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Attribute information evaluation in C&C systems

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Abstract: *This chapter describes what particular pieces of information about a source should be taken into account in order to get a reasonable assessment of an attribute information retrieved based on the sensor data or human originated information. It has been proven that actual sensor weights and hypotheses masses do not change randomly, but they vary in time according to tracked target motion, however not directly to the target position. It is postulated that the knowledge about target position only is insufficient and at least two dynamical coordinates target state vectors are required to reflect the target orientation, which has an influence on actual hypotheses assessment formed, on the basis of the sensor data or visual sightings.*

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11.1 Introduction

Maritime Command and Control (C&C) systems, like other information systems need fusion techniques to deal with evidence (of both kinds: kinematic and attribute) gathered from miscellaneous sensors. When the evidence is imprecise and conflicting, DSmT fusion seems to be an excellent choice. However, DSmT requires basic belief assignment defined to perform the conditioning and combining algorithms [7, 8]. Thus the problem arises, namely how to evaluate the information gathered from diverse sources (including human being), to get a reasonable starting point for the DSmT engine?

The research goal is to invent an attribute information evaluation method for C&C systems purposes to reasonably assess the information from diverse sources. The method must deal with specific sensor characteristics, target motion and provide the results usable for DSmT fusion engine, as well.

Thus, the research problem may be decomposed into two problems:

- Finding a method of evaluating the evidence related to target attributes from diverse types of sources;

- Converting the obtained quality of information into a basic belief assignment.

11.2 Assessing information

Assessing the information source is the first step to be taken in the whole information evaluation process. Usually this kind of evaluation includes source characteristics, like detection and classification zones, reliability parameters and other factors like terrain features, for example.

The analysis of marine C&C systems' needs proves that the evaluation of the information source (even regularly updated) is not enough to perform information fusion on the satisfactory level.

Most of applied soft-decision fusion methods (including DSmT) utilize current state of knowledge related to each possible hypothesis. The hypotheses may be assessed in terms of statistics, how observations differ from the expected values, related to subsequent hypotheses.

11.2.1 Evaluation factors

In order to standardize evaluation terminology it is suggested to accept the following distinction of all the elements of the evaluation process, so called evaluation factors:

- Source related:
  - Time invariant factors:

        - ∗ The number of sources;
        - ∗ Source reliability;
        - ∗ Terrain features (not discussed in this chapter);
    - Time variant factors:
        - ∗ Quality measure, regarding source characteristics;
        - ∗ Quality measure, regarding target motion parameters;

- Hypotheses related:
    - Time invariant factors:
        - ∗ The total number of hypotheses;
    - Time variant factors:
        - ∗ Hypotheses instantaneous quality value.

11.2.2 Not only distance matters

Many methods rely on the target position when defining source time dependent quality parameter [3, 6]. It is quite natural that the distance between the target and the sensor influences the sensor performance. Some of successfully applied information evaluation algorithms [1, 2] assume that the closer the target, the more precise the measurement. This may be correct for specific types of sources however in general there are situations when applying this rule may bring paradoxical results.

Figure 11.1 shows that the classification of a target via visual sightings or a video camera may be imprecise when the target's heading is closely aligned to its bearing from the sensor (or the source) because fewer of its features may be extracted. As such, it may be easily confused with other vessels. However, when the target's heading and bearing from the sensor substantially differ, then more of the structure of the vessel is typically revealed making its classification simpler, even if it lies at a great distance from the sensor.

According to the authors' knowledge and opinion, information evaluation algorithms should be aware of such problems. This may be done if the evaluation process takes two independent steps:

- utilize the information about source classification zones, usually not identical with detection zones;
- utilize the information about the target course (if possible) or retrieve the aspect angle information taking target state vector consisting of two (at least) dynamical coordinates: position and velocity.

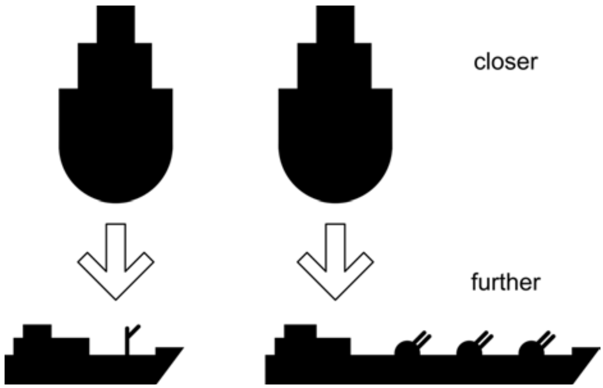

Figure 11.1: Classification problem: not always the distance metric is the best.

That certainly requires state estimation. For the purpose of marine C&C systems that seems not to be problematic for the reason that state estimation is usually performed independently outside attribute information evaluation modules. If that is so, evaluation methods may take advantage of target tracking functions.

11.3 The attribute information evaluation model

Based on observations described in the previous section, the attribute information evaluation process may be expressed with a concept and finally a model is presented below. The basic block scheme of information evaluation process is shown on Figure 11.2.

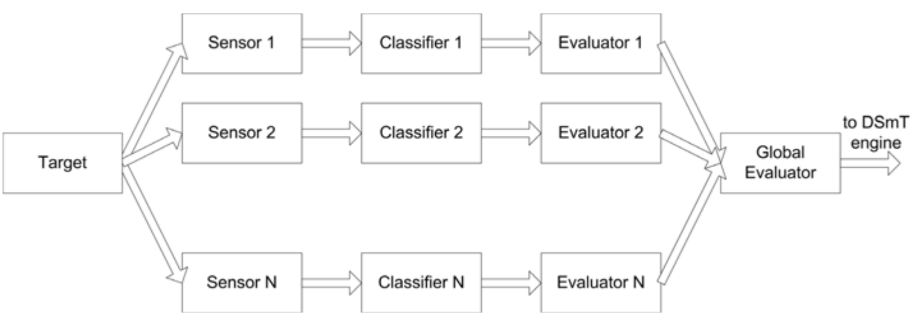

Figure 11.2: Information evaluation basic block scheme.

Target – an object to be detected and classified by subsequent blocks. The target is assumed to be described by a threat attribute and a kinematic state vector.

Sensor – a source of information. There are possible diverse source types, namely radar, video camera and visual sightings, for example. It is assumed that all these types have different characteristics (detection and classification zones) and reliability.

Classifier – a block which associates the sensor data with particular possible hypotheses. Based on primary hypotheses distinguished by the sensor (frame of discernment), the classifier results in creating additional hypotheses using $\cup$ and $\cap$ operators to form an extended set which may be dealt with the DSmT fusion engine.

Evaluator – a block which assesses the classified information. This is the key part of the whole model. The evaluator uses information concerning:

- Information source (source characteristics, source reliability information);
- Sensor measurements (concerning hypotheses actually supported directly by sensors);
- Target kinematics information (to evaluate exact hypotheses).

Global evaluator – an auxiliary evaluation block which updates local evaluation products with external information about the qualities of the sources (not shared by local evaluators) like bias corrections or human-originated preferences, for example.

A more detailed diagram is depicted on Figure 11.3. Each block of Figure 11.2 has been reconsidered to view its main functions. The arrows show the block interactions on the functional level. In addition, a block of the state estimator has been introduced which provides target kinematic information in real systems.

The blocks of Target and State estimator perform auxiliary functions only, to show the reader the point where the exact information is processed. They will not be discussed in details here.

11.3.1 The types of sensors

For the purpose of the evaluation model, the sensor block is assumed to consist of two components:

- Characteristics;
- Observation process.

The characteristics describe theoretically how a source performance should change depending on the tracked target position. It may be treated as a deterministic component.

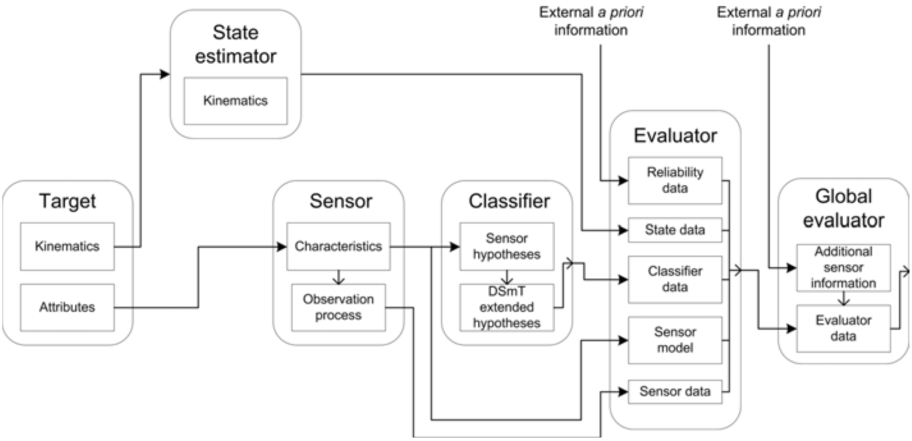

Figure 11.3: Further insight into information evaluation.

The observation process component acts mainly as a stochastic one. It introduces random disturbance noise to model a source imperfection, according to the reliability parameter value;

Such a decomposition of deterministic and stochastic sensor components is required for the reason that sensor performance is going to be modeled in a following (after classifier) block of evaluator. Deterministic information about characteristics is assumed to be possible to share, while stochastic source behavior information is never completely known in the real world, therefore it is assumed to be unknown outside the sensor block.

Concentrating on the characteristics component it is important to notice that one can deal with diverse types of sensors (using diverse ontologies), however it was assumed for simplicity to constrain the sensor model to the classification level.

Therefore, the only two types of zones are to be taken into account:

- Detection zone;
- Classification zones;

The detection zone is a region where the target detection is possible. Any region outside that zone is not taken into account.

The classification zones are the subsets of the detection zone, where the target may be classified with precision determined by its actual kinematic state vector. The classification zones can be distinguished as follows:

- Perfect classification conditions ($F_c = 1$);

- Perfect azimuth and imperfect range conditions;

$$F_c(t) = \omega_\phi(t) \cdot \omega_d(t) \tag{11.1}$$

- Perfect range and imperfect azimuth conditions;

$$F_c(t) = \omega_\phi(t) \cdot \omega_a(t) \tag{11.2}$$

- Imperfect classification conditions;

$$F_c(t) = \omega_\phi(t) \cdot \omega_d \cdot \omega_a(t) \tag{11.3}$$

where F_c (the conditions factor) is a function which summarizes a classification quality and where ω_ϕ, ω_d and ω_a are the target validation weights regarding target aspect, distance and azimuth respectively.

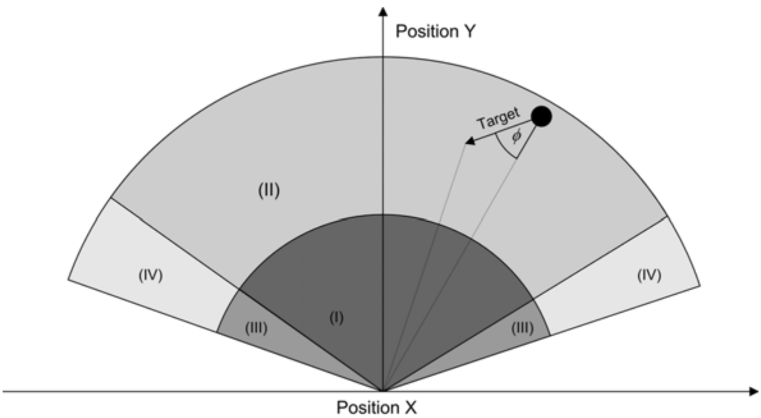

Figure 11.4: Classification zones: (I) perfect classification conditions, (II) – perfect azimuth imperfect range conditions, (III) – perfect range imperfect angle conditions, (IV) imperfect classification conditions.

The observation process disturbance may be modeled using a normal distribution with known mean value, determined by expected undisturbed (simulated) value and standard deviation, depending on the sensor characteristics.

$$\sigma = \sigma_{\min} + \delta(1 - F_c) \tag{11.4}$$

where $\sigma_{\min}$ is the minimal standard deviation value and δ is a condition dependence coefficient.

11.3.2 Classifier

Wherever a soft-decision fusion approach is applied, the classifier block appears. In the evaluation model presented here the classifier has to carry out two tasks.

- Extracting the primary hypotheses (source frame of discernment);
- Generating additional hypotheses using $\cup$ and $\cap$ operators.

Extracting the primary hypotheses is a classical task for classifiers. For a given type of sensor each possible hypothesis is extracted and established in a hypotheses table for future evaluation.

The hypotheses distinguished by sensors are mostly exclusive and the set of possible value depending on the exact source may not be sufficient for proper classification. For this reason it is suggested to append to the classifier an additional function of generating extensional (middle) hypotheses using union and intersection operators.

If the threat attribute is human-originated the following translation rules should be applied[1]:

- SUSPECT = UNKNOWN $\cap$ HOSTILE
- ASSUMED_FRIEND = UNKNOWN $\cap$ FRIEND
- FAKER = FRIEND $\cap$ HOSTILE
- JOKER = SUSPECT $\cap$ FRIEND = UNKNOWN $\cap$ HOSTILE $\cap$ FRIEND

A suspicion that there are two targets within considered area may also be established as union hypothesis, for example: FRIEND $\cup$ HOSTILE.

11.3.3 Evaluator

Some soft-decision fusion models apply the classifier as a module responsible, not only for proper classification (and interpretation) of data obtained from sensors, but also as some kind of evaluator.

Since this chapter refers mainly to attribute information evaluation, the evaluator has been distinguished as a separate block that follows the classifier. However, in the presented model one also receives information directly from other blocks. It is due to the fact that the evaluation process requires a combination of:

- Sensor model: to access the source characteristics information;

[1] Presented threats' values are defined in [4]. It is authors' suggestion to put them in terms of hypotheses union or intersection to be easily dealt by DSmT fusion.

- Classifier information: to acquire information about particular hypotheses to evaluate;
- Target state vector: necessary to utilize the characteristics information;
- Reliability data: to know about how defective the source is;
- Consequently: sensor data to have the basis for the evaluation.

Sensor model information may be easily derived from the deterministic part of the sensor block. If that is so, source related time variant parts may be summarised with one function $F_c(t)$, described as in section 11.3.1.

Considering the distinction presented in section 11.2.1 the evaluation of hypotheses may be expressed by the following formula:

$$m_i(\theta_j) = \frac{\beta R_i F_c(t)}{N_\theta} \cdot \frac{1}{\Delta\Theta_j^2} \tag{11.5}$$

where i is the sensor index; j is the classifier hypotheses index; R_i is the sensor reliability; N_θ number of primary hypotheses; $\Delta\Theta_j$ is the hypothesis weight based distance metric and $\beta \in [2, N_\theta]$ is a compensation coefficient.

The first term acts as a source related component. It consists of conditions factor, source reliability and the number of primary hypotheses[2]. The coefficient β should be treated as a compensator of prior hypotheses number. The second term is related to hypotheses component. For each hypothesis from the set obtained from the classifier, the respective hypothesis weight $\Delta\Theta_j$ is calculated based on the distance metric, as Figure 11.5 shows.

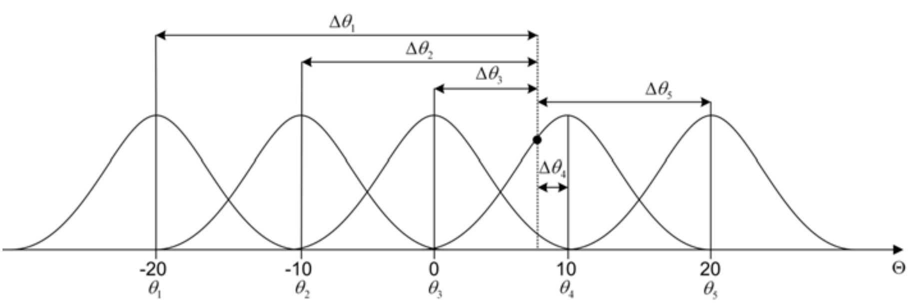

Figure 11.5: Distance metric for calculating hypotheses weights. Numerical values specify distribution distances.

[2]Number of primary hypotheses (not classifier hypotheses) is taken into account, because unlike primary hypotheses classifier, hypotheses may not be treated as an intrinsic feature of the source.

This rule may be easily applied for each prior hypothesis. Otherwise, if for example the hypothesis is created upon intersection of prior hypotheses, it is suggested to apply another rule described below. The problem that occurs concerns the evaluation of hypotheses related to the target threat parameter. It is assumed that:

- The frame of discernment is defined as:

$$\Theta = \{\mathrm{U} \triangleq \mathrm{UNKNOWN}, \mathrm{F} \triangleq \mathrm{FRIEND}, \mathrm{H} \triangleq \mathrm{HOSTILE}\}$$

- The measurements are performed in three steps:
  - Step I: HOSTILE vs. FRIEND;
  - Step II: HOSTILE vs. UNKNOWN;
  - Step III: UNKNOWN vs. FRIEND
- The first (sensor related) term is omitted for simplicity;

Based on the frame of discernment and rules described in this section additional hypotheses may be formed. Graphical relationship among threat attributes are shown in Figure 11.7.

It is important to realize that the method presented here, if applicable to resolve problems other than those related to the target threat evaluation, requires reconsideration since some of prior classes are specific. The class UNKNOWN is specific because, apart from the fact that it is one of prior classes, it represents the ignorance about the target.

The idea the of three-step measurements comes from the fact that in marine systems the most important is to firstly classify the target either FRIEND or HOSTILE. The rest of the observations may be used to update the degree of evidence that the target is a FRIEND or HOSTILE and to update the target classification accordingly. That also may become the basis to create the following additional hypotheses: JOKER, FAKER etc. Certainly, the following measurements may be treated as completely different sources of evidence and hence the DSmT fusion may be applied. However, in this chapter, it is suggested to consider them related to the same source of information and to utilize some extra knowledge about the definition of threat values, described below. Omitting the first (sensor related) term, as assumed, hypotheses weights may be calculated as follows:

$$m_i(\theta_j) \approx \frac{1}{\omega(\theta_j)} \tag{11.6}$$

The weights ω should be calculated as follows:

$$\omega(\theta_j) = \nu^T(\theta_I) \cdot \nu(\theta_I) \tag{11.7}$$

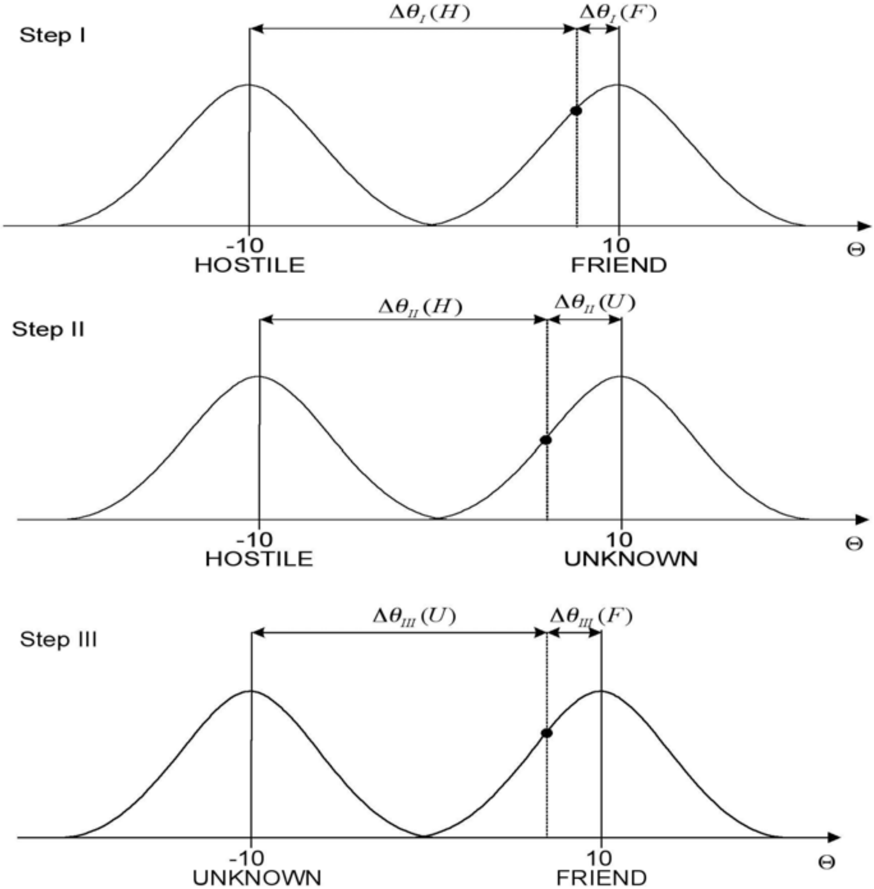

Figure 11.6: Calculating hypotheses weights using distance metric (steps I-III).

where

$$\nu^T(F) = [\Delta\theta_I(F)\ \Delta\theta_{II}(F)\ \Delta\theta_{III}(F)] \tag{11.8}$$

$$\nu^T(H) = [\Delta\theta_I(H)\ \Delta\theta_{II}(H)\ \Delta\theta_{III}(U)] \tag{11.9}$$

$$\nu^T(U) = [D_{HF}\ \Delta\theta_{II}(U)\ \Delta\theta_{III}(U)] \tag{11.10}$$

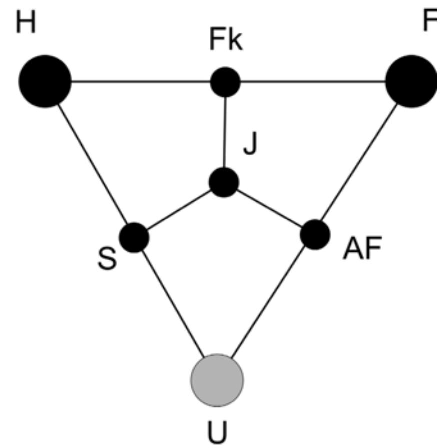

Figure 11.7: Relations among threat values (UNKNOWN is specific) where Fk ≜ FAKER, J ≜ JOKER, S ≜ SUSPECT and AF ≜ ASSUMED_FRIEND.

$$\nu(F \cap H) = \begin{bmatrix} \Delta\theta_I(F) - \Delta\theta_I(H) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(F) \end{bmatrix} \tag{11.11}$$

$$\nu(F \cap U \cap H) = \begin{bmatrix} \Delta\theta_I(F) - \Delta\theta_I(H) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) - \Delta\theta_{III}(F) \end{bmatrix} \tag{11.12}$$

$$\nu(F \cap U) = \begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) - \Delta\theta_{III}(F) \end{bmatrix} \tag{11.13}$$

$$\nu(H \cap U) = \begin{bmatrix} \Delta\theta_I(H) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix} \tag{11.14}$$

$$\nu^T(F \cup H) = [D_{HF}\ \Delta\theta_{II}(H)\ \Delta\theta_{III}(F)] \tag{11.15}$$

where $\omega(F \cap H)$ is the weight of FAKER; $\omega(F \cap U \cap H)$ is the weight of JOKER; $\omega(F \cap U)$ is the weight of ASSUMED FRIEND; $\omega(H \cap U)$ is the weight of SUSPECT according to the translation rules described in the section and D_{HF} is the distance between distributions HOSTILE and FRIEND.

The weights, generally, consist of three terms which represent how much evidence, retrieved based on every measurement step, is for a particular hypothesis (for example: in equation (11.8) they are distances: $\Delta\theta_I(F)$ and $\Delta\theta_{III}(F)$) or how much it is against the contrary hypothesis ($\Delta\theta_{II}(U)$ - for the same equation). However, when creating the hypotheses using $\cap$ operator, it is important to notice that the intersection of particular prior hypotheses changes the graphic interpretation to what extent the evidence is for particular hypothesis. For example equation (11.12) shows that JOKER is the most probable if in all three steps measurements will place somewhere in the middle between distributions. Therefore, each term consists of distance differences, not just distances. It must be also mentioned that in equation (11.11) though defined as $F \cap H$ the second term is $\Delta\theta_{II}(U)$ not $\Delta\theta_{II}(H)$. That results from the fact that the target FAKER is always a friendly (for exercise purposes acting as HOSTILE). The high measurement of 'how much HOSTILE it is' does not really support the hypothesis of FAKER.

11.4 Numerical experiments

The techniques described in previous sections have been subjected to series of numerical experiments. This section presents details of the experiments and is followed by the discussion of obtained results.

11.4.1 Assumptions

Target simulation:

- The target is described with the threat attribute value, which can be changed by the user and a state vector;
- The target is assumed to be moving (with random or deterministic trajectories) to simulate that it can reside in sensors' diverse classification zones;

Sensor (of threat attribute):

- There are three types of sensors (radar, visual sighting and video camera) each of which has different detection and classification parameters;
- All types of the sensors uses different ontology;
- It is possible to set sensor reliability parameter, sensor position
- Sensor performance is target state vector dependent, directly as described in section 11.3.1.
- Sensor performance is modeled stochastically by using Gaussian distributions with specified mean values and standard deviations to represent the measuring noise.

Classifier:

- Classifier extends the set of prior hypotheses with some hypotheses created based on prior hypotheses as described in section 11.3.3.

- It is assumed to extend the hypotheses set with fixed predefined values (SUSPECT, FAKER, ASSUMED_FRIEND);

Evaluator:

- Only the hypotheses related factor is assumed to be normalized (the source related factor is assumed to be excluded from the normalization process);
- An additional class of PENDING is created with mass defined as follows: $m(P) = 1–F_c$, to complete bba;
- β is designed to compensate the prior hypotheses number in the source factor with optimal hypotheses number;
- If the target exceeds the sensor detection range, this results in $m(P) = 1$ and zero for the rest of the values;

Global evaluator:

- It is assumed to utilize here only a priori information about local evaluators (any information about the source quality and reliability should be used in previous stages of evaluation;

11.4.2 Settings and other model information

Three-step measurement enables to identify targets described with the threat attribute outside the sensor ontology. For example if the target is friendly and acts as hostile, the evaluator will place the first step measurement somewhere in between HOSTILE and FRIEND, the second step measurement close to UNKNOWN and the third step measurement close to FRIEND which leads to assigning the FAKER with the biggest mass value, even though, the value of FAKER is not present in the sensor ontology.

Setting the proper value for a ‘beta’ coefficient is very important. In evaluation model particular hypothesis mass is inversely proportional to the number of prior hypotheses. It is due to the fact that diversity of prior hypotheses decreases possible mass value assigned to a particular hypothesis. The value of three seems to be perfect because the basic set consists of {FRIEND, HOSTILE, UNKNOWN}[3] . This optimal value may be transferred to beta to compensate the real (sensor originated) hypotheses number. Ideally, when the hypotheses number is equal to the optimal hypotheses number (beta), the source related factor depends on the source reliability and the conditions factor only.

[3] In some cases (radar equipped with IFF device, distinguishing only HOSTILE and FRIEND) this number should be reduced to the value of two. This seems to be reasonable since the UNKNOWN represents the ignorance thus it may be omitted.

11.4.3 Results

In the first experiment the HOSTILE target track was generated randomly. The threat attribute information evaluation was performed over twenty one samples. The resulting trajectory is shown on Figure 11.8.

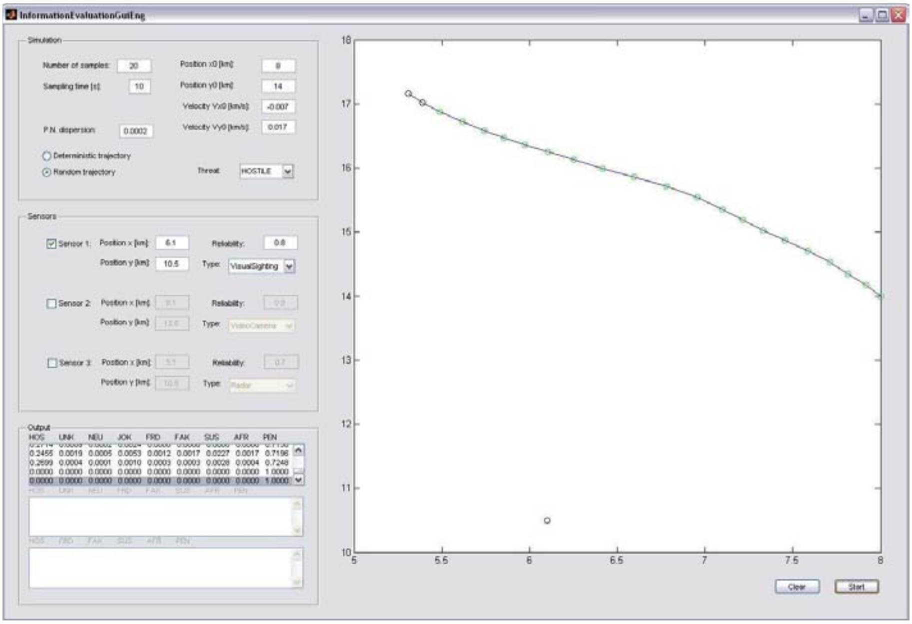

Figure 11.8: Randomly generated target trajectory. Attribute information evaluation performed by a single source - Visual Sighting (VS). Target aspect problem detected.

The figure 11.8 shows that the target was constantly within the sensor range, however some of the measurements have been better conditioned than others. Table 11.1 presents resulting bba calculated for each sample. It is immediately clear from Table 11.1 that in most of cases the bba was mainly distributed between the HOSTILE and the PENDING. It is quite reasonable about the HOSTILE but the PENDING is not so obvious. The reason why the PENDING got relatively high resides in coefficient β, which has been set to three while the prior hypotheses number was five. In all cases where PENDING mass was 0.68, measurements were perfectly conditioned (in terms of $F_c(t)$ function). Starting with 10-th sample PENDING mass began to rise which was caused by the fact that the target passed the perfect classification condition zone (the range condition began to get worse). In last two samples bba was completely transferred to the PENDING which is by default when the target threat attribute evaluation is not possible. In these particular cases it was caused by the target aspect. This phenomenon perfectly illustrates the problem described in section 11.2.

The next thing concerning the Table 11.1 is how the bba was distributed to the rest of the hypotheses. It must be noticed that each time the FRIEND has the least mass assigned while the SUSPECT was always the second high, after the HOSTILE (excluding the PENDING). The abbreviations used in this tables are: HOS=hostile, UNK=unknown, NEU=neutral, JOK=joker, FRD=friend, FAK=faker, SUS=suspect, AFR=assumed friend and PEN=pending.

HOS	UNK	NEU	JOK	FRD	FAK	SUS	AFR	PEN
0.3027	0.0013	0.0004	0.0034	0.0008	0.0011	0.0093	0.0011	0.6800
0.3145	0.0004	0.0001	0.0010	0.0002	0.0003	0.0031	0.0003	0.6800
0.3119	0.0006	0.0002	0.0016	0.0004	0.0005	0.0041	0.0006	0.6800
0.3131	0.0004	0.0001	0.0012	0.0003	0.0004	0.0040	0.0004	0.6800
0.3066	0.0009	0.0002	0.0024	0.0006	0.0008	0.0077	0.0008	0.6800
0.3106	0.0007	0.0002	0.0017	0.0005	0.0006	0.0051	0.0006	0.6800
0.3001	0.0016	0.0005	0.0043	0.0011	0.0014	0.0095	0.0014	0.6800
0.2996	0.0013	0.0004	0.0033	0.0008	0.0011	0.0124	0.0011	0.6800
0.3178	0.0002	0.0000	0.0004	0.0001	0.0001	0.0012	0.0001	0.6800
0.3088	0.0005	0.0001	0.0014	0.0003	0.0005	0.0042	0.0005	0.6836
0.3060	0.0004	0.0001	0.0011	0.0003	0.0004	0.0032	0.0003	0.6882
0.2977	0.0007	0.0002	0.0017	0.0004	0.0006	0.0059	0.0006	0.6922
0.2860	0.0011	0.0003	0.0029	0.0007	0.0010	0.0109	0.0010	0.6961
0.2921	0.0005	0.0001	0.0014	0.0003	0.0004	0.0046	0.0004	0.7002
0.2937	0.0002	0.0000	0.0004	0.0001	0.0001	0.0012	0.0001	0.7041
0.2841	0.0006	0.0002	0.0017	0.0004	0.0005	0.0042	0.0005	0.7078
0.2754	0.0011	0.0003	0.0028	0.0007	0.0009	0.0066	0.0010	0.7112
0.2714	0.0009	0.0002	0.0024	0.0006	0.0008	0.0080	0.0008	0.7150
0.2455	0.0019	0.0005	0.0053	0.0012	0.0017	0.0227	0.0017	0.7196
0.2699	0.0004	0.0001	0.0010	0.0003	0.0003	0.0028	0.0004	0.7248
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Table 11.1: Bba calculated for each of 21 target track sample based on sensor and hypotheses information. The real target is HOSTILE.

The second experiment was meant to show how to retrieve the information the target is of any class, which does not reside in sensor ontology. The real threat attribute value had been set to FRIEND but the measurement was disturbed in such a way so as to provide the uncertainty whether the target is HOSTILE or FRIEND during first stage of measuring process. The obtained measurement numerical values for a single sample have been depicted in Fig. 11.9.

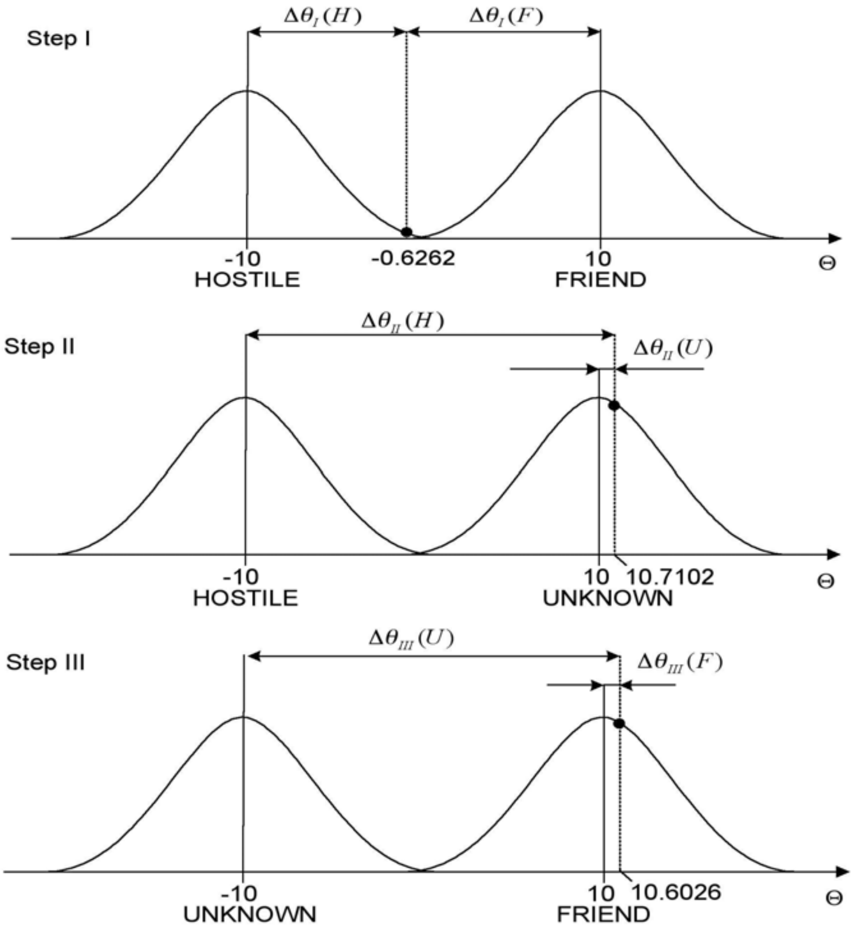

Figure 11.9: The example of hypotheses weights calculation using the distance metric (steps I-III).

The first step measurement places in between the HOSTILE and the FRIEND value, the second step measurement does not prove the hypothesis that the target is HOSTILE and the third step clearly shows the target is FRIEND. Combining these pieces of information it is reasonable to claim that the target is FAKER, which is shown in the resulting Table 11.2.

$Threat\ value$	$Mass$
$HOSTILE(i.e\ HOS)$	0.0007
$UNKNOWN\ (i.e\ UNK)$	0.0012
$NEUTRAL\ (i.e\ NEU)$	0.0028
$JOKER\ (i.e\ JOK)$	0.0028
$FRIEND\ (i.e\ FRD)$	0.0056
$FAKER\ (i.e\ FAK)$	0.5125
$SUSPECT\ (i.e\ SUS)$	0.0010
$ASSUMED\_FRIEND\ (i.e\ AFR)$	0.0029
$PENDING\ (i.e\ PEN)$	0.4704

Table 11.2: Bba calculated for the chosen test sample.

The next experiment aimed at multi-sensor information evaluation. A FRIEND track has been generated randomly starting between two sources: Visual Sighting (VS) and Video Camera (VC). The resulting trajectory is depicted on Fig. 11.10. In this particular case, applying two sources enabled to keep attribute information evaluation continuity. Table 11.3 presents the bba's of the three chosen samples. JOKER dashes for Video Camera (VC) means that it does not recognise the JOKER.

It must be emphasized that VS and VC compensate each other's performances. The reason why any of them could not make a measurement was the aspect problem. It must be noticed that from the 18th up to 22nd sample, the critical aspect is for the visual sighting despite the fact the target is closer to this very source.

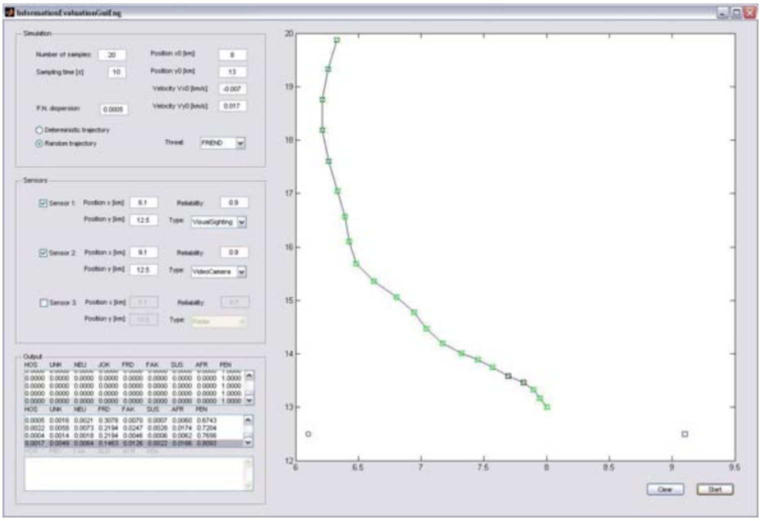

Figure 11.10: Randomly generated target trajectory. Attribute information evaluation performed by two sources: Visual Sighting (o – symbol) and Video Camera (square symbol).

Sample #	5	5	6	6	22	22
Source Type	*VS*	*VC*	*VS*	*VC*	*VS*	*VC*
HOS	0.0019	0	0.0014	0.0024	0	0.0017
UNK	0.0047	0	0.0040	0.0066	0	0.0049
NEU	0.0077	0	0.0038	0.0097	0	0.0064
JOK	0.0075	–	0.0062	–	0	–
FRD	0.2877	0	0.3045	0.3626	0	0.1463
FAK	0.0325	0	0.0206	0.0213	0	0.0126
SUS	0.0025	0	0.0019	0.0030	0	0.0022
AFR	0.0154	0	0.0176	0.0245	0	0.0166
PEN	0.6400	1	0.6400	0.5700	1	0.8093

Table 11.3: Bba's calculated for chosen samples no. 5, 6 and 22 for Visual Sighting (VS) and Video Camera (VC).

The last experiment meant to check the evaluation model accuracy with deterministically generated target trajectory. The figures 11.11 and 11.12 show the evaluation samples of this track.

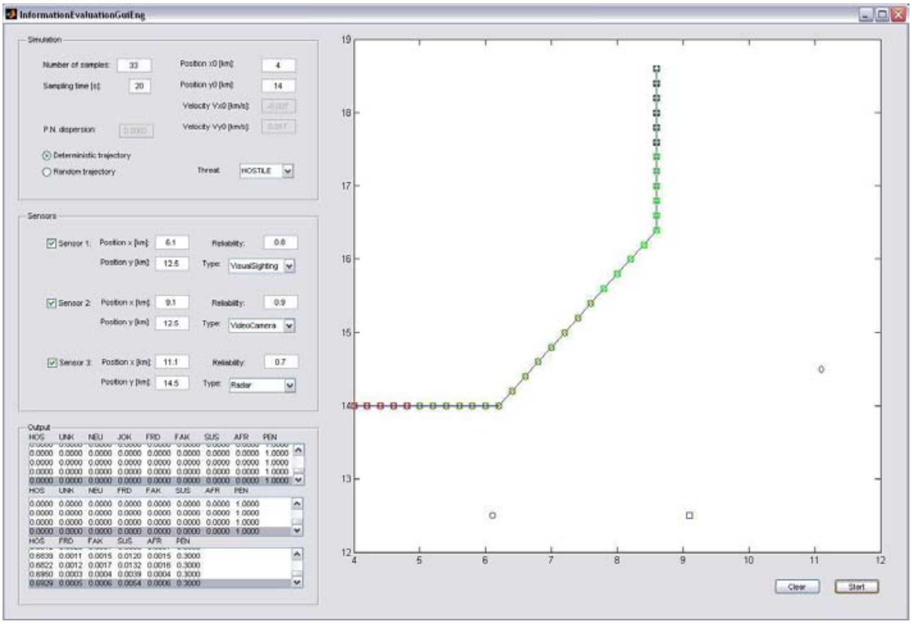

Figure 11.11: Deterministically generated target trajectory. Attribute information evaluation performed by three sources: Visual sighting (o – symbol), Video camera (square symbol) and Radar (diamond symbol).

For a better visualization, the decluttering function has been applied (Fig. 11.12) to spread samples originated from different sources. The figure 11.12 shows that radar attribute evaluation measurements were constrained mainly by the azimuth sector (light symbols), only the upper part of the track is visible (solid symbols). Video camera performance was constrained both by the azimuth sector and the target aspect (dark symbols), while visual sighting measurements were constrained only by the target aspect.

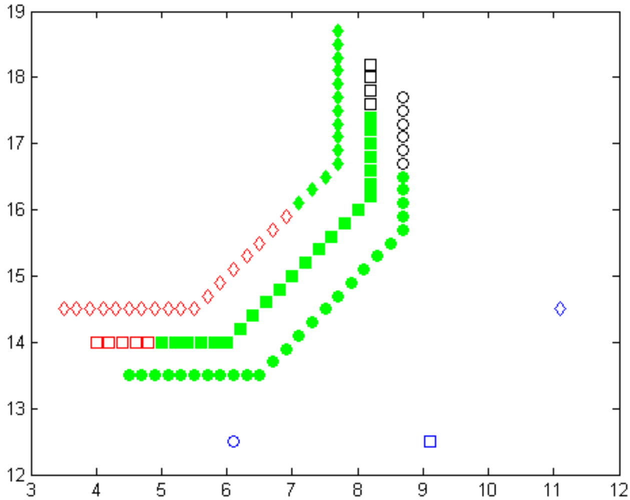

Figure 11.12: Deterministically generated target trajectory as in Fig. 11.11. For better visualization, a decluttering function has been applied.

11.4.4 Discussion

It is worth discussing if a lack of sensor specification, expressed in terms of mass should be transferred to the PENDING or to the UNKNOWN. The UNKNOWN class generally describes the uncertainty of the hypotheses related part. Therefore, the authors decided to transfer the lack of specification to the new class of PENDING, which in terms of [4, 5] means 'any of the rest of the classes'. A demanding reader may raise a question concerning the 'acceptance logic', mentioned in the previous subsection. Why does the target aspect factor act here in a binary manner? Within the perfect classification zone ignores the aspect problem while just after exceeding that zone it completely precludes the whole attribute information evaluation? The answer is very simple: It is not the intention of this model to build as realistic logic as possible. The importance of this evaluation model resides in the fact that calculated masses, resulting from the sensor characteristics and the target motion parameters may be described as reasonable (to be expected in real world). If, for example, the evaluation model assigns the biggest mass to the FAKER it is very unlikely to find the smallest mass assigned to the FRIEND because FAKER = FRIEND ∩ HOSTILE.

11.5 Latest concepts

In our latest research works, we propose two alternative target threat models. The first one is called an "Activity-oriented model" while the second is a "Threat-oriented model. These two models are based on different definitions of the three stages of threat measurement according to Table 11.4.

Threat	Activity-oriented model	Threat-oriented model
FRD	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(F) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(F) \end{bmatrix}$
HOS	$\begin{bmatrix} \Delta\theta_I(H) \\ \Delta\theta_{II}(H) \\ \Delta\theta_{III}(U) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(H) \\ \Delta\theta_{II}(H) \\ \Delta\theta_{III}(U) \end{bmatrix}$
UNK	$\begin{bmatrix} \Delta\theta_I(H) - \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(H) - \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix}$
FAK	$\begin{bmatrix} \Delta\theta_I(F) - \Delta\theta_I(H) \\ \Delta\theta_{II}(H) \\ \Delta\theta_{III}(F) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(H) \\ \Delta\theta_{III}(U) \end{bmatrix}$
JOK	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(F) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix}$
SUS	$\begin{bmatrix} \Delta\theta_I(H) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(H) \\ \Delta\theta_{II}(H) - \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) \end{bmatrix}$
AFR	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) - \Delta\theta_{III}(F) \end{bmatrix}$	$\begin{bmatrix} \Delta\theta_I(F) \\ \Delta\theta_{II}(U) \\ \Delta\theta_{III}(U) - \Delta\theta_{III}(F) \end{bmatrix}$

Table 11.4: Threat target models comparison.

Fig. 11.13 and Fig. 11.14 show threat relations in activity-oriented model and threat-oriented model respectively. The activity-oriented model in the first measurement stage resolves whether (according to observed target's activity) the target seems to be more like FRIEND or HOSTILE. In the following two next stages, the degrees of belief of these two hypotheses are defined by the observation of the real target. This means that the real target's threat description resides in last two measurements whereas the first one influences the possible training type (JOKER or FAKER).

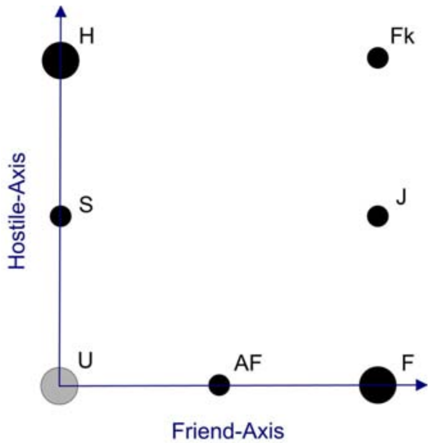

Figure 11.13: Activity-oriented model. Relations among threat values.

The threat-oriented model in the first measurement stage resolves the real threat of the target. In the following two next stages, the degrees of belief (whether the target acts as SUSPECT or HOSTILE) are defined according to the current target's activity. This means that the stage of measurement is the most important from the military point of view due to the fact it clearly shows the real threat. According to this model, JOKER and FAKER types are always described as FRIENDs. Therefore this very model seems to be the most adequate for applicable military solutions.

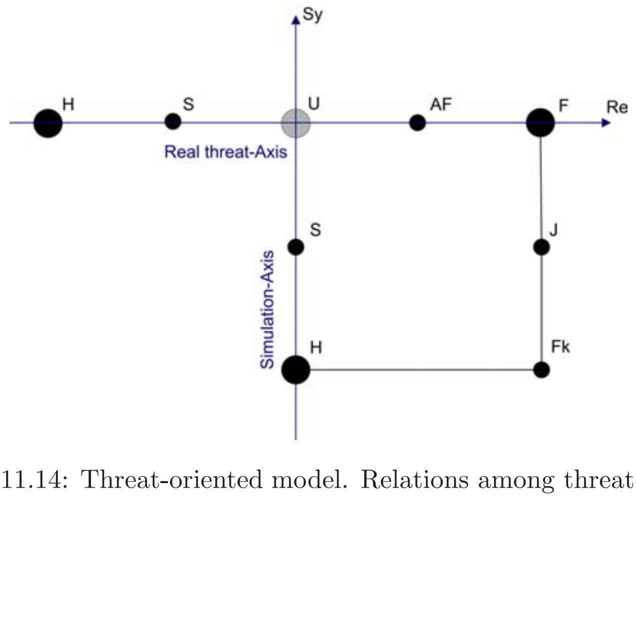

Figure 11.14: Threat-oriented model. Relations among threat values.

11.6 Conclusion

An evaluation of the attribute information plays a very important role in information fusion systems. Among many possible attributes of maneuvering target the threat is one of the most important. Many practical fusion problems proved that this kind of information often happens to be even more important than the precise information about the target position. However, to assess properly the attribute information, the target state vector is necessary, as well as, a specific evaluation method.

Conflicting attribute information needs a reasonable bba calculating method if it is meant to be fused according to DSmT. The research work described in this chapter is a part of extensive works devoted to sensor networks in a NEC environment.

In the near future it is planned to extend the presented evaluation model from the navigation point of view, as well as, from the mathematics (concentrating on attribute-oriented model[4]) and additionally to provide a tool for assessing different attributes (other than the threat) of maneuvering targets.

11.7 References

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[6] NATO Standardization Agreement, Identification Data Combining Process, STANAG No. 4162, Ed. 2.

[7] F. Smarandache and J. Dezert (Editors), *Applications and Advances of DSmT for Information Fusion*, Collected Works, Vol.1, American Research Press, 2004.
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[8] F. Smarandache and J. Dezert (Editors), *Applications and Advances of DSmT for Information Fusion*, Collected Works, Vol.2, American Research Press, 2006.
`http://www.gallup.unm.edu/~smarandache/DSmT-book2.pdf`

[4]Threat-oriented model may be generalized to any attribute model if attributes other than target threat are discussed.