰ($m_1,m_2$) | Ⅱ($m_2,m_3$) | Ⅲ($m_1,m_4$) | Ⅳ($m_1,m_2,m_3,m_4$) |
|---|---|---|---|---|
| D-S | (0,1,0) | | (0.955,0.045,0) | |
| Smete | (0,0.11,0.89) | (0,0,1) | (0.64,0.04,0.35) | (0,0,1) |
| Yager | (0,0.11,0.89) | (0,0,1) | (0.63,0.03,0.34) | (0.71,0.04,0.28) |
| Murlhy | (0.4,0.6,0) | (0.5,0.5,0) | (0.91,0.07,0) | (0.959,0.037,0) |
| Lefever | (0.106,0.596,0) | (0.5,0.5,0) | (0.902,0.098,0) | (0.815,0.167,0) |
| $G\text{-}G_e$ | (0.316,0.43,0.246) | (0.376,0.376,0.26) | (0.815,0.085,0.103) | (0.822,0.079,0.069) |

Use D-S combination rule, Smets combination rule, Yager combination rule, Murphy combination rule, Lefever combination rule, and $G\text{-}G_e$ combination rule to synthesize, respectively, and the 6 results are shown in Table 2.

**3.4.1. The Effectiveness about *G-G_e* Combination Rule Dealing with High Conflict Evidences:** Operation Ⅰ and Ⅱ are two high conflict evidences combination case; the 6 rules above have different effects in dealing with the two operations.

D-S combination rule runs into trouble on dealing with the two operations. The result believes totally B when D-S rule processes operation $m_1$, $m_2$, and ignores totally the evidence 1; this is against human normal reasoned thinking. While D-S rule processes operation Ⅱ it can't synthesize, because two evidences are conflicting completely, namely the conflict coefficient k = 1, cause the normalized coefficient 1 / (1 - k) inexistence.

Smets and Yager combination rules get the same result in dealing with the two operations, but the results are unreasonable. These two kinds of combination rules distribute completely the conflict to discernment framework Θ, lead to the number of $m(\Theta)$ is very big, and the number of $m(A)$ and $m(B)$ is very small, so the results cannot support the decision making, and lost the meaning of evidence combination.

Lefever, Murphy and $G\text{-}G_e$ combination rules obtain better results when dealing with the two operations. These results hold almost the same trust for A and B, Except for this, $G\text{-}G_e$ combination rule also expresses uncertainty, it assigns a part of conflict to discernment framework Θ so that it more accurately reflect real situation for the two evidence combination.

To sum up, when dealing with high conflict evidence combination, Lefever, Murphy and $G$-$G_e$ combination rule are availability, but $G$-$G_e$ combination rule are more accurate than the other two rules.

**3.4.2. The Effectiveness about $G$-$G_e$ Combination Rules Dealing with Low Conflict Evidences:** Operation Ⅲ is a low conflict evidence combination case, the above 6 rules have different effects in dealing with the operation.

Smets and Yager combination rules get the same results in dealing with the operation Ⅲ, but the result is still not unreasonable. These two kinds of combination method distribute completely the conflict to discernment framework $\Theta$, this cause that the synthesis results support for A is lower than the original evidence. So there's huge uncertainty in the results, and bring difficulties to decision making.

The other 4 kinds of rules clearly support A, which accord with the normal human reasoning thinking. As a result, the 4 kinds of synthetic rules are effective for low conflict evidences.

**3.4.3 The Effectiveness about $G$-$G_e$ Rule Dealing with Mixed Evidences:** Mixed evidences include high conflict evidences as well as low conflict evidences, operation Ⅳ reflects the characteristics of the mixed evidences. The above 6 kinds of combination rule are different effects in dealing with the operation Ⅳ.

D-S combination rule cannot deal with the operation $m_1$, $m_2$, $m_3$, $m_4$; the normalized coefficient is inexistence, because two evidences conflict completely.

Smets combination rule's processing result is (0,0,1), because there are total conflict evidences, leads to allocating all support to Θ, and neglects that three of the four evidence support A. For this reason, Smets combination rule may become problem when it synthesizes mixed evidence.

Murphy combination rule's result supports clearly A, but the support is very close to 1. The cause is: Murphy uses D-S combination rule to synthesize them after averaging basic belief assignment function, D-S normalized operation rule cause that the belief assignment focuses rapidly focal elements with high support.

Yager, Lefever and $G$-$G_e$ combination rules obtain better results in the synthesis of mixed evidence. But Yager combination rule's result gives larger trust allocation to Θ, which appears more cautious; and Lefever combination rule's result gives Θ trust allocation 0, which is more radical.

Compared to Murphy combination rule, $G$-$G_e$ combination rule adopts effective conflicting combination rule to replace D-S combination rule, so that the trust distribution focuses focal elements slowed. At the same time, $G$-$G_e$ combination rule assigns a part of pending conflict to Θ, and waits for the next step synthetic, such process distinguishes and deals more accurately than D-S evidence theory for "uncertainty" and "unknown".

Multi-dimensional evidence is hybrid evidences, a set of multi-dimensional evidence may contain high conflict evidences, also contain low conflict evidences. The above discussion shows that $G$-$G_e$ combination rule has superiority in solving synthesis problems with high conflict, low conflict and multi-dimensional evidences. Therefore, $G$-$G_e$ combination rule has fully capabilities to handle synthesis problem for multi-dimensional evidences, and can do a satisfactory job.

## 4. Experiment Analyses

Follow this method introduced above, change multi-dimensional evidence (e-commerce business feedback evidence, network community business feedback evidence and network operation business feedback evidence) into several array such as (1,0,0) and mark their weight, then use $G$-$G_e$ combination rule to synthesize them, the steps are as follows:

(1) Calculate total weight of all basic belief assignment functions.

(2) Use formula (6) to calculate conflicting intensity G between every two evidences, record as $G_{ij}(i,j=1.2,\ldots,)$.

(3) Construct similarity matrix such as formula (7).

(4) Use formula(8)—(10) to calculate basic belief assignment function after weighted average. That is:

$$M^a(T,D,\Theta)=(m^3(\mathrm{T}),m^a\ (D),m^a\ (\Theta))$$

(5) Use formula (13)—(14) to synthesize $n$ times to $\mathrm{m}^a$, $n$ is the number of evidence. The paper uses Algorithm 1 to calculate $m(A)$ in order to reduce the computation complexity.

(6) Calculate the final trust *Tru* according to the *m (A)*.

$$Tru=(Bel(T),Pl(T))$$

Use Netlog as simulation environment for the algorithm, we realize the trust computation, and on this basis, the experimental analysis shows that it can resist collusion and malicious evaluation behavior.

The code pattern of basic belief assignment function *Mass* is:

```
double [] m=new double[3]
public void setMass(double x,double y,double z) {m[0]=x; m[1]=y; m[2]=z;}
```

The critical calculation is follows:

(1) The calculation method of effective conflict $G_e$:

```
double k=Math.round((m1.m[0]*m2.m[1]+m1.m[1]*m2.m[0])*10000)/10000.0;
double h=Math.round((m1.m[0]*m2.m[0]+m1.m[1]*m2.m[1]+m1m[2]*m2.m[2])*10000)/10000.0;
double ge=Math.round(h/(k+h)*10000)/10000.0;
```

(2) The calculation method of basic belief assignment functions after synthesis:

```
m3.m[0]=Math.round((m1.m[0]*m2.m[0]+m1.m[0]*m2.m[2]+m1.m[2]*m2.m[0]+(m1.m[0]+m2.m[0]/(m1.m[0]+m2.m[0]+m1.m[1]+m2.m[1])*ge*k)*10000)/10000.0;
m3.m[1]=Math.round((m1.m[1]*m2.m[1]+m1.m[1]*m2.m[2]+m1.m[2]*m2.m[1]+(m1.m[1]+m2.m[1])/(m1.m[0]+m2.m[0]+m1.m[1]+m2.m[1])*ge*k)*10000)/10000.0;
m3.m[2]=Math.round((m1.m[2]*m2.m[2]+(1-ge)*k)*10000)/10000.0:
```

Algorithm implemented based on the algorithm 1 is:

```
publice class mergeofSeveral(int x,Mass y){…}
```

Final trust computing just call MergeofSeveral

### 4.1. The Role Analysis of Evidences Weight

The weight of evidences grades evidences according to the influence of trust. In trust computing, evidences are treated differently, which accord with the actual needs of realistic human society to build trust.

Experiment 1 Suppose within the time window $t$, 4 evidences about Agent are collected, two e-commerce business feedback evidences, an online community business feedback evidence and a network operation behavior feedback evidence, respectively. Their formal expression is: Evi1(1, 1, $t$, 500, 1, 1), Evi2(1, 1, $t$, 1500, 1, 1), Evi3(2, 1, $t$, 12000) and Evi4(3, $t$, 1). The basic belief assignment functions and its weight about the 4 evidences are recorded in the *mass* table as shown in Table 3.

**Table 3. Mass Table of Experiment 1**

| id | userid | time | *t* | *d* | *u* | weight |
|---|---|---|---|---|---|---|
| 1 | 1 | 2014-12-05 19:00:00 | 1 | 0 | 0 | 5 |
| 2 | 1 | 2014-12-05 19:15:55 | 1 | 0 | 0 | 11.50 |
| 3 | 1 | 2014-12-05 19:25:17 | 1 | 0 | 0 | 11.17 |
| 4 | 1 | 2014-12-05 19:45:57 | 0 | 1 | 0 | 50 |

If you don't consider the weight of evidence, the result of the trust computing is (0.9922, 0.9956), shows that the minimum trust of Agent *A* is 0.9922, the biggest trust is 0.9956; If considering the weight of evidence, the result is (0.0567, 0.1093), shows that the minimum trust of Agent *A* is 0.0567 the biggest trust is 0.1093. Evidence 4 is a network operation behavior, such evidence expresses that Agent *A* has harmed the safety of network, should make his trust attenuation by punitive, and the weight of the evidence just reflects this.

### 4.2 Resistance to Collusion

Experiment 2 The result of the trust computing is (0.0567 0.1093) by experiment 1, assuming that the subject *A* hope to improve their trust value through collusion behavior, his approach is online to sell $100 worth of goods and look for partner to buy the goods. Then the price he pays and gain show in figure 1, plotted by the total amount of transaction on the horizontal axis and trust value on the vertical.

We pick a few important points to research the overhead. Fig. 2 shows, when the trust (Bel) is enhanced up to 0.6, 0.7, 0.8, 0.9, and 0.95, the cost is $750, $900,$1200,$1650 and $2550, respectively, this shows, the cost is large, which Agent hope to enhance trust by collusion.

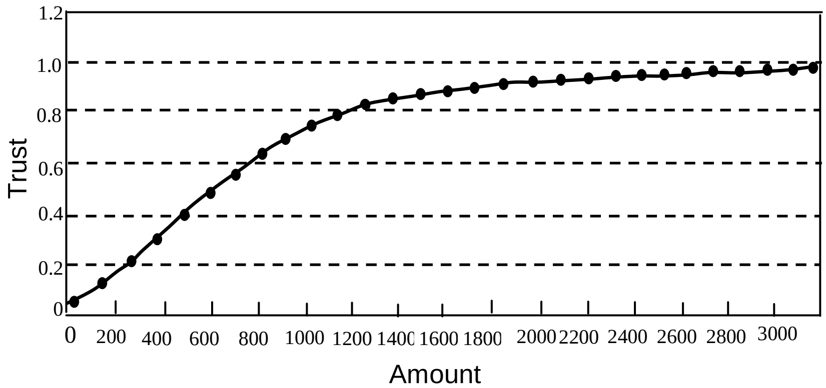


**Figure 1. The Cost of Increasing Trust Index**

### 4.3 Resistance to Malicious Evaluation

Experiment 3 Suppose within the time window *t*, basic trust distribution function are produced by Agent *A*, as shown in table 4, the trust is (1.0, 1.0), while Agent *B* hope to reduce A's trust by giving Agent *A* malicious negative comments with online trading. Suppose *A*'s online store only sells for $100 worth of goods, then the overhead trend of reducing competitor's trust shows in figure 2.

**Table 4. Mass Table of Experiment 3**

| id | userid | time | *t* | *d* | *u* | weight |
|---|---|---|---|---|---|---|
| 1 | 1 | 2014-12-05 19:00:00 | 1 | 0 | 0 | 5 |
| 2 | 1 | 2014-12-05 19:15:55 | 1 | 0 | 0 | 5 |
| 3 | 1 | 2014-12-05 19:15:17 | 1 | 0 | 0 | 17 |
| 4 | 1 | 2014-12-05 19:45:57 | 1 | 0 | 0 | 5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 5 | 1 | 2014-12-05 19:55:57 | 1 | 0 | 0 | 15 |
| 6 | 1 | 2014-12-05 19:55:57 | 1 | 0 | 0 | 17 |
| 7 | 1 | 2014-12-05 19:55:57 | 1 | 0 | 0 | 22 |

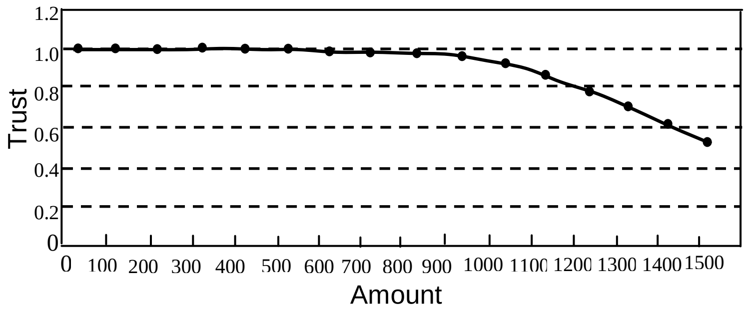


**Figure 2. The Price of Decreasing Competitor's Trust Index**

Figure 2 shows, when Agent B trades up to 11th, Agent A' trust is only less than 0.95, while B's cost is $1100; When B continues to trade with A, and gives A bad review, then A’s trust Continues to decline; When finished 15th trading, A’s trust is below 0.5, while the cost is $1500. It follows that the cost is large, which Agent *B* hopes to reduce A’s trust by giving Agent *A* malicious negative comments. So it can effectively reduce baleful evaluation for the influence of trust.

## 5. Conclusions

The paper does a further study on D-S evidence theory and its improvement, and proposes a new evidence synthesis rule based on conflicting intensity G and effective conflicting intensity $G_e$. In the meantime, propose multi-dimensional evidence concept in order to expand the evidence sources which trust assessment is based on. The multi-dimensional evidence refers to the different types of evidence; this paper involves the multi-dimensional evidence including e-commerce business feedback evidence, network community business feedback evidence and network operation business feedback evidence. On this basis, illustrate formal method of multi-dimensional evidence and the core algorithm of the trusted computing, the experiments prove that the method has the ability of resisting collusion and malicious evaluation behavior.

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