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A Model of Federated Evidence Fusion for Real-Time Traffic State Estimation

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1. Introduction

Due to the rapid development of Intelligent Transportation Systems (ITS), more and more different types of sensors are employed to detect traffic state information, so as to serve traffic agencies and travelers. However, each type of traffic detectors has its inherent drawbacks. For instance, loop detectors, as a kind of economical and efficacious detectors, have been widely used in most advanced cities. However, lots of errors are often induced by their high failure ratio and inaccurate traffic state conversion arithmetic. Similarly, probe vehicles are another type of popular detectors, which also has some problems, such as poor statistical representation and errors in the map matching. Therefore, how to make full use of the data from these detectors to obtain more accurate and comprehensive traffic state information becomes a new urgent problem need to be solved.

Recent years, information fusion as a new technology has been introduced to solve this problem, expecting to get better results by integrating information from multiple types of detectors. In this field, some researchers advanced their fusion methods on how to combine the data from loop detectors and GPS probe vehicles, and achieved good effectiveness to some extent. For example, R.-L. Cheu et al. developed a neural network based model to perform the fusion (Cheu et al., 2001); K. Choi and Y. Chung presented a fusion algorithm based on fuzzy regression (Choi & Chung, 2002); T. Park and S. Lee researched this problem using Bayesian approach, who got good effect in simulation data (Park & Lee, 2004); H.-S. Zhang et al. proposed an architecture to manage, analyze and unify the traffic data (Zhang et al., 2005).

More recently, pointing to the incompleteness and inaccurateness of traffic detector data, El Faouzi and Lefevre originally put forward a classifiers fusion method based on Evidence Theory (El Faouzi & Lefevre, 2006), which provided a new idea toward solving this problem. Also, a prospect to build an adaptive and dynamic fusion scheme was given at the end of their article. According to this prospect, we introduce a new fusion model in this article to meet the requirement of real-time fusion. This model advances over D-S Evidence Theory (Dempster, 1967; Shafer, 1976) in temporal domain, and the idea comes from some thought of the Federated Kalman Filter initially proposed by N. A. Carlson (Carlson, 1988; 1990). Therefore, we call it the Federated Evidence Fusion Model (FEFM). It can be used to fuse not only the two kinds of detectors referred above, but also other information sources

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(cameras, mobile phones etc.). In addition, sensor reliability is considered in this model by the form of evidence reliability to increase the accuracy of estimation. In the experiments, a simulation test is first assumed to explain the advantage of the proposed model, in comparison with conventional D-S Evidence Theory and the other two transformed models. After that, an application case is presented to embody the validity of the model in engineering practice, using the real-world data from the SCATS loop detectors and GPS-equipped taxies in Shanghai.

2. A brief review of Evidence Theory

Evidence Theory was initially introduced by Dempster (Dempster, 1967), and then Shafer (Shafer, 1976) showed the benefits of belief functions for modeling uncertain knowledge. In this section, some mathematical elements of Evidence Theory are recalled.

2.1 Basic concepts

Let $\boldsymbol{\Omega} = \{\omega_1, \omega_2, \ldots, \omega_N\}$ be a frame of discernment, in which all elements are assumed to be mutually exclusive and exhaustive. The power set of $\boldsymbol{\Omega}$ is denoted by $2^{\Omega} = \{\boldsymbol{A} \mid \boldsymbol{A} \subseteq \boldsymbol{\Omega}\}$. Basic Probability Assignment (BPA) is a function that can be mathematically defined by 2^{Ω} in [0, 1], such that $m(\Phi) = 0$ where Φ denotes an empty set, and $\sum_{A \subseteq \Omega} m(\boldsymbol{A}) = 1$.

The belief function (bel) and the plausibility function (pl) are defined as follows:

$$\begin{cases} bel(\boldsymbol{A}) = \sum_{\Phi \neq B \subseteq A} m(\boldsymbol{B}) & \forall \boldsymbol{A} \subseteq \boldsymbol{\Omega} \\ pl(\boldsymbol{A}) = \sum_{B \cap A \neq \Phi} m(\boldsymbol{B}) & \forall \boldsymbol{A} \subseteq \boldsymbol{\Omega} \end{cases} \tag{1}$$

in which $bel(\boldsymbol{A})$ represents the sum of masses in all subsets of $\boldsymbol{A}$, whereas $pl(\boldsymbol{A})$ corresponds to the sum of masses committed to those subsets which don't discredit $\boldsymbol{A}$.

2.2 Combination of belief functions

Multiple evidences can be fused by using Dempster's combination rules, shown in equation (2), which also is known as the orthogonal sum. This sum is both commutative and associative.

$$m(\boldsymbol{C}) = \begin{cases} 0, & \boldsymbol{A} \cap \boldsymbol{B} = \Phi \\ \dfrac{1}{1-K} \sum_{A \cap B = C, \forall A, B \subseteq \Omega} m_i(\boldsymbol{A}) \cdot m_j(\boldsymbol{B}), & \boldsymbol{A} \cap \boldsymbol{B} \neq \Phi \end{cases} \tag{2}$$

with

$$K = \sum_{A \cap B = \Phi, \forall A, B \subseteq \Omega} m_i(\boldsymbol{A}) \cdot m_j(\boldsymbol{B}) \tag{3}$$

where the term K is called the conflict factor between two evidences, which reflects the conflict degree between them.

2.3 Evidence reliability

When the information provided by sensors is not totally reliable to result in the belief functions, a coefficient a is used to discount the belief. This coefficient will transfer the belief into the set $\boldsymbol{\Omega}$. Thus, the discounted belief function m_a can be obtained by the following formula:

$$\begin{cases} m_a(\boldsymbol{A}) = am(\boldsymbol{A}) \\ m_a(\boldsymbol{\Omega}) = am(\boldsymbol{\Omega}) + 1 - a \end{cases} \quad \boldsymbol{A} \subset \boldsymbol{\Omega} \tag{4}$$

where $a \in [0,1]$.

2.4 Evidence distance

A. L. Jousselme et al. presented a principled metric distance between two BPAs (Jousselme et al., 2001). The authors treat BPA as a vector in a $2^{|\boldsymbol{\Omega}|}$ linear space, where $|\boldsymbol{\Omega}|$ denotes the cardinality of $\boldsymbol{\Omega}$. Then, they define the distance between m_i and m_j as

$$d_{BPA}(m_i, m_j) = \sqrt{\frac{1}{2}(\vec{m}_i - \vec{m}_j)\boldsymbol{D}(\vec{m}_i - \vec{m}_j)^T} \tag{5}$$

in which $\boldsymbol{D}$ is a matrix with size of $2^{|\boldsymbol{\Omega}|} \times 2^{|\boldsymbol{\Omega}|}$, whose elements can be calculated by formula (6).

$$\boldsymbol{D}(\boldsymbol{A}, \boldsymbol{B}) = \frac{|\boldsymbol{A} \cap \boldsymbol{B}|}{|\boldsymbol{A} \cup \boldsymbol{B}|} \quad \forall \boldsymbol{A}, \boldsymbol{B} \subseteq \boldsymbol{\Omega} \tag{6}$$

Furthermore, the evidence distance satisfies the below restriction:

$$0 \le d_{BPA}(m_i, m_j) \le 1 \tag{7}$$

3. Federated evidence fusion model

In this section, we introduce the FEFM in three steps: first, the reliability matrix is discussed; then, we build the frame of the FEFM; finally, the fusion algorithm is presented. Besides, the other two models with different forms are also given like the Federated Kalman Filter.

3.1 The improved evidence reliability

From engineering practice, we find that different evidence sources have different reliabilities in estimating the same state; similarly, the same evidence sources also have different reliabilities in measuring different states. Therefore, we define a reliability weight $w_{i,j}(0 \le w_{i,j} \le 1)$, which is used to reflect the degree of the reliability that one evidence corresponds to each state. The reliability matrix $\boldsymbol{W}$ is shown in (8).

$$\boldsymbol{W} = \begin{array}{c} \\ E_1 \\ E_2 \\ \vdots \\ E_M \end{array} \!\!\begin{array}{c} \begin{matrix} S_1 & S_2 & \cdots & S_N \end{matrix} \\ \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{M,1} & w_{M,2} & \cdots & w_{M,N} \end{bmatrix} \end{array} \tag{8}$$

where $w_{i,j} \in [0,1], (i = 1,2,\ldots,M; j = 1,2,\ldots,N)$; S_j denotes the *jth* independent state to be recognized; E_i denotes the *ith* independent evidence.

In some sense, the reliability that the evidence corresponds to different states can be deemed as the probability that the evidence exactly estimates the state, because it accords with the definition of probability. Thus, we can draw a conclusion that, a reliability matrix $\boldsymbol{W}^*$ between evidences and all of the subsets of $\boldsymbol{\Omega}$ is defined as follows:

$$\boldsymbol{W^*} = \begin{array}{cc} & \begin{array}{ccccccccccc} \{S_1\} & \{S_2\} & \cdots & \{S_N\} & \{S_1,S_2\} & \{S_1,S_3\} & \cdots & \{S_2,S_3\} & \cdots & \{S_j \mid j \neq N\} & \boldsymbol{\Omega} \end{array} \\ \begin{array}{c} E_1 \\ E_2 \\ \vdots \\ E_M \end{array} & \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N} & \mathop{P}\limits_{j=1,2} w_{1,j} & \mathop{P}\limits_{j=1,3} w_{1,j} & \cdots & \mathop{P}\limits_{j=2,3} w_{1,j} & \cdots & \mathop{P}\limits_{j\neq N} w_{1,j} & \mathop{P}\limits_{j} w_{1,j} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N} & \mathop{P}\limits_{j=1,2} w_{2,j} & \mathop{P}\limits_{j=1,3} w_{2,j} & \cdots & \mathop{P}\limits_{j=2,3} w_{2,j} & \cdots & \mathop{P}\limits_{j\neq N} w_{2,j} & \mathop{P}\limits_{j} w_{2,j} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ w_{M,1} & w_{M,2} & \cdots & w_{M,N} & \mathop{P}\limits_{j=1,2} w_{M,j} & \mathop{P}\limits_{j=1,3} w_{M,j} & \cdots & \mathop{P}\limits_{j=2,3} w_{M,j} & \cdots & \mathop{P}\limits_{j\neq N} w_{M,j} & \mathop{P}\limits_{j} w_{M,j} \end{bmatrix} \end{array} \tag{9}$$

When $i = 1$, we have

$$\begin{cases} \mathop{P}\limits_{j=1,2} w_{i,j} = w_{i,1} \hat{+} w_{i,2} = w_{i,1} + w_{i,2} - w_{i,1} \cdot w_{i,2} \\ \mathop{P}\limits_{j=1,2,3} w_{i,j} = w_{i,1} \hat{+} w_{i,2} \hat{+} w_{i,3} = w_{i,1} + w_{i,2} - w_{i,1} \cdot w_{i,2} - w_{i,1} \cdot w_{i,3} - w_{i,2} \cdot w_{i,3} + w_{i,1} \cdot w_{i,2} \cdot w_{i,3} \\ \vdots \\ \mathop{P}\limits_{j=1,2,\ldots,N} w_{i,j} = w_{i,1} \hat{+} w_{i,2} \hat{+} \cdots \hat{+} w_{i,N} \end{cases} \tag{10}$$

where $\hat{+}$ denotes the addition operation in probability theory.

Likewise, when $i = 2,\ldots,M$, we can also obtain the above conclusions respectively. This issue comes from the addition formula in probability theory, as the **N** states are irrelevant with each other.

Representing every weight with $v_{i,j'}$, a reliability index matrix $\boldsymbol{V}$ can be shown as:

$$\boldsymbol{V} = \begin{array}{cc} & \begin{array}{ccccccccc} \{S_1\} & \{S_2\} & \cdots & \{S_N\} & \{S_1,S_2\} & \{S_1,S_3\} & \cdots & \{S_2,S_3\} & \cdots & \{S_j \mid j \neq N\} & \boldsymbol{\Omega} \end{array} \\ \begin{array}{c} E_1 \\ E_2 \\ \vdots \\ E_M \end{array} & \begin{bmatrix} v_{1,1} & v_{1,2} & \cdots & v_{1,N} & v_{1,N+1} & v_{1,N+2} & \cdots & v_{1,2N} & \cdots & v_{1,2^N-2} & v_{1,2^N-1} \\ v_{2,1} & v_{2,2} & \cdots & v_{2,N} & v_{2,N+1} & v_{2,N+2} & \cdots & v_{2,2N} & \cdots & v_{2,2^N-2} & v_{2,2^N-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ v_{M,1} & v_{M,2} & \cdots & v_{M,N} & v_{M,N+1} & v_{M,N+2} & \cdots & v_{M,2N} & \cdots & v_{M,2^N-2} & v_{M,2^N-1} \end{bmatrix} \end{array} \tag{11}$$

where $v_{i,j'} \in [0,1], (i = 1,2,\ldots,M; j' = 1,2,\ldots,2^N - 1)$.

In this case, the modified BPA can be shown in equation (12):

$$\begin{cases} m'_i(\boldsymbol{A}) = v_{i,j'} \cdot m_i(\boldsymbol{A}), \\ m'_i(\boldsymbol{\Omega}) = 1 - \sum_{A \subset \boldsymbol{\Omega}} v_{i,j'} \cdot m_i(\boldsymbol{A}), \end{cases} \quad \boldsymbol{A} \subset \boldsymbol{\Omega} \tag{12}$$

where $m'_i(\ )$ indicates that the BPA has been modified by the reliability index of evidences.

The proposed reliability index matrix $\boldsymbol{V}$ can also be generalized to denote other weight meanings, such as measure accuracy or evidence importance. Among them evidence importance was referred in (Fan & Zuo, 2006). For example, $v_{1,1} > v_{2,1}$ indicates that evidence 1 is more reliable than evidence 2 to judge state 1. We can also think that evidence 1 is more important than evidence 2. All of the other generalizations can be explained as the same.

By considering evidence reliability, the uncertainty and inaccuracy of evidences are greatly decreased. Meanwhile, the conflict between two evidences may be weakened to some degree.

3.2 Federated evidence fusion frame

The combination rule proposed by Dempster provided a convenient tool for us to fuse multi-source information. In our case, we are going to fuse the data obtained from multiple types of traffic detectors in real-time. Therefore, we build the FEFM in a structure with feedback, which was inspired by the theory of Federated Kalman Filter first proposed by Carlson (Carlson, 1988; 1990). The proposed fusion frame with feedback is illustrated in figure 1. As the figure shows, the whole fusion system consists of four parts, which are the input level, the feature extracting level, the fusion level and the output level. Among them, the fusion level can be further divided into two components: main fusion system and sub-fusion system.

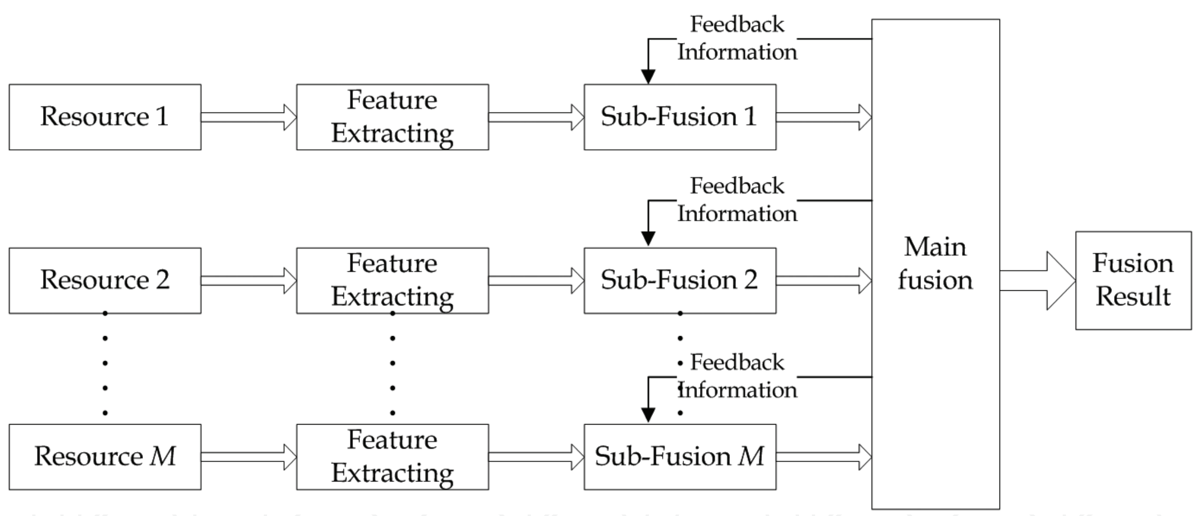


Fig. 1. Frame of the FEFM.

3.3 Federated fusion algorithm

In this algorithm, we use $m_i\left(\boldsymbol{A}_{i,t}\right), i = 1,2,\ldots,M$ to represent the BPA extracted from the data from the *ith* type of detectors at time *t*.

For the sub-fusion systems, the fusing rule makes use of the combining formula (2). It is shown as follows:

$$m_i\left(\boldsymbol{B}_{i,t}\right) = m\left(\boldsymbol{C}_{t-1}\right) \oplus m_i\left(\boldsymbol{A}_{i,t}\right) = \frac{\sum_{\boldsymbol{C}_{t-1} \cap \boldsymbol{A}_{i,t} = \boldsymbol{B}_{i,t}} g\left(m\left(\boldsymbol{C}_{t-1}\right)\right) \times m_i\left(\boldsymbol{A}_{i,t}\right)}{1 - \sum_{\boldsymbol{C}_{t-1} \cap \boldsymbol{A}_{i,t} = \Phi} g\left(m\left(\boldsymbol{C}_{t-1}\right)\right) \times m_i\left(\boldsymbol{A}_{i,t}\right)} \tag{13}$$

where $m_i\left(\boldsymbol{B}_{i,t}\right), i=1,2,\ldots,M$ denotes the fusion result of subsystem *i* at time *t*, and $m\left(C_{t-1}\right)$ represents the fusion result of the main system at time $t-1$. They both are in the form of BPA. The function $g(\ )$ is the operation shown as follows:

$$\begin{cases} g\left(m\left(\boldsymbol{C}_{t-1}\right)\right)=\lambda m\left(\boldsymbol{C}_{t-1}\right) \\ g\left(m\left(\boldsymbol{\Omega}\right)\right)=1-\sum_{\boldsymbol{C}_{t-1}\subset\boldsymbol{\Omega}}\lambda m\left(\boldsymbol{C}_{t-1}\right) \end{cases} \tag{14}$$

where λ is a variable, which represents the degree that $m\left(C_{t-1}\right)$ is weakened, and its value satisfies the restriction $0\le\lambda\le1$. The value of this parameter can be determined under the condition that the fusion result is identical with the real state at all time in the training set. By this means, we can weaken the feedback, i.e. avoid the feedback leading the fusion result at this time.

For the main fusion system, the fusion rule also use the combining algorithm of D-S Evidence Theory, which is

$$\begin{aligned} m\left(\boldsymbol{C}_t\right) &= m_1\left(\boldsymbol{B}_{1,t}\right)\oplus m_2\left(\boldsymbol{B}_{2,t}\right)\oplus\cdots\oplus m_M\left(\boldsymbol{B}_{M,t}\right) \\ &= \frac{\sum_{\bigcap_{i=1}^{M}\boldsymbol{B}_{i,t}=\boldsymbol{C}_t}\left(\prod_{i=1}^{M}m_i\left(\boldsymbol{B}_{i,t}\right)\right)}{1-\sum_{\bigcap_{i=1}^{M}\boldsymbol{B}_{i,t}=\Phi}\left(\prod_{i=1}^{M}m_i\left(\boldsymbol{B}_{i,t}\right)\right)} \end{aligned} \tag{15}$$

where $m(C_t)$ denotes the integrated result of the main fusion system at time *t*, which also is the final fusion result at time *t*.

Then, we can obtain the conclusion of state estimation at that time through a certain decision rule: the maximum belief or the maximum plausibility etc.

3.4 The other two structures

Similar to the Federated Kalman Filter, the FEFM also has the other two transformed structures. They are named the Distributed Feedback Fusion (DFF) and the no feedback fusion (NFF).

3.4.1 Structure of the distributed feedback fusion

The distributed feedback fusion structure is shown in figure 2. In this structure, feedback information to every subsystem does not come from the main fusion system any more, but be produced by themselves. After every fusion cycle, the fusion results obtained by the sub-fusion systems are all sent back to their inputs to be integrated with the inputted state features at the next time. The detailed algorithm is given as follows:

For the sub-fusion systems,

$$\begin{aligned} m_i(B_{i,t}) &= m_i(B_{i,t-1})\oplus m_i(A_{i,t}) \\ &= \frac{\sum_{B_{i,t-1}\cap A_{i,t}=B_{i,t}} g\left(m_i(B_{i,t-1})\right)\times m_i(A_{i,t})}{1-\sum_{B_{i,t-1}\cap A_{i,t}=\Phi} g\left(m(B_{i,t-1})\right)\times m_i(A_{i,t})} \end{aligned} \tag{16}$$

in which, $m_i(B_{i,t-1}), i=1,2,\ldots,M$ denotes the feedback information from the output of subsystem *i*, which is the fusion result of this subsystem at time $t-1$.

As to the main fusion system, the formula is the same as the standard FEFM algorithm.

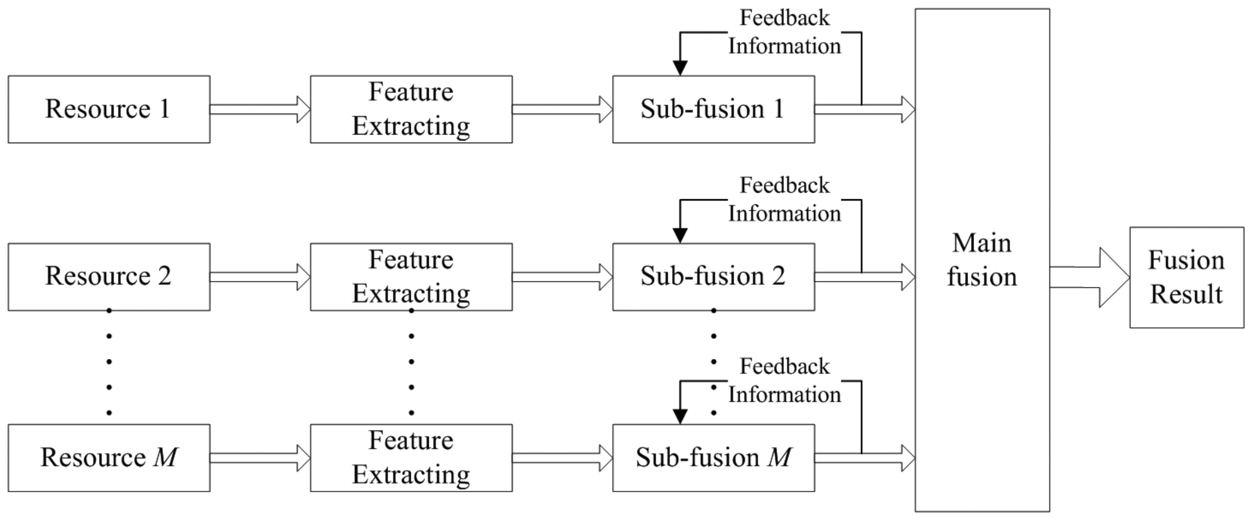


Fig. 2. Frame of the distributed feedback fusion

3.4.2 Structure of the no feedback fusion

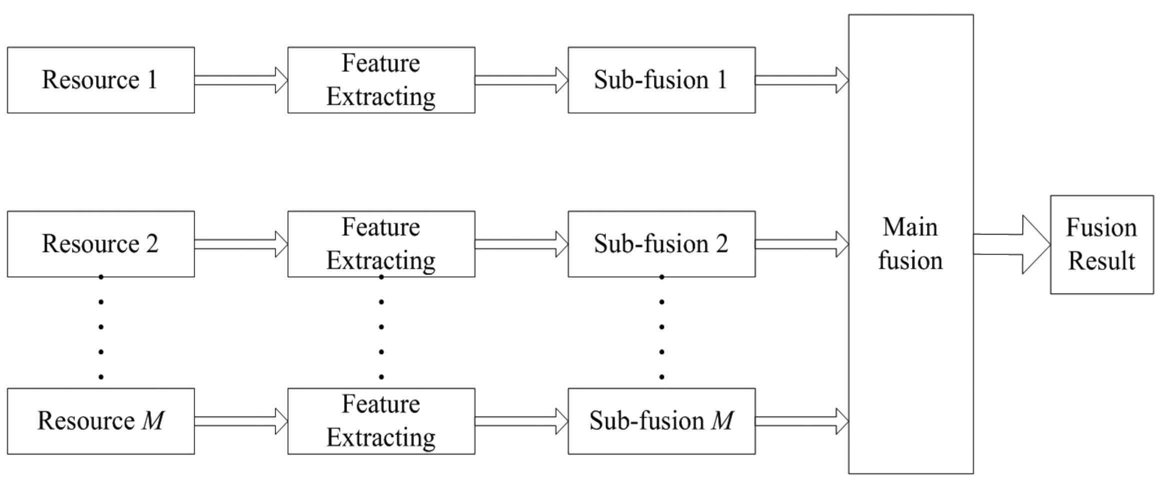


Fig. 3. Frame of the no feedback fusion

As is shown above, this type of structure has neither any feedback information from the main fusion system, nor from the sub-fusion system. Therefore, in this model, the fusion outputs of the sub-fusion systems are directly sent into the main fusion system. This fusion outputs are attained by combining the inputs of the sub-fusion systems at this time and those at the last time. The difference of this algorithm lies in:

For the sub-fusion systems,

$$\begin{aligned} m_i(B_{i,t}) &= m_i(A_{i,t-1}) \oplus m_i(A_{i,t}) \\ &= \frac{\sum_{A_{i,t-1}\cap A_{i,t}=B_{i,t}} g\big(m_i(A_{i,t-1})\big)\times m_i(A_{i,t})}{1-\sum_{A_{i,t-1}\cap A_{i,t}=\Phi} g\big(m_i(A_{i,t-1})\big)\times m_i(A_{i,t})} \end{aligned} \tag{17}$$

in which, $m_i(A_{i,t-1}), i=1,2,\ldots,M$ denotes the BPA of state feature put in sub-fusion system i at time t-1.

Likewise, in the main fusion system, the fusion algorithm also is the same as the standard FEFM algorithm.

4. Implementation of fusion algorithm

In the last section, we have introduced the core algorithms of the FEFM; however, it still needs more procedures, if we want to veritably apply the whole model to the practice. They will be presented in this section.

4.1 Determination of reliability matrix

In Reference (Guo et al., 2006), reliability was divided into static reliability and dynamic reliability. Herein, we only consider the static one. Thus, reliability weight $w_{i,j}^{s}$ can be calculated by (18).

$$\begin{cases} w_{i,j}^{s} = f\left(d_{BPA}\left(m_{i,j}^{s}, m_{i,j}^{o}\right)\right) \\ f = b - a \cdot d_{BPA} \end{cases} \tag{18}$$

in which d_{BPA} is the evidence distance that can be computed by (5); $m_{i,j}^{s}$ denotes the BPA output of the sensor i about the state class j in the training set; $m_{i,j}^{o}$ represents the BPA of what we have known about the class membership of the same data; a=1 and b=1, due to the boundary condition: $w_{i,j} \in [0,1]$.

4.2 Creation of masses

Above all, we use the negative exponential proposed by Denoeux (Denoeux, 1995) to create the masses, shown in (19).

$$m_i\left(\{\omega_n\}\right) = \exp\left(-\gamma_i d_i^{\beta}\right) \tag{19}$$

where d_i is a type of distance between the data detected by the i *th* kind of detectors and the prototype of each state class. The prototype can be designated artificially or be obtained by clustering the historical data. The parameters β and r_i are decided depending on the real-world data in the training set.
Afterward, we define the conversions below to create the BPAs.

$$\begin{cases} kth\max\left(m^{*}_{i}\left(\{\omega_k\}\right)\right) = \dfrac{kth\max\left(m_i\left(\{\omega_k\}\right)\right)}{\sum\limits_{l=1th}^{kth}\max\left(m_i\left(\{\omega_l\}\right)\right)} \\ kth\max\left(m'_{i}\left(\{\omega_k\}\right)\right) = v_{i,k}^{s} \cdot kth\max\left(m^{*}_{i}\left(\{\omega_k\}\right)\right) \\ m'_{i}\left(\{\boldsymbol{\Omega}\}\right) = 1 - \sum\limits_{k=1}^{N} kth\max\left(m'_{i}\left(\{\omega_k\}\right)\right) \end{cases} \tag{20}$$

in which the $kth\max$ denotes the kth maximum value in all the masses derived from the results computed by (19); k is a natural number in the range from 1 to N; N is the total number of elements in the frame of discernment; $v_{i,k}^{s}$ represents the static reliability index weight, which has been computed beforehand.

4.3 Decision-making rules

Herein, we choose the maximum belief rule as the decision-making principle. Also, some additional conditions are provided according to the context of traffic engineering. The decision-making rules are shown as follows:

$$Dst = \begin{cases} st_{\max m}, & if \quad st_{\max m} - st_{2th\max} = 1, \\ \boldsymbol{\Omega}, & otherwise, \end{cases} \tag{21}$$

where Dst indicates the decision output of state value; $st_{\max m}$ denotes the state value corresponding to the mass with the maximum value; if the output is $\boldsymbol{\Omega}$, it means no verdict. In this case, we may give an output of state 0.

5. Experiments

5.1 Synthetic data

First, we use synthetic traffic data to demonstrate the effectiveness of the proposed model. Assume the discernment framework of traffic state is $\boldsymbol{\Omega} = \{S_1, S_2, S_3, S_4\}$, and the evidence set is $\boldsymbol{E} = \{E_1, E_2\}$. The BPAs based on both evidences are listed in Table 1.

Time	Evidence	{S1}	{S2}	{S3}	{S4}	$\boldsymbol{\Omega}$
T_1	E_1: $m_1(A_{1,t1})$	0.7	0.1	0	0	0.2
	E_2: $m_2(A_{2,t1})$	0.1	0.8	0	0	0.1
T_2	E_1: $m_1(A_{1,t2})$	0.25	0.55	0	0	0.2
	E_2: $m_2(A_{2,t2})$	0	0.6	0.25	0	0.15
T_3	E_1: $m_1(A_{1,t3})$	0	0.1	0.8	0	0.1
	E_2: $m_2(A_{2,t3})$	0	0	0.6	0.25	0.15
T_4	E_1: $m_1(A_{1,t4})$	0	0	0.2	0.7	0.1
	E_2: $m_2(A_{2,t4})$	0.8	0.1	0	0	0.1
T_5	E_1: $m_1(A_{1,t5})$	0	0	0.1	0.8	0.1
	E_2: $m_2(A_{2,t5})$	0	0	0.2	0.75	0.05

Table 1. BPAs for the case

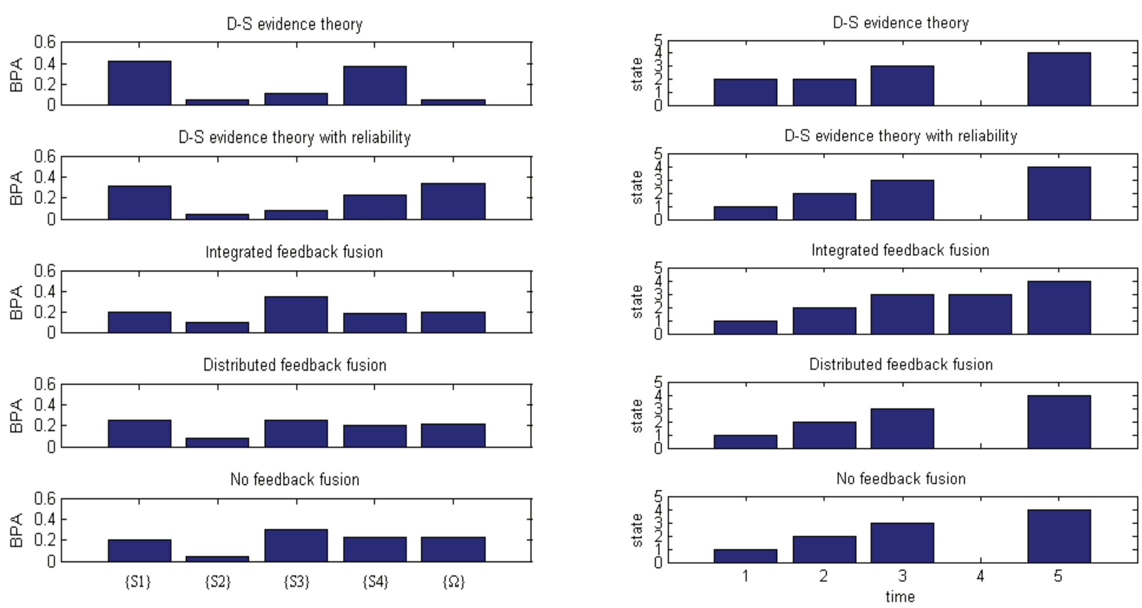
Herein, we provide 5 pairs of evidences at 5 continuous times respectively, among which the two evidences at time T_1 have a partial conflict, and the pair of evidences is completely conflict at time T_4. Whereas, the evidences at other three times have little conflicts and only embody the state transferring.

The BPAs after being fused are listed in Table 2, which shows the comparison of the fusion results of the five models. They are the conventional Evidence Theory, Evidence Theory considering reliability, standard FEFM, DFF and NFF, which are orderly denoted by $m(C_{t1})$, $m'(C_{t1})$, $mI(C_{t1})$, $mD(C_{t1})$ and $mN(C_{t1})$.

Time	Evidence	{S1}	{S2}	{S3}	{S4}	Ω
T_1	$m(C_{t1})$	0.37	0.58	0	0	0.05
	$m'(C_{t1})$	0.48	0.33	0	0	0.19
	$mI(C_{t1})$	0.48	0.33	0	0	0.19
	$mD(C_{t1})$	0.48	0.33	0	0	0.19
	$mN(C_{t1})$	0.48	0.33	0	0	0.19
T_2	$m(C_{t2})$	0.06	0.82	0	0.08	0.04
	$m'(C_{t2})$	0.12	0.62	0.09	0	0.17
	$mI(C_{t2})$	0.23	0.63	0.05	0	0.09
	$mD(C_{t2})$	0.28	0.64	0.03	0	0.05
	$mN(C_{t2})$	0.18	0.64	0.06	0	0.12
T_3	$m(C_{t3})$	0	0.02	0.92	0.03	0.03
	$m'(C_{t3})$	0	0.03	0.71	0.13	0.13
	$mI(C_{t3})$	0.05	0.19	0.57	0.09	0.1
	$mD(C_{t3})$	0.06	0.14	0.6	0.1	0.1
	$mN(C_{t3})$	0.02	0.11	0.66	0.1	0.1
T_4	$m(C_{t4})$	0.42	0.05	0.11	0.37	0.05
	$m'(C_{t4})$	0.31	0.04	0.08	0.23	0.34
	$mI(C_{t4})$	0.19	0.1	0.34	0.18	0.19
	$mD(C_{t4})$	0.25	0.08	0.25	0.2	0.22
	$mN(C_{t4})$	0.2	0.04	0.3	0.23	0.23
T_5	$m(C_{t5})$	0	0	0.06	0.93	0.01
	$m'(C_{t5})$	0	0	0.12	0.81	0.07
	$mI(C_{t5})$	0.02	0.01	0.17	0.76	0.04
	$mD(C_{t5})$	0.02	0.01	0.13	0.79	0.05
	$mN(C_{t5})$	0.02	0	0.11	0.82	0.05

Table 2. Results of fusion. $m(C_{t1})$, $m'(C_{t1})$, $mI(C_{t1})$, $mD(C_{t1})$ and $mN(C_{t1})$ respectively denotes the conventional Evidence Theory, Evidence Theory considering reliability, standard FEFM, DFF and NFF.

In figure 4(a), the bar plot of the fusion consequences at time T_4 is shown to display the predominance of the FEFM. In the third row, the integrated feedback fusion represents the standard FEFM. From the figure, we can find that the former two methods can not give a clear answer due to the huge conflict. However, the standard FEFM gives a definite choice. We can also see that the other two forms of the FEFM do not perform well at this situation, although a little of progress is made. This phenomenon can also be seen in figure 4(b), which shows us a course of estimation during the whole 5 times. Moreover, we can find a different determination between the first model and the other four models at time T_1, which is because there is a partial conflict between the two evidences, whereas the reliability mitigates its effect to some extent.



(a) (b)

Fig. 4. Bar plot of the fusion results. (a) is the fusion results using the five models at time T_4; (b) is the fusion results using these models during the 5 times.

5.2 Data from real traffic

In this section, we employ two types of traffic mean-speeds on an urban link in Shanghai to carry out the fusion estimation experiment. The two speeds were derived by estimating with the SCATS loop detector data and GPS-equipped taxi data. The detailed algorithms were provided in reference (Kong et al., 2007). The real-world data were collected at a section of Zhao Jia Bang Road of Shanghai through a whole day, which was from 0 o'clock to 24 o'clock on Sep. 26, 2006, and the average speeds were computed in every five minutes. Also, we screened a segment of surveillance video during 2:00 PM-4:00 PM at this link on the same day in order to validate the model.

The fusion consequence of the standard FEFM is shown in figure 5, from which we can clearly see that the traffic state is reasoned and tracked at the feature level. According to the verifying test by replaying the video, the estimation accuracy of our model is beyond 95%. Herein, we define five different traffic states, corresponding to 'very congested', 'congested', 'medium', 'smooth' or 'very smooth', respectively.

Moreover, the fusion algorithm was embedded into the Shanghai Urban Traffic Information System developed by our laboratory to implement the fusion estimation. The estimation results were displayed on the traffic information display platform, as figure 6 shows. Figure 6(a) and 6(b) respectively illustrates the results estimated only by the SCATS data or the GPS data; and figure 6(c) shows the results by fusing the two types of data. In these figures, the color of the road sections, red, orange, yellow, green, or dark green, represents the corresponding traffic states defined above respectively.

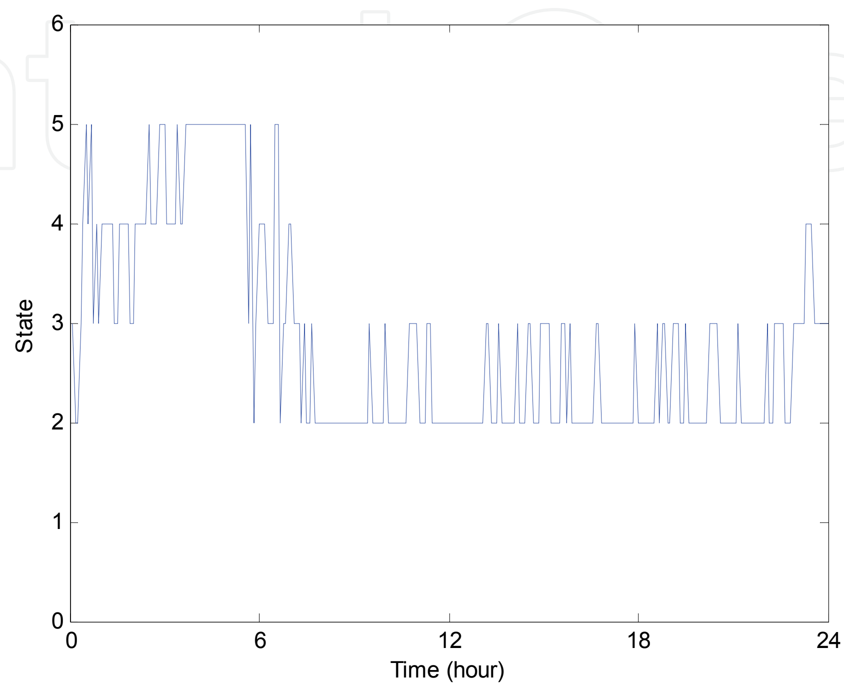
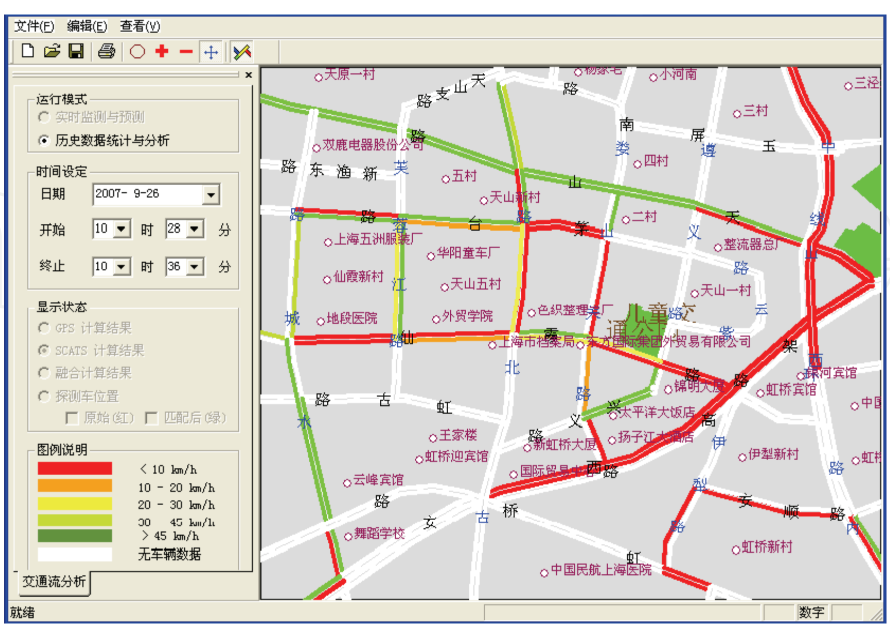
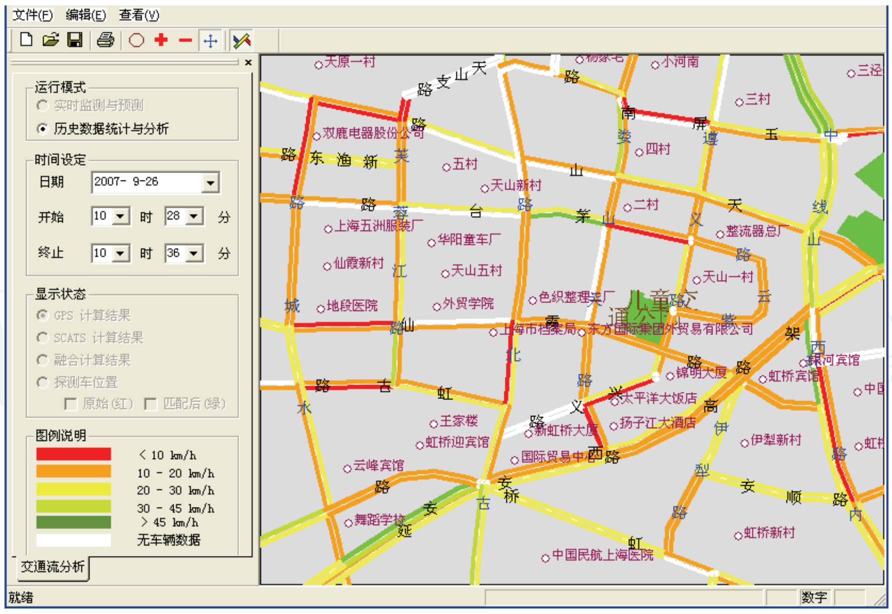


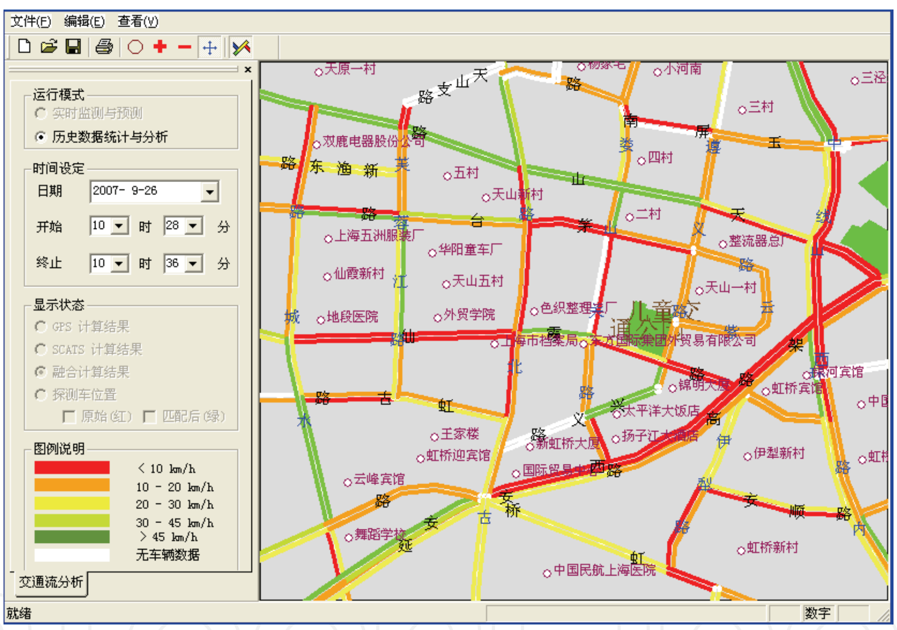
Fig. 5. Traffic state estimation results of the standard FEFM with the real-world data on the link in Shanghai through 24 hours.



(a)



(b)



(c)

Fig. 6. Estimation results displayed on the platform. (a) is the result from the SCATS loop detector data; (b) is the result from the GPS-equipped taxi data; (c) is the result by fusing the two types of data.

6. Conclusions

This paper has proposed a model for real-time traffic state estimation by developing D-S Evidence Theory in temporal domain. As it realizes online fusion of heterogeneous detector data at the feature level, the method has strong application potentials in fusing data from many other different types of sensors (cameras, cell phones, etc.). Furthermore, the evidence reliability to every state is considered in the FEFM. Finally, the model shows great advantages over conventional D-S Evidence Theory in the simulation test and good accuracy by the tests with the real-world data.

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Data fusion is a research area that is growing rapidly due to the fact that it provides means for combining pieces of information coming from different sources/sensors, resulting in ameliorated overall system performance (improved decision making, increased detection capabilities, diminished number of false alarms, improved reliability in various situations at hand) with respect to separate sensors/sources. Different data fusion methods have been developed in order to optimize the overall system output in a variety of applications for which data fusion might be useful: security (humanitarian, military), medical diagnosis, environmental monitoring, remote sensing, robotics, etc.