Improving Situation Awareness Using Aerial-Mission Recognition and Temporal Information

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Abstract – *The paper describes a procedure for improving human effectiveness and situation awareness on a platform system. The procedure is based on aerial-mission recognition and temporal display. The algorithm for aerial-mission recognition consists of Hidden Markov Models. The algorithm fuses information on object tracks and assumed behavior of different missions. The temporal display is based on time intervals for events that can happen and actions that can be performed. The algorithm fuses object position, speed and assumed weapon range. In the temporal display there is no information on object type. In the procedure for improved situation awareness, aerial-mission estimates are integrated into the temporal display, and the display can thereby present mission uncertainties. Consequently, the temporal display will then present a more realistic description of the environment.*

Keywords: Mission recognition, system effectiveness, temporal display, situation awareness, decision support.

1 Introduction

High combined human-system effectiveness is an important goal when air combat systems are developed. The goal can be hard to reach if the situation awareness in the combined systems is not high enough. Especially in environments with a large amount of objects, there is a need for sets of functional tools in the onboard decision support system.

The paper presents a procedure for enhancing effectiveness for fighter pilots. The procedure consists of a mission-recognition algorithm and a temporal algorithm.

The mission-recognition algorithm helps the pilot to estimate missions of the objects. Missions that can be estimated are fight, attack, surveillance, transport and general aviation.

The temporal algorithm makes projections of object kinematics and object characteristics to a temporal representation of events and actions. The temporal display presents action capabilities as time zones in which different events can happen and different actions can be performed.

Instead of presenting mission recognition and temporal information separately, mission estimates can be integrated into a temporal display. Together the two algorithms will give a more correct view of the situation, i.e. a more realistic environment will be presented. The combination of the two algorithms makes possible a better basis for e.g. sensor management, compared to the bases the algorithms achieve separately.

The two algorithms have been implemented into a software system, the so-called data fusion node (DF). DF includes various algorithms which aim at describing the different steps of the JDL model [1]. The different steps are data collection, data analysis, situation assessment, threat assessment and adaptation. DF algorithms represent object tracking, sensor models, scenario generation facilities, simulation facilities, sensor management, DF network systems, aerial-mission recognition and temporal display [2, 3]. DF is used to simulate different scenarios and to study the effect of new algorithms on situation awareness. DF has been used to study the aerial-mission recognition model and the temporal display.

In Sec. 2 the paper presents the mission-recognition algorithm. In Sec. 3 the meaning of time for situation awareness is shortly discussed, as well as the temporal display. In Sec. 4 a simulation example is presented, showing mission estimates and temporal display for a scenario with three objects. Sec. 4 also presents four ways of integrating mission estimates into the temporal display. Sec. 5 presents discussion and conclusion.

2 Aerial-mission recognition

2.1 Different motion patterns

The model for aerial-mission recognition is based on the fact that different aerial missions, at least occasionally, have different motion patterns.

Large transport aircraft performing *transport* missions have a cruising speed which in most cases is lower than the maximum speed of small military aircraft. Civil passenger aircraft fly in predefined airways characterized by certain altitudes and directions. Large and heavy aircraft fly mainly in straight lines and wide turns.

General aviation is represented by e.g. sports planes, training aircraft and sightseeing aircraft. General aviation is, in this application mainly characterized by relatively low flight altitude and low speed.

Reconnaissance missions can be performed at very low or very high altitudes depending on the purpose of the reconnaissance. Reconnaissance at low altitudes gives a detailed picture of a smaller area. Reconnaissance at high altitudes gives a less detailed picture, but instead an overview of a larger area.

Fight and *attack* missions can in exceptional cases show a fast course of events. The aircraft is often small and light and has high maneuver capability in contrary to the large and heavy transport aircraft. Attack missions are often performed at very low altitudes while fight missions are often performed at higher altitudes. The small aircraft can fly in straight lines as well as sharp turns.

Information on object tracks, typical motion patterns as well as information on e.g. airways for civil transport is fused in the HMM.

It is the combination of speed, altitude and direction (maneuver or straight line), and how these factors change over time that constitutes the mission characteristics.

2.2 Hidden Markov Model (HMM)

The HMM is a stochastic model used for time series analysis. A system is observed through observation symbols. Meanwhile observation symbols are obtained, the system undergoes a random walk between states, which can not be observed, i.e. the states are hidden.

The theory of HMM was presented in the 1960s. HMM has since then been used in different areas for recognizing different patterns, e.g. speech recognition [4], word recognition [5], molecule recognition [6], colon recognition [7] and aircraft recognition based on electromagnetic emissions [8].

This section gives a brief description of the discrete HMM of the first order. The description is based on [9].

An HMM, λ, consists of a number of states, N, and a number of observation symbols, M. States are denoted $S=\{S_1,S_2,...,S_N\}$ and observation symbols are denoted $V=\{v_1,v_2,...,v_M\}$. The model λ is described by the following parameters:

$$\lambda = (A,B,\pi) \quad (1)$$

$$A = \{a_{ij}\} = \{P[q_{t+1} = S_j \mid q_t = S_i]\} \quad (2)$$

$$B = \{b_j(k)\} = \{P[O_t = v_k \mid q_t = S_j]\} \quad (3)$$

$$\pi = \{\pi_i\} = \{P[q_1 = S_i]\} \quad (4)$$

$$1 \le i, j \le N \quad (5)$$

$$1 \le k \le M \ . \quad (6)$$

Probabilities for state transitions are given by matrix A, where a_{ij} is the probability for changing the state of the system from state i to state j. Probability distributions for observation symbols v_k are given by matrix B. The probability for the system to show symbol v_k under the condition that the system is in state S_j, is given by $b_j(k)$. Current state of the system is denoted q_t and current observation is denoted O_t. The probability distribution for the states initially ($t=1$) is given by π.

In the mission-recognition problem the likelihood L_n is calculated for all n models λ, for a certain observation sequence O. The λ_n that gives the highest value of L_n is assumed to be representing the mission.

L_n equals the likelihood of obtaining O, given the specific model λ_n, i.e.

$$L_n = P(O \mid \lambda_n) \quad (7)$$

where O consists of system observations observed at T points of time, i.e.

$$O = (O_1 O_2 ... O_T) \ . \quad (8)$$

To calculate L_n, the forward variable $\alpha_t(i)$ is introduced as follows:

$$\alpha_t(i) = P(O_1 O_2 ... O_t, q_1 = S_i \mid \lambda_n) \ . \quad (9)$$

The forward variable describes the probability for observing a partial observation sequence $O_1O_2...O_t$ in state S_i at time t, given the model λ_n. For the first observation O_1, $\alpha_1(i)$ is calculated as follows:

$$\alpha_1(i) = \pi_i b_i(O_1) \ . \quad (10)$$

For the following observations $\alpha_{t+1}(j)$ is calculated according to:

$$\alpha_{t+1}(j) = [\sum_{i=1}^{N} \alpha_t(i) a_{ij}] b_j(O_{t+1}) \quad (11)$$

where $1 \le t \le T$. Eq. (11) describes how the system attains state S_j at time $t+1$ from N possible states at time t. The calculation is performed iteratively for $t=1,2,...T-1$. The final result is given by the sum of the forward variables for the different states, at final time T, i.e.

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i) \ . \quad (12)$$

At some occasions multiplications with numbers close to zero are performed. The final result will therefore be close to zero. Problems arise when the result is smaller than the smallest number the computer can represent. In [9] the problem is solved by introducing the scale factor c_t:

$$c_t = \frac{1}{\sum_{i=1}^{N} \alpha_t(i)} . \tag{13}$$

The final equation becomes as follows:

$$\log[P(O \mid \lambda)] = -\sum_{t=1}^{T} \log c_t . \tag{14}$$

2.3 HMM for aerial-mission recognition

Each mission is described by a model λ_n. The model has a specific set of probability distributions that roughly describes the most important motion characteristics.

A first version of a model for aerial-mission recognition is described in [10]. This paper presents a further development of the model, and a discussion on different ways of presenting mission estimates from a temporal aspect.

2.3.1 States

The description of motion patterns can be divided into three levels. The first level is the mission, which is represented by λ_n. The second level corresponds to parts of a mission, which are represented by states.

A mission is divided into two states, S_1 and S_2. The state S_1 corresponds to a mix of straight lines and sharp turns, where elements of *straight lines* dominate over elements of sharp turns.

The state S_2 corresponds to a mix of straight lines and sharp turns, where elements of *sharp turns* dominate over elements of straight lines.

S_2 is assumed to be typical just before an attack in a fight or attack mission. S_1 is assumed to be everything else that is not S_2.

The purpose of the aerial-mission recognition model is to detect deviations from a normal behavior. A deviation may imply a threatening object. However, it is not the small differences in behavior that are the basis for the model. Instead it is the large differences that are of interest, e.g. when the object suddenly makes sharp turns, changes altitude or speed in a short time. It is assumed that the HMMs need relatively few states to reflect these large deviations.

2.3.2 Observations

The third level in the description of the motion pattern represents observations, i.e. object speed, altitude and maneuver. Observations are denoted O_t. When the observation is obtained, the state of the mission is unknown. A specific observation can originate from a landing procedure as well as a beginning of an attack.

Observations for speed, altitude and maneuver are obtained from an object-tracking algorithm. The observations are combined to one observation O_t which is used for the HMM. O_t is obtained from the observation diagram in Fig. 1.

The observation diagram constitutes a link between object tracking and mission recognition. The x-axis represents object speed and the y-axis represents object altitude. The diagram is divided into different areas. Each area is denoted by two figures representing object direction. The lower figure implies that the object moves in a straight line, compared to the foregoing observation. The higher figure implies that the object changes direction i.e. performs a maneuver.

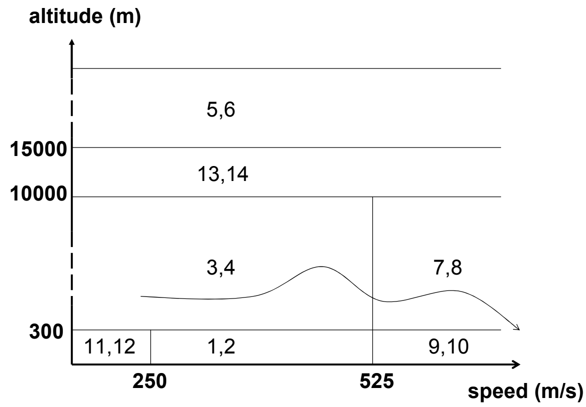

Fig. 1. Observation diagram

The speed and altitude intervals in Fig. 1 are assumed to reflect the main differences of the missions.

Assume that the tracking algorithm produces the following information; object speed = 300 m/s, object altitude = 5000 m, object direction = turn. From this information the observation diagram yields $O_1=4$. The latest observation is placed to the left in the observation sequence. Eq. (15) shows an observation sequence.

$$O = [O_1, O_2, O_3, O_4, O_5] = [4,3,3,3,3] . \tag{15}$$

The observation sequence describes a situation where an object during the four first occasions *(O_5-O_2)* moves at an altitude somewhere between 300 and 10 000 meters, with a speed somewhere between 0 and 525 m/s, and in a straight line. The latest observation *(O_1)* indicates that the object maneuvers, but still within the same speed and altitude intervals.

2.3.3 Calculation procedure

Mission estimates are calculated each time the tracking algorithm estimates a new position, speed and altitude. When a new object has been detected, the first estimate is calculated after the fifth observation. If an observation is received each second it will take 5 seconds before the algorithm presents the first mission estimates.

Fig. 2 presents the procedure for mission recognition. The grey components belong to the mission recognition algorithm. The white components belong to the object-tracking algorithm. The likelihood of observation sequence *O,* given a specific model λ, is calculated for all models λ_1 to λ_5. Finally the results are normalized for λ_1 to λ_5. Normalization makes comparisons between different missions easier. The update of the track estimate is used, not only for mission recognition, but also for other processes, such as temporal display and sensor management.

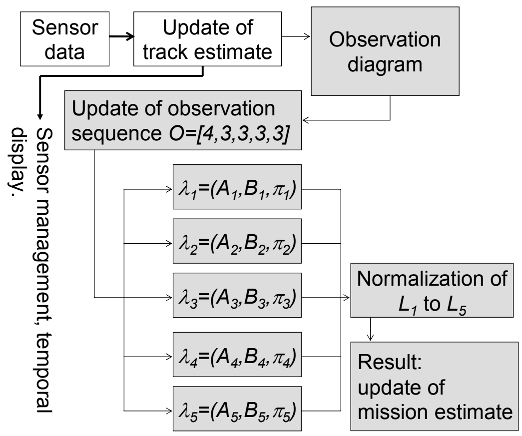

Fig. 2. Procedure for mission recognition

2.3.4 Model learning

The model parameters, $\lambda=(A,B,\pi)$, have been estimated using model learning according to the Viterbi algorithm [9]. Artificial training data for the different missions have been used for model learning [11, 12].

Each mission has been given training data that include first of all typical sequences of motion patterns, but also less typical sequences. The purpose was to concentrate on the most important differences of the missions, as described in Sec. 2.1. The artificial training data are based on time intervals of 1 second. The model learning was performed using Matlab.

2.3.5 Some viewpoints on the model

An HMM of the first order only considers the situation at time t when estimating the situation at time $t+1$. This simplification reduces the complexity of the problem. The number of equations to be solved depends first of all on the number of states N and the number of observations in the observation sequence T. As long as N and T are small, the number of equations to be calculated is relatively small. For this example, with $N=2$ and $T=5$, 130 equations are calculated each time a mission estimate is performed for an object. This includes Eqs. (10-14). To illustrate the increase in equations as N increases, while T is still 5, two examples are given. If $N=3$, the number of equations to be calculated is 180. If $N=10$, the number of calculations is 530. In a real application N should probably be larger than 2. On the other hand it should not be necessary to have a very detailed state division; i. e. a large number of N, to reflect deviations from a normal behavior.

As long as the object tracking process works well, the model will have a good basis for mission recognition. On the other hand, if the tracking quality is low the model will produce unreliable results. Information on tracking quality is given by the covariance matrix. By introducing the quality information into the model, it should be possible to control the use of the model. When the tracking quality is low, no mission estimates are produced.

If the radar does not receive information during a period then tracking, mission estimates and situation assessment based on kinematic data can not be performed. To have robust object recognition there should be at least one more model for object recognition. Such a model could be based on e.g. ESM (electronic support measures) data. The models should be able to co-operate with each other, but also function independently, if only one type of data is available.

In [13] there is a general discussion on the use of kinematic data for target and mission recognition. For example, with the HMM approach information associated with important events may disappear. This happens if the object permanently changes motion pattern from abnormal to normal behavior. In the model there should be a procedure that can remember important motion patterns for the future. Moreover, observation sequences, or mission estimates, can be used for object track associations between platforms. If two platforms have the same observation sequence, or mission estimates, for an object, the platforms are probably observing the same object.

A mission can show different motion patterns in different environments. For example, an environment that includes an airport will show specific motion patterns associated with landing and take-off. To represent different behaviors of a mission in different environments, the model could consist of several sets of HMMs for one mission, where each set represents a specific environment.

3 Temporal information

3.1 Time and action

Time and action are closely a coupled pair because all management of actions, such as planning, execution, monitoring, validation and assessment takes time. In early phases of a combat situation is it important to assess threat or object class and if possible also object identification. In later phases it may be more important to have focus on hostile object actions.

Aspects of time in design of decision support system have earlier been introduced in [14] where the concept of time and action is introduced as an approach to threat assessment in the JDL model. In [15] the discussion about the temporal action concept is extended to involve fusion of temporal actions. Benefits with temporal data displays have been shown in BVR combat [16]. Team effectiveness or the ratio between number of hitting and number of launched missile, kill rate, was improved in a number of two versus many objects scenarios. Temporal design guidelines, with aim to improve effectiveness and safety have been proposed in [17].

Temporal descriptions of the environment could however be more precise and show better accuracy. If the temporal calculations could be enforced with hostile object class or identity, the precision in the temporal calculations would be higher. Object action capabilities and behavior during temporal restrictions can be detected and recognized and give additional information of object characteristics. Temporal descriptions of threat action capability can on the other hand be used as input feedback to the recognition process. Temporal representation facilitates also estimation of a threat rank list and a prioritized object value list.

3.2 Temporal display

A temporal display has been developed and evaluated in simulator tests [16]. The display is based on the temporal concept of time and action. Concentric circles on the display represent borders when own or hostile actions can or have to be executed. Object location on the display relates to the action capability, not to the spatial location. The object location on the display, Fig. 6 (down to the right), is determined by the following factors:

- Real bearing to the object
- Temporal distance related to action circles
- The real or tracked heading angle of the object

The temporal distance is a projection of hostile object action capability based on estimations of hostile object characteristics and tracked location. Until now has characteristics for the worst threat case been used in the algorithm. Recognition and identification of objects will result in higher quality and precision of the action capability data. This admits higher accuracy in the calculations of temporal action projections.

4 Simulations and results

In this example it is assumed that a radar sensor on a fighter aircraft detects three objects T1, T2 and T3. The simulations are performed using DF. It is assumed that the objects are observed during approximately 60 seconds.

4.1 Aerial-mission estimates

The HMMs produce mission estimates for each object, during 60 seconds. The results are presented in Figs. 3–5. In the figures Tr = transport, Ga = general aviation, Re = reconnaissance, Fi = fight and At = attack.

4.1.1 Mission estimates for object 1 (T1)

T1 moves at a constant speed of 260 m/s, at a constant altitude of 11000 meters, and in a straight line. It is assumed that this altitude and direction correspond to an airway for civil transport aircraft. The HMMs estimate T1 as a transport mission to the likelihood of 0.9, see Fig. 3. The other missions are given values well below 0.1. The estimates are stable over time. The stability indicates that speed and altitude observations from the object-tracking algorithm are not close to any limits in the observation diagram in Fig. 1. In such a case the HMM observations will not necessarily change because of small variations in speed and altitude.

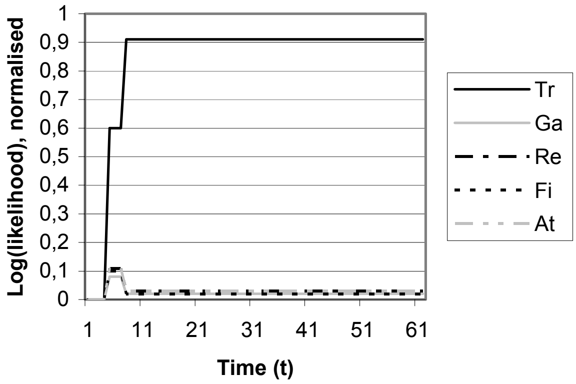

Fig. 3. Normalized likelihood for object T1

4.1.2 Mission estimates for object 2 (T2)

T2 moves at high speed. The speed changes from 520 to 560 m/s. The altitude changes from 10000 to 9000 meters. In the observation diagram there is a speed limit at 525 m/s and an altitude limit at 10000 meters. Consequently, T2 passes limits in the observation diagram.

The HMMs estimate T2 as a fight mission for almost the entire time period, see Fig. 4. The mission estimates vary continuously since the speed and altitude are close to the limits in the observation diagram. Small changes in speed and altitude lead to changes of HMM observations, and consequently changes of likelihood values.

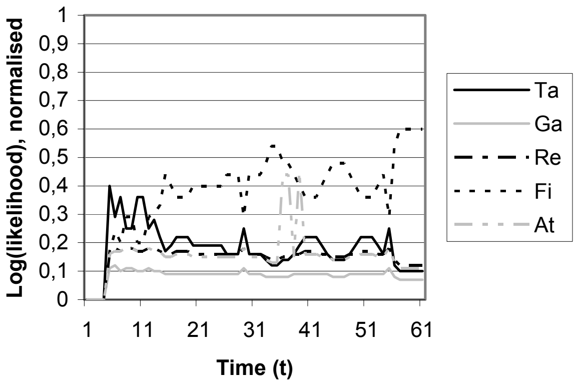

Fig. 4. Normalized likelihood for object T2

Initially the HMMs estimate T2 as performing a transport mission, since the object is at the altitude corresponding to a predefined airway. As time proceeds the object descends below 10000 meters, which is assumed to be the lower limit of the airway. At the same time the speed increases well above the limit of 525 m/s and the likelihood of a fight mission becomes more stable.

4.1.3 Mission estimates for object 3 (T3)

T3 moves at a constant speed of 260 m/s, at an altitude of 7000 meters, and in a non-straight line. The HMMs estimate T3 as a fight mission to a likelihood of nearly 0.4, see Fig. 5. The estimate is relatively stable, except for the time period in the middle when no estimates are produced. The other missions are estimated to approximately half the likelihood of the fight mission.

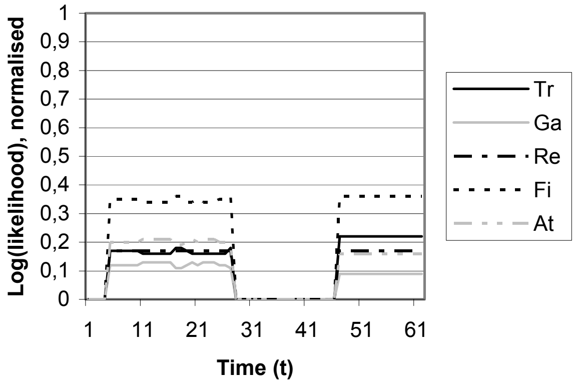

Fig. 5. Normalized likelihood for T3

During approximately 10 seconds the radar does not receive any observations. When the radar detects T3 again, it takes 5 seconds before the HMMs can produce mission estimates, since a sequence of 5 consecutive observations is the basis for the model.

4.1.4 The temporal display for T1, T2 and T3

Fig. 6 presents the operator interface in DF. The different displays show, for a certain point of time, the actual situation from different points of view. At this time, all objects are viewed by the sensor, according to the sensor indicator in Fig. 6 (the upper display to the right).

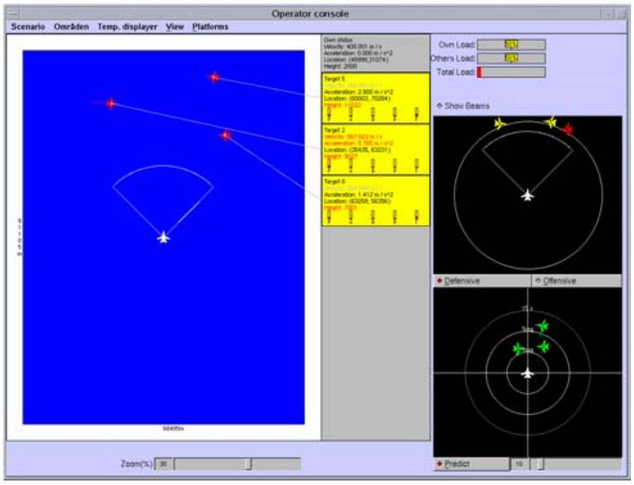

Fig. 6. Operator interface

The tactical indicator to the left in Fig. 6 describes the situation based on distances. The own platform is in the middle. The object that is farthest away from the own platform is T1. The object that is the second farthest away is T2 and the object that is closest is T3.

The temporal display in Fig. 6 (the lower display to the right) describes the situation based on temporal information. The own platform is placed in the middle. The inner circle area describes a situation where the own platform can not escape from a threatening object. The second circle area describes a situation where the own platform can escape. Hence the most threatening situation appears when the object enters the inner circle area.

T2 is, according to the temporal display, the most threatening object, despite the fact that T3 is closer to the own platform, according to the tactical indicator. In a temporal aspect, T2 is more threatening because it is at a higher altitude and moves with higher speed. Its possible weapon range will therefore be longer. Furthermore, T2 can reach the inner circle area in a shorter time.

T1 is at the time the least threatening object, since it moves with quite a low speed.

The bar charts between the displays in Fig. 6 show the normalized mission estimates for each of the three targets.

4.2 Temporal display and aerial-mission uncertainties

The section presents four ways for integrating mission estimates in the temporal display.

Fig. 7a represents the original display showing the same situation as in Fig. 6 (except for that the aircraft symbols have been replaced by dots). In the original display there is no information on object or mission type. It is assumed that all objects perform fight missions.

4.2.1 Continuous presentation – no thresholds

Fig. 7b represents a display that is assumed to show the most likely mission of each object, and the corresponding likelihood value. No thresholds for the likelihood values are assumed. As soon as the likelihood value changes, the display is updated.

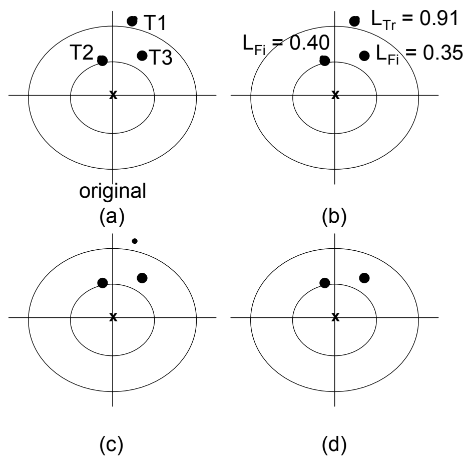

Fig. 7. Three ways of integrating mission estimates

4.2.3 Likelihood thresholds

Fig. 7c represents a display that presents mission estimates without presenting figures. Instead the object symbols change as the likelihood value passes a threshold. In this case there are two symbol categories; small symbols illustrate non-threatening missions and large symbols illustrate threatening missions. Initially it is assumed that the objects perform one of the two categories. If the likelihood for the other category exceeds a certain threshold, the object symbol is changed.

4.2.4 Objects excluded

Fig. 7d represents a display where non-threatening missions are excluded, since they are not a threat to the own platform. The amount of information is thereby reduced. If the likelihood for the non-threatening mission is reduced below the threshold, the object will appear on the display again.

4.2.5 Changes in temporal information

A fourth way of integrating mission estimates is to introduce in the temporal algorithm a set of temporal equations for each mission. Each mission will get specific time intervals for actions and events. Object performances and weapon ranges for military missions will decide the location of the object on the display. If an object is assumed to perform a fight mission it will be located closer to the own platform. If the same object is assumed to perform an attack or reconnaissance mission it will be located farther away from the own platform, if their weapons can be assumed to have shorter ranges than the weapons associated with the fight mission.

The procedure is illustrated in Fig. 8. Except for the objects in Fig. 7, a new object (T4) has been added for illustrating the procedure. T4 is assumed to perform an attack mission. Fig. 8a represents the original display. Fig. 8b shows the changes, as a result of a projection of mission estimates to a temporal representation. The additional temporal information is fused with the original temporal information. Fig. 8c shows the final display. The objects representing attack and transport missions have been moved farther away from the own platform, since they are assumed to be less threatening than a fight mission.

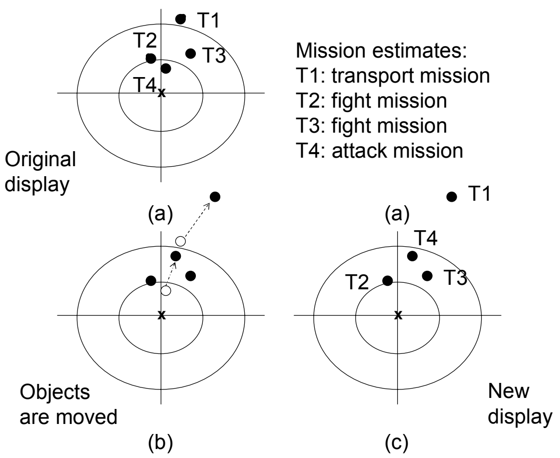

Fig. 8. A fourth way of integrating mission estimates

5 Discussion and conclusion

Mission recognition as well as situation and threat assessment are complicated processes that also include uncertainties, especially in high density environments.

The paper suggests a procedure that can improve situation awareness for a fighter pilot. By integrating mission estimates in a temporal display, the situation awareness for the pilot can be improved, compared to the situation awareness given by each algorithm separately.

Four ways of integrating mission estimates are briefly discussed. In the first example, likelihood values for the most likely mission of each object are presented to the operator, without thresholds. In this way, continuous changes can be looked at. The operator can see if the mission estimate is stable, alternatively unstable. The operator can thereby estimate mission uncertainties as well. On the other hand, it may be hard for the operator to follow the continuous changes of mission estimates, especially in cases with many objects.

The second example shows two mission categories, i.e. non-threatening and threatening missions. Likelihood thresholds are introduced. The display will show a more stable, but less detailed environment to the operator. The operator will not know the changes in mission estimates, unless the changes lead to a change of the most likely mission.

In the third example non-threatening objects are excluded from the display. In this way the amount of information is reduced. However, the uncertainty of the mission estimates need to be very small, since the operator will not pay any attention at all to objects that are considered as non-threatening.

If proper a priori data exist concerning possible missions and their possible weapon capacities, specific time intervals for each mission can be introduced**.** In this way the results from the HMMs are fully projected to a temporal representation. Consequently, a specific mission will be associated with specific time intervals for actions and events, relatively the own platform. Mission uncertainties need to be considered. Further more, what likelihood value should be the basis for applying a certain set of temporal equations? What type of mission should be assumed initially, a threatening or a non-threatening mission?

Sensor management can be performed at different levels in a sensor system [18]. On a lower system level sensor management is based on results from signal analysis. On a higher system level sensor management is often based on object prioritization, according to some criteria.

Object prioritization can be performed using the HMM algorithm, which can distinguish between different missions. On the other hand, the algorithm will not allow prioritization between objects within the same mission.

Object prioritization based on the temporal algorithm can be performed using the original temporal display. On the other hand, all objects are assumed to perform the same mission and prioritizing the objects in a correct way, without knowledge on object or mission type, may result in incorrect prioritization.

If mission estimates are integrated into the temporal display, object prioritization will hopefully be more correct. The best basis for object prioritization is probably given by the one presented in Sec. 4.2.5, where each mission is associated with a set of temporal equations.

If any of the other ways are applied, there is no projection of mission estimates to a temporal representation. The objects have the same locations as in the original display, but the object symbols are added with information on mission estimates.

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