An Extended Event Reasoning Framework for Decision Support under Uncertainty

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Abstract. To provide in-time reactions to a large volume of surveillance data, uncertainty-enabled event reasoning frameworks for CCTV and sensor based intelligent surveillance system have been integrated to model and infer events of interest. However, most of the existing works do not consider decision making under uncertainty which is important for surveillance operators. In this paper, we extend an event reasoning framework for decision support, which enables our framework to predict, rank and alarm threats from multiple heterogeneous sources.

1 Introduction

In recent years, intelligent surveillance systems have received significant attentions for public safety due to the increasing threat of terrorist attack, anti-social and criminal behaviors in the present world. In order to analyze a large volume of surveillance data, in the literature, there are a couple of event modeling and reasoning systems. For example, Finite State Machines [5], Bayesian Networks [3], and Event composition with imperfect information [10, 11], etc.

However, the decision support issue has not been properly addressed, especially on how to rank the potential threats of multiple suspects and then focus on some of the suspects for further appropriate actions (taking immediate actions or reenforced monitoring, etc.) based on imperfect and conflicting information from different sources. This problem is extremely important in the sense that in real-world situations, a security operator is likely to make decisions under a condition that the security resources are limited whilst several malicious behaviors happen simultaneously. Consider an airport scenario, a surveillance system detects that there is a very high chance that two young people are fighting in the shopping area, and at the same time, there are a medium chance that a person may leave a bomb in airport terminal 1. Now suppose there is only one security team available at that moment, which security problem should be first presented to the security team?

In order to address this problem, in this paper, we extend the event modeling framework [10, 11] with a decision support model for distributed intelligent surveillance systems, using a multi-criteria fusion architecture. More specifically, based on Dempster-Shafer (D-S) theory [14], we first improve the event modeling framework proposed in [10, 11] to handle the multi-criteria event modeling.

Then we use a normalized version of the Hurwicz's criterion [4] to obtain the degree of potential threat of each suspect (or suspects if they work as a team) with respect to each criterion. Finally, according to some background knowledge in surveillance, we apply a weighted aggregation operation to obtain the overall degree of potential threat for each suspect after considering all related criteria, from which we can set the priority for each subject.

This paper advances the state of the art on information analysis for intelligent surveillance systems in the following aspects. (i) We identify two factors that influence the potential threats in surveillance system: belief and utility. (ii) We propose an event modeling and reasoning framework to estimate the potential threats based on heterogeneous information from multiple sources. (iii) We introduce a weighted aggregation operator to combine the degrees of potential threats of each criterion and give an overall estimation to each subject.

The rest of this paper is organized as follows. Section 2 recaps D-S theory and the event modeling framework in [10, 11]. Section 3 extends the event modeling framework in [10, 11] to handle the multi-criteria issue. Section 4 develops a decision support model with an aggregation operator to handle the problem of judging the degrees of potential threats for multiple suspects. 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

This section recaps some basic concepts in D-S theory [14].

Definition 1 *Let Θ 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 $\sum_{A\subseteq\Theta} m(A)=1$.*

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 Θ. Then Dempster combination rule $m_{12} = m_1 \bigoplus m_2$ is given by:*

$$m_{12}(x) = \begin{cases} 0 & \text{if } x = \emptyset \\ \frac{\sum_{A_i \bigcap B_j = x} m_1(A_i) m_2(B_j)}{1 - \sum_{A_i \bigcap B_j = \emptyset} m_1(A_i) m_2(B_j)} & \text{if } x \neq \emptyset \end{cases} \quad (1)$$

In order to reflect the reliability of evidence, a *Discount rate* was introduced by which a mass function can be discounted [8]:

Definition 3 *Let m be a mass function over frame Θ and τ ($0 \leq \tau \leq 1$) be a discount rate, then the discounted mass function m^{τ} is defined as:*

$$m^{\tau}(A) = \begin{cases} (1-\tau)m(A) & \text{if } A \subset \Theta \\ \tau + (1-\tau)m(\Theta) & \text{if } A = \Theta \end{cases} \quad (2)$$

Finally, in order to reflect the belief distributions from preconditions to the conclusion in an inference rule, in [9], a modeling and propagation approach was proposed based on the notion of *evidential mapping* Γ^*.

Definition 4 $\Gamma^* : 2^{\Theta_E} \to 2^{2^{\Theta_H} \times [0,1]}$ *is an evidential mapping, which establishes relationships between two frames of discernment* Θ_E, Θ_H, *if* Γ^* *assigns a subset* $E_i \subseteq \Theta_E$ *to a set of subset-mass pairs in the following way:*

$$\Gamma^*(E_i) = ((H_{i1},\ f(E_i \to H_{i1})),\ \ldots,\ (H_{it},\ f(E_i \to H_{it}))) \tag{3}$$

where $H_{ij} \subseteq \Theta_H$, $i = 1,\ \ldots,\ n$, $j = 1,\ \ldots,\ t$, *and* $f : 2^{\Theta_E} \times 2^{\Theta_H} \to [0,\ 1]$ *satisfying: (i)* $H_{ij} \neq \emptyset$, $j = 1,\ \ldots,\ t$; *(ii)* $f(E_i \to H_{ij}) \geq 0$, $j = 1,\ \ldots,\ t$; *(iii)* $\sum_{j=1}^{t} f(E_i \to H_{ij}) = 1$; *(iv)* $\Gamma^*(\Theta_E) = ((\Theta_H, 1))$.

So a piece of evidence on Θ_E can be propagated to Θ_H through evidential mapping Γ^* as follows:

$$m_{\Theta_H}(H_j) = \sum_i m_{\Theta_E}(E_i) f(E_i \to H_{ij}). \tag{4}$$

3 Multiple Criteria Event Modeling Framework

In this section, we extend the event reasoning framework introduced in [10] to include multi-criteria, in order to allow for better decision making.

Definition 5 *In a multi-criteria event modeling framework, an elementary event e for detecting the potential threats is a tuple* $(EType,\ occT,\ ID_s,\ rb,\ sig,\ Criterion,\ Weight,\ ID_p,\ s_1\ ,\ldots,\ s_n)$, *where: (i)* $EType$*: describes the event type; (ii)* $occT$*: a time point (or duration) for the observed event; (iii)* ID_s*: the source ID for a detected event; (iv)* rb*: the degree of reliability of a source; (v)* sig*: the degree of significance of a given event based on domain knowledge; (vi)* $Criterion$*: describes one of the attributes that can reveal some level of potential threat for a target, such as age, gender, and so on;*[1] *(vii)* $Weight$*: the degree of a criterion's importance for detecting a potential threat; (viii)* ID_p*: person ID for a detected event; (ix)* s_i*: additional attributes required to define event* e.

We can associate an event with a mass value and a utility function for a given criterion. For example: $\mathsf{e}_{42}^{\mathsf{g},1}$=($\mathsf{FCE}$, $\mathsf{9{:}01pm - 9{:}05pm}$, 42, 0.9, 0.6, gender, 0.2, 13, $\mathsf{m}_{42}^{\mathsf{g},1}(\{\mathsf{male}\})=0.3$, $\mathsf{U^g}$) means that for an event type FCE at 9:01pm to 9:05pm, the *gender* classification program used by camera 42, whose degree of reliability is 0.9, detects that at Foreign Currency Exchange office (FCE), person with $ID = 13$ is recognized as *male* with a certainty of 30%. The significance of this event is 0.6, the weight of *gender* criterion for detecting a potential threat is

[1] We will use the word "criterion" in this paper to define an attribute that can reveal some level of potential threat of an observed subject. Therefore, we can distinguish "criterion" from other attributes, such as person ID, location, etc.

0.2, and U^g is the utility function that shows the level of potential threat for the *gender* criterion. Related events are grouped together to form *event clusters* where events in the same cluster share the same *event type, occT, Criterion,* ID_s, ID_p, but may assign different mass values to subsets of the same frame. For example, two events for the person with ID 13 that detects by camera 42 at 9:01pm to 9:05pm at FCE with the mass function $m_{42}^{g,1}(\{male\}) = 0.3$ and $m_{42}^{g,2}(\{female,\ male\}) = 0.7$ respectively are both in the same cluster. Moreover, the mass values within each cluster come from the same mass function.

Compared with the model in [10], we retain the components $EType$, sID and *rb*, whilst the differences are: (i) We represent events with a time duration, which is more realistic in real-life applications. (ii) We keep the person ID as a common attribute, since it is important for surveillance applications. (iii) The degree of significance in our definition indicates the relative importance of a given event based on the background information. For example, an event detected in an area with high crime statistics at midnight is more significant than that in an area of low-crime in the morning. (iv) In our model, an elementary event can only have one criterion attribute. For example, a *man* boards a bus at 8:00am is an elementary event, but a *young man* boards a bus at 8:00am is not an elementary event since both age (yonng) and gender (man) are criterion attributes. In fact, since a classification algorithm only focuses on one criterion attribute, this semantics of *elementary* is natural. (v) We introduce the attribute $Weight$ to reflect the importance of a criterion when determining a potential threat. For example, *age* and *gender* usually are not the critical evidence to detect the potential threat, while *behaviors*, such as holding a knife, fighting, etc., are more important in determining the dangerous level of a subject. (iv) We introduce the Utility function to distinguish different levels of threat for the outcomes of each criterion. For example, the threat level of a young person should be higher than the threat level of an old person.

There might be a set of event clusters that have the same criterion and event type but with different source IDs or observation times. For example, a person broads a bus with its back facing camera 4 at 9:15pm and then sits down with its face partially detected by camera 6 at 9:20pm. Suppose the gender classification algorithm shows that $m_4^{g,1}(\{male\}) = 0.5$ and $m_4^{g,2}(\{female,\ male\}) = 0.5$ by camera 4 and $m_6^{g,1}(\{male\}) = 0.7$ and $m_6^{g,2}(\{female,\ male\}) = 0.3$ by camera 6. Since these two classification results (in two clusters) refer to the same criterion about the same subject from different sources, mass functions (after possible discounting) defined in the two clusters are combined using Dempster's rule. When an event is described with a duration, then this event can be instantiated at any time point within this duration, That is, we can replace the duration with any time point within the duration. This is particularly useful when combining mass functions from different clusters, since events in these clusters may not share exactly the same time points or durations, but as long as their durations overlap, they can be combined. This is an improvement over [10], which cannot handle such situation. Finally, a combined mass function must assign mass values to events in a derived event cluster. In this cluster, every derived event shares the same $EType$, sig, $Criterion$, $Weight$, ID_p, $location$, U_c as the original events, but $occT$, ID_s, and rb are the union of those of the original events, respectively.

Now, we consider the event inference in our framework. Different definitions of rules in [10], an inference rule in our framework is defined as a tuple ($EType$, $Condition, m^{IET}, U^{IET}$), where: (i) m^{IET} in our method is the mass function for the possible intention of a subject. It means that after detecting the target's behavior, which satisfies the inference rule, the prediction for the target's intention based on the historic data or experts judgement. For example, m^{IET} for the event inference rule about loitering in a ticker counter would be over a frame of discernment $\{Rob,\ Wait\ For\ Some\ Friends\}$. (ii) We only consider the behavior of the subjects to infer their intentions. Here, we divide behavior into different categories, such as movements (obtained by trajectory tracking), relations with objects, relations with peoples (obtained by the binary spatial relations of objects or people [12]), hand actions to detect a fight (obtained by 2D locations of the hands), etc.

The reasons of these changes are: (i) It is not reasonable to ask experts to directly assign the degree of a potential threat without any aggregation method about the factors that contribute to the threat, such as the significance of an event, the weight of different attributes, the values of each criterion, etc.. Thus, defining m_{IET} over the frame of discernment about the possible intention of a subject is more reasonable than the frame of discernment about the potential threat: $\{Theart,\ Not\ Theart\}$. (ii) It can reduce the amount of inference rules since we only consider the behavior of the subjects to infer their intentions. (iii) It satisfies the result of many social psychology studies that humans can infer the intentions of others through observations of their behaviors [6].

Finally, since events appeared in the condition of inference rules are themselves uncertain, we also apply the notion *evidential mapping* to obtain the mass functions of inferred events as [11]. Here is an example for the event inference rule in our model about the intention of a subject in the shopping area.

Example 1 *The rule describing that a person loitering in the Foreign Currency Exchange office (FCE) could be suspicious can be defined as* ($EType$, $Conditions, m^{IPL}, U^{IPL}$) *where* $EType$ *is the Intention of Person loitering in FCE; Conditions is* $m_i^m(\{loitering\}) > 0.5$ AND $e.location = FCE$ AND $t_n - t_0 > 10\ min$*;* m^{IPL} *can be* $m^{IPL}(\{Rob\}) = 0.5$, $m^{IPL}(\{Waiting\ Friends\}) = 0.3$, $m^{IPL}(\{Rob,\ Waiting\ Friends\}) = 0.2$*; and* U^{IPL} *can be* $U^{IPL} = \{u(Rob) = 9,\ u(Waiting\ Friends) = 3\}$.

4 A Multi-Criteria System for Threat Ranking

In this section, we will construct a decision support system that can automatically rank the potential threat degree of different subjects in a multiple criteria surveillance environment under uncertainty.

First, calculate the degrees of potential threat for each criterion by extending the approach in [15]:

Definition 6 *For a subject with ID x w.r.t. a given criterion c specified by mass function $m_{c,x}$ over $\Theta = \{h_1, ..., h_n\}$, where h_i is a positive value indicating the utility (level of potential threat) of each possible outcome for criterion c, its expected utility interval (interval degree of potential threat) is $EUI_c(x) = [\underline{E}_c(x), \overline{E}_c(x)]$, where*

$$\underline{E}_c(x) = \sum_{A \subseteq \Theta} m_{x,c}(A) \min\{h_i \mid h_i \in A\}, \overline{E}_c(x) = \sum_{A \subseteq \Theta} m_{x,c}(A) \max\{h_i \mid h_i \in A\}.$$

Second, apply the transformational form of the Hurwicz's criterion [4], to find the point-valued degree of potential threat w.r.t. each criterion:

Definition 7 *Let $EUI_c(x) = [\underline{E}_c(x), \overline{E}_c(x)]$ be an interval-valued expected level of potential threat of criterion c for subject with ID x, $\delta_c(x) = sig$ be the degree of significance for the events, then the point-valued degree of potential threat for subject with ID x w.r.t. criterion c is given by:*

$$\nu_c(x) = (1 - \delta_c(x))\underline{E}_c(x) + \delta_c(x)\overline{E}_c(x). \tag{5}$$

Finally, combine the potential threats w.r.t. each criterion by the following aggregation operator and then obtain the overall degree of potential threat of each subject.

Definition 8 *Let C be the whole set of related criteria, $nu_c(x)$ be the point-valued degree of potential threat for subject with ID x w.r.t. criterion c, w_c be the weight of each criterion c, and k be the highest utility value for the outcomes of all criteria, then the overall degree of potential threat for subject x, denoted as O_x, is given by*

$$O_x = \frac{2\sum_{c \subseteq C} w_c nu_c(x)}{\sum_{c \subseteq C}(k+1)w_c} \tag{6}$$

In fact, Equation (6) is a form of weighting average, where $\sum_{c \subseteq C} w_c nu_c(x)$ is the overall value that considers the weighting effect of each criterion for the overall evaluation of potential threat, $\sum_{c \subseteq C}(k+1)w_c/2$ is the averaging operator designed to avoid the situation that the more criteria the surveillance system detects, the higher value the potential threat is, and $(k+1)/2$ can be consider as an intermediate value to distinguish low threat levels from high threat levels.

Now, we reveal some properties of our model by the following Theorems:

Theorem 1 *Let $EUI_c(x) = [\underline{E}_c(x), \overline{E}_c(x)]$ be an interval-valued expected utility of criterion c for subject x, $\delta_c(x)$ and $\delta'_c(x)$ be the degrees of significance for two different surveillance scenarios, and $\delta_c(x) \geq \delta'_c(x)$, then $\nu_c(x) \geq \nu'_c(x)$*

Proof. By Equation (5), $\delta_c(x) \geq \delta'_c(x)$ and $\overline{E} \geq \underline{E}$, we have:

$$\nu_c(x) - \nu'_c(x) = (\delta_c(x) - \delta'_c(x))(\overline{E}_c(x) - \underline{E}_c(x)) > 0 \qquad \square$$

From Theorem 1 with $\delta_c(x)$ representing *significance*, we can see that the point-valued degree of potential threats w.r.t. each criterion for the subjects would be higher if the set of events happen in an area with high crime statistics than that if the set of events happen in a lower crime area.

Theorem 2 *Let $EUI_c(i) = [\underline{E}_c(i), \overline{E}_c(i)]$ be an interval-valued expected level of potential threat of the criterion c for subject with ID i ($i \in \{x, y\}$), and $\delta_c(i)$ be the degrees of significance for the event of subject with ID i, then the point-valued degree of potential threat for these two subjects satisfies:*
(i) if $\underline{E}_c(x) > \overline{E}_c(y)$, then $\nu_c(x) > \nu_c(y)$;
(ii) if $\underline{E}_c(x) > \underline{E}_c(y)$, $\overline{E}_c(x) > \overline{E}_c(y)$, and $\delta_c(x) \geq \delta_c(y)$, then $\nu_c(x) > \nu_c(y)$.

Proof. (i) By $\delta_c(k) \in [0, 1]$ ($k \in \{x, y\}$) and Definition 7, we have $\underline{E}_c(k) \leq \nu_c(k) \leq \overline{E}_c(k)$. As a result, by $\underline{E}_c(x) > \overline{E}_c(y)$, we have

$$\nu_c(x) - \nu_c(y) \geq \underline{E}_c(k) - \nu_c(y) \geq \underline{E}_c(k) - \overline{E}_c(y) > 0.$$

So, item (i) holds.

(ii) When $\underline{E}_c(x) > \underline{E}_c(y)$, $\overline{E}_c(x) > \overline{E}_c(y)$, and $0 \leq \delta_c(y) \leq \delta_c(x) \leq 1$, we have

$$\begin{aligned}\nu_c(x) - \nu_c(y) &\geq (\underline{E}_c(x) - \underline{E}_c(y)) + \delta_c(x)(\overline{E}_c(x) - \underline{E}_c(x)) - \delta_c(x)(\overline{E}_c(y) - \underline{E}_c(y)) \\ &= (1 - \delta_c(x))(\underline{E}_c(x) - \underline{E}_c(y)) + \delta_c(x)(\overline{E}_c(x) - (\overline{E}_c(y)) \\ &> 0\end{aligned}$$

So, item (ii) holds. □

In fact, Theorem 2 states two intuitions when considering the point-valued degree of potential threat of any two suspects: (i) for a given criterion, if the lowest expected level of potential threat for a suspect is higher than the highest expected level of potential threat of another suspect, the point-valued degree of potential threat of the first one should be higher; and (ii) if the degree of significance for the events of a suspect is not less than that of another, and the lowest and highest expected levels of potential threat of this suspect are higher than those of another respectively, the point-valued degree of potential threat of the first one should be higher.

Theorem 3 *Let O_x and O_y be the overall degrees of potential threat for subject x and y, $C' = C \cup s$ and $C'' = C \cup r$ be the whole sets of related criteria for subjects x and y, k be the highest utility value for the outcomes of all criteria, and for any criterion $c \in C$, we have $nu_c(x) = nu_c(y)$. Suppose $\nu_s(x) > \nu_r(y)$ and $w_s = w_r$, then $O_x > O_y$.*

Proof. By Definition 8, $nu_c(x) = nu_c(y)$, $\nu_s(x) > \nu_r(y)$, and $w_s = w_r$ we have:

$$\begin{aligned}O_x - O_y &= \frac{2(w_s nu_s(x) + \sum_{c \subseteq C} w_c nu_c(x))}{(k+1)(w_s + \sum_{c \subseteq C} w_c)} - \frac{2(w_r nu_r(y) + \sum_{c \subseteq C} w_c nu_c(x))}{(k+1)(w_r + \sum_{c \subseteq C} w_c)} \\ &= \frac{2w_s(nu_s(x) - \nu_r(y))}{(k+1)(w_s + \sum_{c \subseteq C} w_c)} \\ &> 0\end{aligned}$$

Actually, Theorem 3 means that the increase of the point-valued degree of potential threat about a given criterion for a subject will cause the increase of the overall degree of potential threat for this subject, *ceteris paribus*.

Table 1. Event modeling for the airport security surveillance scenario

event	Etype	occT	ID_s	rb	sig	Criterion	Weight	ID_p	Location	mass value	utility
$e_{42}^{a,1}$	SA	9:01pm	42	0.9	0.7	age	0.3	13	FCE	$\{young\}, 0.3$	U^a
$e_{42}^{a,2}$	SA	9:01pm	42	0.9	0.7	age	0.3	13	FCE	$\{young, old\}, 0.7$	U^a
$e_{45}^{a,1}$	SA	9:03-9:15pm	45	0.9	0.7	age	0.3	13	FCE	$\{young\}, 0.6$	U^a
$e_{45}^{a,2}$	SA	9:03-9:15pm	45	0.9	0.7	age	0.3	13	FCE	$\{young, old\}, 0.4$	U^a
$e_{42}^{g,1}$	SA	9:01pm	42	0.9	0.7	gender	0.3	13	FCE	$\{female\}, 0.4$	U^g
$e_{42}^{g,2}$	SA	9:01pm	42	0.9	0.7	gender	0.3	13	FCE	$\{female, male\}, 0.6$	U^g
$e_{45}^{g,1}$	SA	9:03-9:15pm	45	0.9	0.7	gender	0.3	13	FCE	$\{male\}, 0.7$	U^g
$e_{45}^{g,2}$	SA	9:03-9:15pm	45	0.9	0.7	gender	0.3	13	FCE	$\{female, male\}, 0.3$	U^g
$e_{42}^{m,1}$	SA	9:01pm	42	0.9	0.7	move	0.8	13	FCE	$\{to\,east, loitering\}, 0.8$	
$e_{42}^{m,2}$	SA	9:01pm	42	0.9	0.7	move	0.8	13	FCE	$\Theta_m, 0.2$	
$e_{45}^{m,1}$	SA	9:03-9:15pm	45	0.9	0.7	move	0.8	13	FCE	$\{loiter\}, 0.9$	
$e_{45}^{m,2}$	SA	9:03-9:15pm	45	0.9	0.7	move	0.8	13	FCE	$\Theta_m, 0.1$	
$e_{29}^{a,1}$	CC	9:03pm	29	1	0.9	age	0.3	19	MoC	$\{young\}, 0.7$	U^a
$e_{29}^{a,2}$	CC	9:03pm	29	1	0.9	age	0.3	19	MoC	$\{young, old\}, 0.3$	U^a
$e_{29}^{g,1}$	CC	9:03pm	29	1	0.9	age	0.3	19	MoC	$\{male\}, 0.7$	U^g
$e_{29}^{g,2}$	CC	9:03pm	29	1	0.9	age	0.3	19	MoC	$\{male, female\}, 0.3$	U^g
$e_{29}^{sr,1}$	CC	9:03pm	29	1	0.9	sr	0.8	19	MoC	$\{unmatch\}, 0.8$	U^{sr}
$e_{29}^{sr,2}$	CC	9:03pm	29	1	0.9	sr	0.8	19	MoC	$\{unmatch, match\}, 0.2$	U^{sr}

Where $\Theta_m = \{to\,east, \ldots, to\,north, stay, loitering\}$; $U^a : \{u^a(young)=6,\ u^a(old)=2\}$; $U^g : \{u^g(male)=6,\ u^g(female)=4\}$; $U^{sr} = \{u^{sr}(notmatch) = 8, u^{sr}(match) = 4\}$; and the scale of measurement for the level of potential threat is $H = \{1, \ldots, 9\}$.

5 Case Study

Let us consider a scenario in an airport between at 9:00pm to 9:15pm, 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 9:01pm and camera 45 catches its side face image at FCE from 9:03pm to 9:15pm;
- in the Control Center (CC), the face of a person (id: 19) appears in the camera 29 in the middle of the corridor (MoC) to the control center at 9:03pm. However, the person's face does not appear in camera 23 monitoring the entrance to the corridor.

We assume that video classification algorithms can detect age, gender, behavior, and then re-acquire subjects (sr) when needed. We also assume that there is only one security team available. What should the system do at this moment?

First, the surveillance system detects the elementary events for each person as shown in Table 1 based on the information of multiple sensors.

For example, the first row in Table 2 means that for an event type SA in FCE at 9:01pm, the *age* classification program used by camera 42, whose degree of reliability is 0.9, detects a person with $ID = 13$ as *male* with a certainty of 30%. The significance of this event is 0.6, the weight of *age* criterion for detecting a potential threat is 0.3, and U^a is the utility function that shows the level of potential threat for the *age* criterion. Moreover, some events in the table are within the same event cluster, such as $e_{42}^{a,1}$ and $e_{42}^{a,2}$ which share the same *event type, occT, Criterion, ID_s, ID_p*, but assign different mass values to different subsets of the same frame and the sum of these mass values is 1.

Second, since some sensors are not completely reliable in our example, we obtain the discounted mass functions by Definition 2. For example, consider the *age* criterion for the person in FCE, we have :

$m^{a,1}_{42}(\{young\}) = 0.3 \times 0.9 = 0.27, m^{a,2}_{42}(\{young, old\}) = 0.1 + 0.7 \times 0.9 = 0.73;$
$m^{a,1}_{45}(\{young\}) = 0.54, m^{a,2}_{45}(\{young, old\}) = 0.46.$

Third, we consider the combination of mass functions associated with events in different clusters (from different sources) where these events are all about a common criterion, using Dempster's rule in Definition 1. For example, consider the *age* criterion for the person in FCE, we have:

$$m^{a,1}_{42\&45}(\{young\}) = (0.27 \times 0.54 + 0.27 \times 0.46 + 0.73 \times 0.54)/1 = 0.664,$$
$$m^{a,2}_{42\&45}(\{young, old\}) = (0.73 \times 0.46)/1 = 0.336.$$

Note that each mass value is associated with a derived event, such as, for the person in FCE, $m^{a,1}_{42\&45}(\{young\}) = 0.664$ is associated with $\mathsf{e}^{a,1}_{42\&45}$=(SA, 9:01 − 9:15 pm, 42&45, 0.9, 0.7, age, 0.3, 13, FCE, $\mathsf{m}^{a,1}_{42\&45}$({young})=0.664, U^{a}).

Forth, we consider event inference. For the person in FCE, by the inference rule in Example 1, $m^{m,1}_{42\&45}(\{to\ east, lotering\}) = 0.137$, $m^{m,2}_{42\&45}(\{lotering\}) = 0.81$, $m^{m,3}_{42\&45}(\Theta_m) = 0.053$, and Equation (4), we have $m^{IPL}(\{Rob\}) = 0.41$, $m^{IPL}(\{Waiting\ Friends\}) = 0.24$, $m^{IPL}(\{Rob,\ Waiting\ Friends\}) = 0.35$.

Fifth, we obtain the expected utility interval for each criterion of each person by Definition 6. For example, for the person (id:13) in FCE, we have

$\underline{E}_{13,a} = 4.656, \overline{E}_{13,a} = 6;$ $\underline{E}_{13,g} = 5.044$, $\overline{E}_{13,g} = 5.656$; $\underline{E}_{13,IPL} = 5.43$, $\overline{E}_{13,IPL} = 7.542$.

Sixth, we obtain the point-valued degree of potential threat for each criterion of each person by Definition 7. For example, for the person (id:13) in FCE:

$\nu_a(13) = (1 - 0.7) \times 4.656 + 0.7 \times 6 = 5.6$; $\nu_g(13) = 5.47$; $\nu_{IPL}(13) = 6.91$.

Seventh, we get the overall degree of potential threat of each target after considering all relative criteria at 9:15pm by Definition 8:

$$O_{13} = \frac{2(0.3 \times 5.6 + 0.3 \times 5.47 + 0.8 \times 6.91)}{(9+1)(0.3 + 0.3 + 0.8)} = 1.26;\ O_{19} = 1.41.$$

Hence, in this example, we derive that $id\,19 \succ id\,13$. Thus, If we have only one security team available at that moment, the surveillance system will suggest to prevent the further action of the person (id: 19) in the control center first.

6 Related Work and Summary

Ahmed and Shirmohammadi in [1] designed a probabilistic decision support engine to prioritizes multiple events in different cameras. In this model, they incorporated the feedbacks of operators, event correlation and decision modulation to rank the importance of events. Jousselme *et al.* [7] presented the concept of a decision support tool together with the underlying multi-objective optimization algorithm for a ground air traffic control application. However, none of these models provides a method to handle multiple criteria information under uncertainty as our model does. Moreover, the problem of information fusion has become a key challenge in the realm of intelligent systems. A common method to handle this challenge is to introduce aggregation operators. Albusac *et al.* in [2] 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 [13] 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 considering the decision making problem under uncertainty in surveillance systems.

In this paper, we introduced our extended event reasoning framework, integrating a multi-criteria decision making element in sensor network based surveillance systems. We also discussed some properties of our framework. Our next step of work is to experiment the decision making element with surveillance data.

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