# Fusion of Static and Temporal Information for Threat Evaluation in Sensor Networks

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**Abstract.** In many CCTV and sensor network based intelligent surveillance systems, a number of attributes or criteria are used to individually evaluate the degree of potential threat of a suspect. The outcomes for these attributes are in general from analytical algorithms where data are often pervaded with uncertainty and incompleteness. As a result, such individual threat evaluations are often inconsistent, and individual evaluations can change as time elapses. Therefore, integrating heterogeneous threat evaluations with temporal influence to obtain a better overall evaluation is a challenging issue. So far, this issue has rarely be considered by existing event reasoning frameworks under uncertainty in sensor network based surveillance. In this paper, we first propose a weighted aggregation operator based on a set of principles that constraints the fusion of individual threat evaluations. Then, we propose a method to integrate the temporal influence on threat evaluation changes. Finally, we demonstrate the usefulness of our system with a decision support event modeling framework using an airport security surveillance scenario.

## 1 Introduction

CCTV and sensor network-based intelligent surveillance systems are increasingly critical for public security and infrastructure protection due to the growing threat of terrorist attack, anti-social and criminal behaviors. Since events in surveillance systems are detected from different intelligent sensor technologies including audio, video and infrared, RFID, logs, or other sensory devices, how to combine events detected from multiple sources relating to the same suspect (hereafter, we refer it as *subject* ) to obtain an overall estimation of its potential threat is a challenging problem. For example, a scenario can be of that from a camera in a security domain a male is detected (with a higher degree of threat) while from the personnel authentication identification system it indicates the person is a new member of staff (with a lower degree of threat). A straightforward method to handle this problem is to apply a number of independent criteria (e.g., gender, age, ID, behavior) to individually assess the potential threat of a subject, and then to combine these individual evaluations to produce an overall assessment. Since these individual evaluations cannot always be in complete agreement and the priorities of these criteria are different, adequate fusion operators (e.g., weighted aggregation operators) are necessary to obtain the overall estimation of potential threat for each subject and resolve the inconsistent or conflicting information.

At the same time, there may be multiple subjects with potential threats occurring simultaneously. Either due to the limited security resources, or due to the degree of potential threat is not significant enough to trigger an action, sometimes a security force will not take actions to prevent a potential threat immediately. In this case, the temporal influence on the threat degree, i.e., how the threat degree changes with time without external intervention, or how the threat degree changes with time when new evidence is collected, are both important to consider in an intelligence surveillance system.

In the literature, although there have been several event modeling and reasoning systems proposed [2, 3, 5, 6, 8], however, none of the models has properly addressed these two issues (detailed discussions will be in the related work section). In order to address these problems, in this paper, we first analyze general principles that should be obeyed by a fusion process that combines individual threat evaluations. Then, we introduce a weighted aggregation operator to obtain the overall degree of potential threat for each subject after considering all related criteria, from which we can set the priority for each subject. After that, we propose a method to revise the potential threat degree based on elaping time to take into account the temporal influence of that criteria of each subject. Finally, we will illustrate our method with an airport security surveillance scenario.

This paper advances the state of the art on information fusion for decision support for intelligent surveillance systems in the following aspects. (i) We analyze general principles for an appropriate aggregation operator in the surveillance system. It gives a cornerstone to build up a generic axiomatic framework for the integration of heterogeneous threat evaluation. (ii) We introduce a weighted aggregation operator to combine the degrees of potential threats of each criterion and give an overall estimation to each subject. (iii) We propose a method to deal with two types of temporal influence for the potential threats.

The rest of this paper is organized as follows. Section 2 recaps some basic concepts in Dempster-Shafer theory. Section 3 discusses some principles govern threat evaluation fusion processes. Section 4 introduces an aggregation operator that obeys the principles to fuse degrees of potential threats. Sections 5 provides a case study to illustrate the usefulness of our model. Finally, Section 6 discusses the related work and concludes the paper with future work.

## 2 Preliminaries

**Definition 1** *[10] Let $\Theta$ be a set of exhaustive and mutually exclusive elements, called a frame of discernment (or simple a frame). Function $m: 2^{\Theta} \to [0,1]$ is a mass function if $m(\emptyset)=0$ and $\sum_{A \subseteq \Theta} m(A)=1$. And a function $Pl : 2^{\Theta} \to [0,1]$, defined as follows, is called a plausibility function over $\Theta$:*

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B). \tag{1}$$

One advantage of D-S theory is that it provides a method to accumulate and combine evidence from multiple sources by using *Dempster combination rule.*

**Definition 2 (Dempster combination rule)** *Let $m_1$ and $m_2$ be two mass functions over a frame of discernment $\Theta$. Then Dempster combination function $m_{12} = m_1 \bigoplus m_2$ is given by:*

$$m_{12}(X) = \begin{cases} 0 & \textit{if } X = \emptyset \\ \frac{\sum\limits_{A \bigcap B = X} m_1(A)m_2(B)}{1 - \sum\limits_{A \bigcap B = \emptyset} m_1(A)m_2(B)} & \textit{if } X \neq \emptyset \end{cases} \tag{2}$$

When a new piece of evidence, which is collected after fusion, Jeffrey-Dempster revision rule [7] can be applied to update the current evidence. This rule is useful for considering the temporal influence for the DPTC (Degree of Potential Threat for a subject w.r.t a given Criterion ).

**Definition 3 (Jeffrey-Dempster revision rule)** *Let $m$ and $m_I$ be two mass functions over a frame of discernment $\Theta$. The Jeffrey-Dempster revision function of $m$ by $m_I$, denoted as $m \circ_{JD} m_I$, is defined by:*

$$(m \circ_{JD} m_I)(C) = \sum_{A \cap B = C} \sigma_m(A,\ B) m_I(B),\ \textit{for any } C \neq \emptyset, \tag{3}$$

$$\textit{where } \sigma_m(A,\ B) = \begin{cases} \frac{m(A)}{Pl(B)} & \textit{for } Pl(B) > 0, \\ 0 & \textit{for } Pl(B) = 0 \textit{ and } A \neq B, \\ 1 & \textit{for } Pl(B) = 0 \textit{ and } A = B. \end{cases}$$

## 3 Principles of Threat Evaluation Aggregation

In order to hold commonalities for the aggregation process in different specific surveillance situations and develop adequate weighted aggregation operators for specific applications, in this section, we propose some basic principles for threat evaluation aggregation. These principles aim for revealing commonalities for general aggregation processes, that specific, appropriate weighted aggregation operators should satisfy.

(i) **Conclusion Modification**: Consider one more threat evaluation for a given subject w.r.t a new criterion can modify the current evaluation to either increase, decrease, or unchange.

(ii) **Evaluation Consistency**: The overall potential threat evaluation for a given subject should increase when the point valued degree of potential threat for such subject w.r.t each related criterion increase.

(iii) **Evaluation commensurability**: A system shall provide an overall evaluation for each subject after the aggregation process, and the overall evaluations for different subjects are comparable (on a commensurable scale).

(iv) **Irrelevance of evidence ordering**: The result of an aggregation should not be affected by the ordering of aggregation.

(v) **Importance Dependency**: The effect of the DPTC for the overall evaluation is dependent on the importance (reflected as a weight) of this criterion.

The *first* principle translates the DPTC into three types of influence for the overall evaluation. (i) Positive evidence: the degree of threat will increase after considering a DPTC. For example, the fact that a person holding a knife will enhance our belief that this person is dangerous. (ii) Negative evidence: the degree of threat will decrease after considering a DPTC. For instance, age-information with an age value as *old* will weaken our belief that this person is dangerous. And (iii) neutral evidence, the degree of threat is not affected after considering a DPTC. for example, the evidence that a person has been waiting for friends has no influence on our beliefs about his degree of threat.

The *second* principle captures the monotonicity of the aggregation operation: the higher value a DPTC will be, the higher value the overall degree of threat for the subject is, *ceteris paribus*. Also, the second principle guarantees the property of strict transitivity for the ranking order about potential threat for the subjects in a surveillance environment. That is, suppose $a \succ b$ means subject $a$ is more dangerous than subject $b$, if for subjects $a$, $b$, $c$, we have $a \succ b$ and $b \succ c$, then $a \succ c$. The violation of the strict transitivity axiom implies that an intelligence surveillance system will be unable to determine the most dangerous subject.

The *third* principle means that a surveillance system can give a complete ranking order for subjects in a given situation based on their overall potential threat evaluations. Hence, the requirement of overall commensurability among the subjects of different situations suggests that all the outcomes of overall evaluations need to be in a unified bounded range.

The *forth* principle guarantees that the overall potential threat evaluation shall not be influenced by the order of fusing the individual DPTCs. Thus, it reveals two properties in the surveillance system (let $R(x_i, x_j)$ be the aggregation of evaluations about $x_i$ and $x_j$.). (i) Associativity: $R(R(x_1, x_2), x_3) = R(x_1, R(x_2, x_3))$. (ii) Symmetry: $R(x_1, x_2) = R(x_2, x_1)$

The *fifth* principle reveals the essential meaning of weights: (i) when a DPTC increases, the weighted DPTC should also increase; (ii) after considering the effect of weight in our aggregation operator, the first principle to the forth principle should be remained.

## 4 A Weighted Aggregation Operator

The basic principles for the weighted aggregation operator in surveillance systems, proposed in the previous section, is a set of constraints of information fusion frameworks. It can be instantiated in different ways. We discuss one weighted aggregation operator in this section that satisfies these principles (below, without losing general, we assume the individual DPTC is a point-value in [0,1]).

Since a DPTC is a point value in a range, the distinction of three types of evidence (positive, neutral, negative) to some extent suggests the setting of an expectation threshold for the degrees of potential threats w.r.t each criterion. Thus, when a DPTC exceeds the threshold, it is positive evidence; when equals to the threshold, neutral evidence; and when below the threshold, negative evidence. Table 1 summarizes a list of terms (and notations) used in a weighted aggregation operator.

**Table 1.** The terms in weighted aggregation operators

| Terms | Interpretation |
|---|---|
| $\nu_i(x)$ | DPTC of subject $x$ for criterion $i$ |
| $w_i$ | the weight for criterion $w_i$ |
| $g(w_i, \nu_i(x))$ | weighted DPTC |
| $R(g(w_i, \nu_i(x)), g(w_j, \nu_j(x)))$ | aggregated assessment of $g(w_i, \nu_i(x))$ and $g(w_j, \nu_j(x))$ |
| $e \in (0,1)$ | the threshold to distinguish different types of evidence |

Now, we can introduce a weighted aggregation operator for the overall degree of potential threat for any two criteria 1 and 2 as follow:

$$\begin{aligned}&R(g(w_1, \nu_1(x)), g(w_2, \nu_2(x)))\\ =&\frac{(1-e)g(w_1,\nu_1(x))g(w_2,\nu_2(x))}{(1-e)g(w_1,\nu_1(x))g(w_2,\nu_2(x))+e(1-g(w_1,\nu_1(x)))(1-g(w_2,\nu_2(x)))}, \qquad (4)\\ &where\\ &g(w_i, \nu_i(x)) = w_i\nu_i(x) + (1-w_i)e. \qquad (5)\end{aligned}$$

Here, $e$ is the threshold value to distinguish different types of evidence. Moreover, in Equation (5), we combine a uninorm aggregation operator $R(x,y) = \frac{(1-e)xy}{(1-e)xy+e(1-x)(1-y)}$ as shown in [4] with a weighting function $g(w_i, \nu_i(x)) = w_i\nu_i(x) + (1-w_i)e$ in [11]. Finally, with the proof in [11], the weighting function $g(w_i, \nu_i(x)) = w_i\nu_i(x) + (1-w_i)e$ satisfies the following four conditions:

- Monotonicity in value: if $\nu_i(x) > \nu_i(y)$, then $g(w_i, \nu_i(x)) > g(w_i, \nu_i(y))$. It means that as the degree of potential threat with respect to a given criterion $i$ for subject $x$ increases, the weighted value should also increase.
- Normality of importance of one: $g(1, \nu_i(x)) = \nu_i(x)$. Thus, when the weight is set to 1, the weighted value does not change.
- No effect for zero importance elements: $g(0, \nu_i(x)) = e$, where $e$ is a threshold in our operator $R(\nu_1(x), \nu_2(x))$.
- Consistency of effect on $w_i$: for $a \geq b$, $g(a, \nu_i(x)) \geq g(b, \nu_i(x))$ if $\nu_i(x) \geq e$; for $a \geq b$, $g(a, \nu_i(x)) \leq g(b, \nu_i(x))$ if $\nu_i(x) \leq e$. Here consistency means that after considering the effect of weight in our aggregation operator, the property of the uninorm aggregation operator as shown in the following Equations (6)-(8) will be remained.

The aggregation operator introduced is a weighted uninorm aggregation operator [11] that satisfies: (i) Monotonicity: $x_1 \geq y_1 \wedge x_2 \geq y_2 \Rightarrow R(x_1, x_2) \geq$

$R(y_1, y_2)$. (ii) Boundary conditions: $R(0, 0) = 0$; $R(1, 1) = 1$. (iii) Associativity: $R(R(x_1, x_2), x_3) = R(x_1, R(x_2, x_3))$. (iv) Symmetry: $R(x_1, x_2) = R(x_2, x_1)$. (v) Neutral element: $\exists e \in (0, 1)$, $\forall x \in [0, 1], R(e, x) = x$.

Finally, we introduce the preference ordering to rank the potential threat of subjects according to their overall evaluations with the following definition.

**Definition 4** *For two subjects $x$ and $y$, the strict preference ordering $\succ$ is defined as follows:*

$$x \succ y \Leftrightarrow R(g(w_i, \nu_i(x)), \ldots, g(w_n, \nu_n(x))) > R(g(w_j, \nu_j(y)), \ldots, g(w_m, \nu_m(y)))$$

This ordering states that the potential threat of $x$ is higher than that of $y$, if the overall evaluation of $x$ is greater than that of $y$. Thus, with the equivalence relation $\sim$ (i.e., $x \sim y$ if $x \not\succ y$ and $y \not\succ x$), we can compare any two subjects as shown in the following theorem.

**Theorem 1** *For a set of subjects $X$, the strict preference ordering $\succ$ in Definition 4 satisfies:*

- ***Completeness*** *For any subjects $x$ and $y$ in $X$, we have $x \succ y$ or $x \prec y$ or $x \sim y$.*
- ***Strict Transitivity*** *For any subjects $x$, $y$ and $z$ in $X$, if $x \succ y$ and $y \succ z$, then $x \succ z$.*

*Proof.* (i) By Definition 4, we have

$$x \succ y \Leftrightarrow R(g(w_i, \nu_i(x)), \ldots, g(w_n, \nu_n(x))) > R(g(w_j, \nu_j(y)), \ldots, g(w_m, \nu_m(y))),$$

which means that $y \not\succ x$. That is, the preference order $\succ$ satisfies asymmetry: if $x$ is strictly preferred to $y$, then $y$ is not strictly preferred to $x$. Also $x \sim y$ iff $x \not\succ y$ and $y \not\succ x$. As a result, the preference order $\succ$ satisfies the completeness that follows from the definition of $\sim$ and the fact that $\succ$ is asymmetric. So, property (i) holds.

(ii) Suppose $x \succ y$ and $y \succ z$. By Definition 4, $x \succ y$ and $y \succ z$ imply that $R(g(w_i, \nu_i(x)), \ldots, g(w_n, \nu_n(x))) > R(g(w_j, \nu_j(y)), \ldots, g(w_m, \nu_m(y)))$ and $R(g(w_j, \nu_j(y)), \ldots, g(w_m, \nu_m(y))) > R(g\ (w_k, \nu_k(z)), \ldots, g(w_o, \nu_o(z)))$, respectively. As a result, $R(g(w_i, \nu_i(x)), \ldots, g(w_n, \nu_n(x))) > R(g(w_k, \nu_k(z)), \ldots, g(w_o, \nu_o(z)))$. Thus $x \succ z$. So, propertyp (ii) holds. □

Now, we show that such a weighted aggregation operator satisfies the principles that we proposed in the previous section.

For the *first* principle about Conclusion Modification, it is equivalent to prove that our operator satisfies the following Theorem:

**Theorem 2** *Let $\nu_c(x)$ be the point valued degree of potential threat for subject $x$ with respect to criterion $c$, $w_c$ be the weight of criterion $c$, $e \in (0, 1)$ be the threshold to distinguish different types of evidence, $D(x)$ be the degree of overall potential threat for all related criteria except criterion $c$ for subject $x$, and $R(A, B)$ be the combined assessment of degrees of two potential threat $A$ and $B$. Then we have*

*(i) Effect of positive evidence: if $\nu_c(x) > e$, then $R(D(x), g(w_c, \nu_c(x)) \geq D(x)$.*
*(ii) Effect of negative evidence: if $\nu_c(x) < e$, then $R(D(x), g(w_c, \nu_c(x)) \leq D(x)$.*
*(iii) Effect of neutral evidence: if $\nu_c(x) = e$, then $R(D(x), g(w_c, \nu_c(x)) = D(x)$.*

*Proof.* By Equation (5), we have

$$g(w_c, \nu_c(x)) - e = w_c\nu_c(x) + (1 - w_c)e - e = w_c(\nu_c(x) - e)$$

Thus, if $\nu_c(x) > e$, $g(w_c, \nu_c(x)) > e$ and if $\nu_c(x) < e$, $g(w_c, \nu_c(x)) < e$. So, since $D(x) = R(D(x), e)$, by Monotonicity, items (i) and (ii) holds. Moreover, by the property of Neutral element for our aggregation operator, we have $R(D(x), e) = D(x)$. Then item (iii) holds. □

For the *second* principle of Evaluation Consistency, the monotonicity of the aggregation operator is proved in [11] and the strict transitivity for the ranking order is shown by the second item of Theorem 1.

For the *third* principle of Evaluation Commensurability, the completeness of the ranking order over potential threats for the subjects is shown by the first item of Theorem 1. With monotonicity, the property of boundary conditions says that the aggregated assessment value is in the interval $[0, 1]$. Thus, our operator gives a unified range for the value of overall evaluation as well.

For the *forth* principle of Irrelevance of Evidence Ordering, the properties of associativity and commutativity together show that we can combine the weighted DPTCs in any order. Thus, our operator satisfies the forth principle.

For the *fifth* principle, it is guaranteed by the four conditions about the weighting function $g(w_i, \nu_i(x)) = w_i\nu_i(x) + (1 - w_i)e$ in our operator.

Finally, our aggregation operator also satisfies the properties in [11] that:

$$\forall x, y \in (e, 1), R(x, y) \geq \max\{x, y\} \tag{6}$$

$$\forall x, y \in (0, e), R(x, y) \leq \min\{x, y\} \tag{7}$$

$$\forall x \in (0, e), y \in (e, 1), x \leq R(x, y) \leq y \tag{8}$$

These three equations (Equations (6)-(8)) not only point out the different aggregation results of our operator, but also reveal a desirable property in our operator: if all the degrees of potential threats exceed a threshold, the operator should produce a higher degree of threat, hence, the corresponding subject is of higher priority to deal with. If all of the degrees are below a threshold, the operator produces a lower level degree of threat and hence no immediate actions taken. For example, suppose a young man holds a knife and intrudes into a secured area. All criteria: age, gender, intentions show that the person is dangerous, then the surveillance system (after aggregating all the evidence) should produce a strong alert indicator for taking actions. On the other hand, in the case that an old lady holds a walking stick and passes the security door, since all criteria show that the person is harmless, the surveillance system will not raise any alert unless other strong evidence has emerged showing that the woman is dangerous. In terms of fusion, it has an reinforcement effect: when all the evidence are strongly suggesting a subject is dangerous, the overall degree of threat of the subject is increased above any individual degrees.

## 5 Temporal Influence for Point Valued Potential Threats

Now, we consider the temporal influence issue in surveillance systems. Generally speaking, a temporal influence of a given criterion on the assessment of the degree of threat of a subject can be divided into two categories: the temporal influence without external intervention and the temporal influence with new evidence observed.

To investigate the first category of temporal influence, let us consider the following scenario. A person is loitering near the ticket counter at 9:10 pm. The security team for the area cannot take any action due to limited security resources. Twenty minutes later, one security team returned. Now, the security manager should pay more attention to this person since it is unusual for a person to loiter near the ticket counter for such a long time, even without any new evidence about the subject w.r.t this criterion.

Intuitively, there should be three types of temporal influences without external intervention for the point valued degree of potential threat with respect to different criteria: increase, neutral, and decrease. For example, for age or gender, their threat degrees will not change with time; for leaving objects (e.g., a bag) alone, the threat degree should change over time; but for some emotions, such as anger, their threat degrees should decrease with time (a person will fight with others when he is very angry. However, after a while, his potential threat for engaging into a fight will decrease). Based on this intuition, we can obtain the following equation.

$$\upsilon_c(x) = \nu_c(x)^{\gamma^{\lfloor \frac{t-t_0}{n} \rfloor}} \tag{9}$$

where

$$\begin{cases} \gamma < 1 \text{ increasing DPTC with time change;} \\ \gamma = 1 \text{ neutral DPTC with time change;} \\ \gamma > 1 \text{ decreasing DPTC with time change.} \end{cases} \tag{10}$$

Here, $\nu_c(x)$ is the point valued degree of potential threat for subject $x$ w.r.t. criterion $c$ that is calculated at point of time $t_o$ (here $t_o$ is the latest time-point for the *occT*s of all related events to generate $\nu_c(x)$), $t$ is the current time-point, $n$ ($n > 0$) is the time interval between two key time points for updating, and $\gamma$ ($\gamma \in (0, +\infty)$) is the influence rate. Moreover, in real-life applications, surveillance systems will update evidence regularly, we introduce the time interval $n$, and $\lfloor \frac{t-t_0}{n} \rfloor$ means that we will take integers downwards in function $\frac{t-t_0}{n}$. Hence, in real-life applications, always the change of the DPTC is limited: a positive evidence will never turn out to be a negative evidence no matter how much time elapse. For example, for the emotion of anger, it will be positive evidence that will increase the potential threat, even after a moment of calming down, it will not become negative evidence, which will decrease the potential threat of a given subject. Similarly, most negative evidence will not become positive evidence, even though it might be natural. However, some negative evidence may become positive evidence, such as a member of staff staying overly long in a security field. Based on Equation (9), it is possible to obtain the following definition for the degree of potential threats updated by temporal influences without external intervention.

**Definition 5** *Consider the condition that the temporal influences without external intervention, let $\nu_c(x)$ be the degree of potential threat with respect to criterion $c$ for subject $x$ generated at point of time $t_o$ (here $t_o$ is the latest time point for the $occTs$ of all related events to generate $\nu_c(x)$), $t$ be the current time, $n$ ($n > 0$) be the time interval between two key time points for updating, $\gamma$ be the degree of influence rate that $\gamma \in (0, +\infty)$, and $e \in (0, 1)$ be the threshold to distinguish different types of evidence, then the degrees of potential threats w.r.t. criterion $c$ for subject $x$ for temporal influence, denote as $a_c(x)$ is*

$$a_c(x) = h^{-1}(\nu_c(x)^{\gamma^{\lfloor \frac{t-t_0}{n} \rfloor}}) \tag{11}$$

*where*

$$\begin{cases} h(x) = \frac{1}{e}x & \textit{if } \gamma < 1, \textit{ negative evidence will not become positive,} \\ & \quad \textit{and } \nu_c(x) < e; \\ h(x) = \frac{1}{1-e}(x - e) & \textit{if } \gamma > 1, \textit{ positive evidence will not become negative,} \\ & \quad \textit{and } \nu_c(x) > e \ ; \\ h(x) = x & \textit{otherwise.} \end{cases} \tag{12}$$

The first condition means that the updated degree of potential threat will not be greater than the threshold $e$ when evidence is negative, i.e., $a_c(x) \in [0, e]$ when $\nu_c(x) < e$. Hence, if $\gamma \geq 1$, it is clear that $a_c(x) \in [0, e]$ if $\nu_c(x) < e$. Similarly, the updated degree of potential threat will not be less than the threshold $e$ when $\nu_c(x) > e$, i.e., $a_c(x) \in [e, 1]$ when $\nu_c(x) > e$. This is the exact meaning of the function $h(x)$.

Moreover, when $\gamma \neq 1$, the value of $\gamma$ is determined by the real-time duration of observing a given criterion or the termination of observing the criterion. For example, consider the criterion of *person leaving an item*, after detecting a person abandoning an items, it can be set as that 15-minutes is the maximum time duration for taking a further action. Suppose the time interval between two key time points for updating evidence is 1 minute, the significant figure is 0.001, and the potential threat higher than 0.9 means a very dangerous situation that the security team has to take further action, then for any $\nu_{PL}(x) > e$, we should have $\nu_{PL}(x)^{\gamma^{15}} \geq 0.9$ by Definition 5. Hence, we can obtain that $\gamma = \sqrt[15]{\log_{e+0.001} 0.9}$. Similarly, consider the criterion of emotion, after detecting the person is angry, 10-minutes can be the maximum time period for angry emotion to disappear. As a result, suppose the time interval between two key time points for updating evidence is 1 minute, the significant figure is 0.001, and the potential threat lower than $e$+0.01 means the effect can be ignored, consider that such positive evidence will not become a negative one, by Definition 5, we have $(1 - e)(\nu_c(x)^{\gamma^{10}}) + e = e + 0.01$. Then, we have $\gamma = \sqrt[10]{\log_{0.999} \frac{0.01}{1-e}}$.

Now, we consider the second category of time influence: the temporal influence with new evidence occurs. For example, in the case of a person loitering near the ticket counter at 9:10 p.m., if there is new information in 9:10 p.m. to 9:30 p.m., which points out that the person had met a friend and left in the passed 20 minutes. Then, in this case, we should consider the effect of new evidence for the threat degree of this person. In fact, since the effect of new event is to update the belief for the possible outcomes related to a given criterion for a given subject. Hence, since the new evidence reveals the more recent situation for the subject, i.e., the new evidence is more reliable than the pervious one, it should be retained whilst the prior belief of the system should be changed.

As a result, first, we will use the Dempster combination rule (Equation (2)) to obtain the overall mass function for all new evidence of a given criterion. Then, we apply the Jeffrey-Dempster revision rule (Equation (3)) to update the mass function for the possible outcome of a given criterion. After considering all evidence that are related to the belief about the possible outcomes w.r.t a given criterion, we can apply the model in [8] to obtain the degree of potential threat with time influence in this condition directly. Finally, our weighted aggregation operator can be applied to obtain the overall degree of a potential threat for each subject.

## 6 Case Study

Let us consider a scenario in an airport, which covers the following two areas: Shopping Area (SA) and Control Center (CC).

- in the Shopping Area (SA), a person (id: 13) loiters near a Foreign Currency Exchange office (FCE) for a long time. Also, camera 42 catches its back image at the entrance of the shopping area at 9:01 pm and camera 45 catches its side face image at FCE from 9:03 pm to 9:15 pm;
- In airport terminal 1 a person (id: 21) leaved a bag and disappeared. That is, camera 49 captures its side face and that it brings a bag at 9:01 pm, camera 44 captures its back at 9:02 pm and camera 43 captures the bag on the ground without a person around from 9:03 pm to 9:15 pm.

Now, suppose the only one security team was at another area to prevent threat and returned at 9:30 pm. And during this time period, camera 45 captured the person (id:13) leaving the shopping area and walking towards east. Suppose there are no other emergency happening during this time interval, then what will the surveillance system suggest to do?

As the security team does not eliminate these two potential threats (id:13 and id:21) immediately, the surveillance system has to consider the new evidence and the temporal influence for the point valued degrees of potential threats for each criterion of these two subject at 9:30 pm. Moreover, with the event modeling in [8], for the person (id: 13) in FCEC, we have a piece of new evidence about the movement criterion: $e_5^m$=(FCEC, 9:03-9:15 p.m, 45, 0.9, 0.6, movement, 0.8, 13, FCEC, $m_2^m(\{toward\,east\}) = 1$). Thus, by the degree of reliability of sensor 42, $m_3^m(\{walk\,east\}) = 0.9$, $m_3^m(\{walk\,east, \ldots, run\,east, \ldots, stay,\, loiter\}) = 0.1$.

Hence, considering the temporal influence with new evidence occurs by Jeffrey-Dempster revision rule (Equation (3)), we have $m^m_{123}(\{walk\,east\})=0.9$, $m^m_{123}(\{walk\ east,\ loiter\})=0.0137$, $m^m_{123}(\{loiter\})=0.081$, $m^m_{123}(\{walk\,east, \ldots, run\,east, \ldots, stay,\ loiter\})=0.0053$. As a result, since the mass value $m^m_{123}(\{loiter\})=0.081$ and we suppose the condition of the only one inference rule about the movement is defined as $m^m_i(\{loiter\}) > 0.5 \wedge e.location = FCEC \wedge t_n - t_0 > 10\ min$, we will omit the criterion of movement for the reason that we cannot confirm the intention of the subject based on the already known evidence about behaviors.

Now, we consider the time influence for the criteria without external intervention for two potential threats (id:13 and id:21) by Definition 5. Clearly, the degrees of potential threats for the criteria of *age* and *gender* should not change with time ($\gamma = 1$) and the degrees of potential threats for the criteria of *PL (Intention of Person loitering)* and *PLI (Intention of Person Leaving an Item)* should increase with time. Moreover, for the criterion of *PL*, since there exists new evidence about it, we do not need to consider the temporal influence for the degree of potential threat with respect to the criterion of *PL*. Now, suppose the degree of influence rate for the criteria of *PLI* is ($\gamma = 0.8$). Then, by Definition 5 and $\nu_a(21) > e$ $(e = 0.5)$, we have $a_a(13) = \nu_a(13) = 0.56$, $a_g(13) = 0.547$; $a_a(21) = 0.565$, $a_g(21) = 0.582$, $a_{PLI}(21) = (0.672)^{0.8^{\lfloor \frac{9:30-9:15}{1} \rfloor}} = 0.986$.

Moreover, by the weighted aggregation operator, we have

$$R(g(0.3, \nu_a(13)), g(0.3, \nu_g(13))) = 0.518 * 0.514 = 0.532$$
$$R(g(0.3, \nu_a(21)), g(0.3, \nu_g(21)), g(0.8, \nu_{IPLI}(21))) = 0.906$$

Finally, by Definition 4, we have $id\,21 \succ id\,13$. So the surveillance system will suggest the security team to intervene $id\,21$. That is, to find out what is contained in the abandoned bag and arrest the person (id:21) if it is necessary.

## 7 Related Work and Summary

In the literature, there are plenty of event modeling and reasoning systems, such as Finite State Machines [3], Bayesian Networks [2], and event composition with imperfect information [5, 6], event modeling with decision support[8], etc. In general, these systems consider two branches to address the integration of heterogeneous information: most of them consider all information in a scenario as a whole, and with rules or fusion algorithms for each specific scenario. So, if we add a new criterion into a scenario, all of these systems must modify the knowledge base and other related aspects with the new criterion. Therefore, these systems are somehow not flexible and effective for dynamic surveillance environment with a huge volume of surveillance data from different sensors. Another line of research [8] applies aggregation process we suggested in this paper. However, the operator proposed in [8] does not satisfy all the basic principles for an adequate aggregation operator. Moreover, the aggregation process in surveillance systems have also been discussed in the literature. Albusac *et al.* in [1] analyzed different aggregation operators and proposed a new aggregation method based on the

Sugeno integral for multiple criteria in the domain of intelligent surveillance. Also, Rudas *et al.* in [9] offered a comprehensive study of information aggregation in intelligence systems from different application fields such as robotics, vision, knowledge based systems and data mining, etc. However, to the best of our knowledge, there is no research suggesting a set of basic principles to define an adequate operator for the aggregation process or considering the temporal influence in surveillance systems.

In this paper, we introduced the basic principles to handle the integration of heterogeneous threat evaluation in surveillance systems and proposed a weighted aggregation operator to instantiate such principle. We also discussed the temporal influence in the aggregation process. Our next step of work is to build up a general axiom framework for the aggregation process and test such framework with surveillance data.

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