obtain the overall mass function of attacker's types by combining all elements in $\{m_{c,t}(x)\}$ with Dempster's combine rule [5].

$$m_{c,t}(x)=\sum_{v_c^i\in\Omega_c V}\sum_{\bigcap v_c^i\neq\emptyset}\frac{u(v_c^i)}{\sum\{u(v_c^j)\mid v_c^j\in V\}}m_c(V)m_{v_c^i,t}(x). \quad (1)$$

where m_c is a mass function over frame Ω_c, $m_{v_c^i,t}$ is a mass functions over Θ about an attacker's types for the states v_c^i of the criterion c, $u(v_c^i)$ is the utility value for the state v_c^i, and V is any subset of Ω_c.

3. THREAT INTERVENTION GAME

Since Different types of attackers might have different preferences over the choices of their next move, we can construct a game-theoretic model for the ambiguous threat intervention problem. Moreover, since such a game model is different from the static Bayesian game, or the Stackelberg's game, in which players' types are determined by a probability distribution, while in our problem, due to ambiguous information, players' types are determined by the mass function. We propose a new solution concept for the threat intervention game.

First, we will predict attacker's strategies by *the principle of acceptable costs of minimax regret*, which suggests that the decision maker will consider not only the maximin regret but also the minimum utility he can obtain in decision making. Formally, we have:

DEFINITION 1. *Let $S_2=\{s_2^1,\ldots,s_2^m\}$ be a set of an attacker's mixed strategies, $\sigma_{2,t}\in[0,1]$ be the threshold of acceptable costs that an attacker of type t can bear and $a_t\in A_1$ is the pure strategy of a defender. Then the optimal strategy for attacker type t, denoted as $s_{2,t}^*$ ($s_{2,t}^*\in S_2$), is given by:*

$$s_{2,t}^*=\arg\min\{\overline{r}(s_2^i)\mid\overline{r}(s_2^i)=\max_{a_h}\{\max_{j\neq i}u_{2,t}(a_h,s_2^j)-u_{2,t}(a_h,s_2^i)\}\}, \quad (2)$$

where

$$\min_{a_s}u_{2,t}(a_s,s_2^i)\geq\max_{s_2^k}\min_{a_r}u_{2,t}(a_r,s_2^k)-\sigma_{2,t}\varsigma_{a,t}, \quad (3)$$

$$\varsigma_{a,t}=\max_{s_2^k}\min_{a_r}u_{2,t}(a_r,s_2^k)-\min_{s_2^l}\min_{a_w}u_{2,t}(a_w,s_2^l). \quad (4)$$

In the above definition, the higher $\sigma_{2,t}$ is, the higher potential loss for the minimum utility a type of attacker can accept. Moreover, $\varsigma_{a,t}$ means the maximum costs that a type t attacker might pay in a threat intervention game. Thus, $\sigma_{2,t}\varsigma_{a,t}$ means the highest costs that a type t attacker is willing to pay given his type. Finally, in real-world applications, $\sigma_{2,t}$ for each type of attacker can be obtained by historical data and the judgement of criminology expects.

After that, the security team's optimal strategy for threat intervention can be obtained as follow:

DEFINITION 2. *Let $S_1=\{s_1^1,\ldots,s_1^n\}$ be a set of defender's mixed strategies, Θ be the set of types of an attacker, $\sigma_1\in[0,1]$ be the threshold of acceptable costs that a defender can bear, $EUI(s_1^i)=[\underline{E}(s_1^i),\overline{E}(s_1^i)]$ be an expected utility interval [6], $\delta(s_1^i)$ be the normalized nonspecificity degree [3], and $b_{l,t}^*\in A_{2,t}^*\subseteq A_2$ be a pure strategy for which the optimal mixed strategy $s_{2,t}^*$ assigns a positive probability. Then a defender's optimal strategy, denoted as s_1^*, is given by:*

$$s_1^*=\arg\min\{\overline{r}(s_1^i)\mid\overline{r}(s_1^i)=\max_{j\neq i}\varepsilon(s_1^j)-\underline{E}(s_1^i)\}, \quad (5)$$

where

$$\min_{s\in\Theta}\min_{b_{2,t}^*}u_{1,t}(s_1,b_{2,t}^*)\geq\max_{s_1^k}\min_{r\in\Theta}\min_{b_{2,r}^*}u_{1,t}(s_1^k,b_{2,r}^*)-\sigma_1\varsigma_d, \quad (6)$$

$$\varsigma_d=\max_{s_1^k}\min_{r\in\Theta}\min_{b_{2,r}^*}u_{1,t}(s_1^k,b_{2,r}^*)-\min_{s_1^l}\min_{u\in\Theta}\min_{b_{2,u}^*}u_{1,t}(s_1^l,b_{2,u}^*), \quad (7)$$

$$\varepsilon(s_1^j)=\underline{E}(s_1^j)+(1-\delta(s_1^j))(\overline{E}(s_1^j)-\underline{E}(s_1^j)). \quad (8)$$

Actually, Eq. (5) means that given the expected utility intervals of all defender's strategies, he will elicit the maximum regret of a given mixed strategy by a (counterfactual) comparison between the lower expected utility of a reality choice, and the maximum upper expected utility of a foregone rejected alternative that might have been. And because only one pure strategy of an attacker's optimal mixed strategy will actually be taken, Eqs. (6) and (7) mean a defender will consider the potential reduction of maximum minimum utility given such a pure strategy of an attacker. Hence, $\varepsilon(s_1^j)$ is an ambiguity aversion upper expected utility for a defender. From Eq. (8), nonspecificity degree $\delta(s_1^j)$ actually works as a discount factor: the higher the degree, the more the upper utility of a choice is discounted. In fact, Eq. (8) is based on the consideration of ambiguity aversion that describes an attitude of preference for known risks over unknown risks, when the decision maker faces an ambiguous decision problem [2].

In fact, by Definition 2, a security manager can tune the value of σ_1 to reflect different (real-time) situations at different security area. Thus, our method is more flexible in balancing returns and risks, where returns is interpreted as the expected payoff of successfully preventing an attack, while risks mean the possibility of unaffordable losses and the severity of loss that are caused by the failure of intervention.

4. CONCLUSION

This paper addresses the threat detection and intervention problem in intelligence surveillance. First, we introduced an attacker's type analysis method according to information obtained by a surveillance system. Then, we developed a game-theoretic model for the ambiguous threat intervention problem and proposed a principle of acceptable costs of minimax regret to predict the strategy of an attacker and accordingly determine the optimal strategy for a defender. Based on our method, we can address both the problem of predicting attackers' intentions and the problem of allocating security resources in intelligence surveillance.

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