Reasoning with uncertainty in the situational awareness of air targets

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***Abstract*— In combat simulations target classification and identification are very important. In this research area several studies about simulating identification have been done, most of them take a set of information like "the target is visually identified hostile" to start the simulation with. Mostly classification is not taken into account in identification problems.**

In this paper the input consists of basic sensor data and a priori knowledge. This will be combined into information which is necessary to evaluate the situation. Based on this information the complete situational awareness is evaluated.

To derive information out of data, facts have to be derived into three areas, these are facts concerning position, identity and behaviour. Based on these derived facts a decision will be made about the classification and the identification of the target.

Two Bayesian reasoning models were designed for the decision processes of the target's classification and identification. These models are designed as much alike as possible. An implementation was made to test the models. In the implementation temporal aspects are not taken into account but the results were promising.

To conclude we conducted a literature survey to investigate the possibilities of temporal reasoning in this project.

***Index Terms*— Classification, Identification, DBN, BBN, Reasoning, Dempster-Shafer, air targets.**

I. Introduction

On board a combat vessel a clear picture of all surrounding targets is essential. Therefore a team of experts evaluates all information gathered by sensors on board the vessel and data communication with allied forces. In the evaluation process they deal with a lot of uncertainty, this uncertainty has to be modeled [8] and [9]. Based on this information together with guidelines and rules supplied by the government (rules of engagement - ROE) a decision is made on several topics for each target. These topics are classification, identification and attack-decision evaluation. In the classification the target type is specified, in the identification the model determines whether the target is a friend or a foe.

In a combat it is of great importance to have a reliable classification and identification process. In this paper a classification and identification system is presented which is based on expert knowledge and strict rules and is tested using a modeled environment.

The complete system consists of three parts, first all necessary information is gathered, then as much facts as possible are derived and to conclude a decision is made for the classification and identification of the target based on the derived facts, using a Bayesian belief network [2]. These three parts are shown in Figure 2 and will be worked out in the following sections.

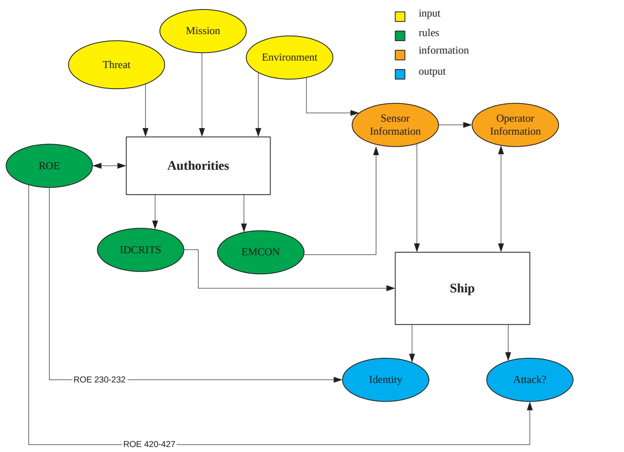

Fig. 1. Overview of the situation on board combat vessels

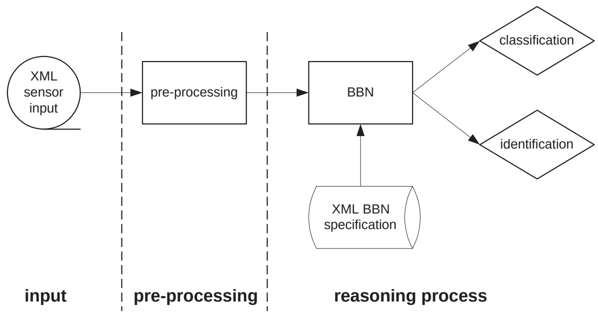

Fig. 2. Overview of the entire system

II. Input

The input is an XML file which contains for each target all available sensor data at different timepoints, together with a priori knowledge. This file is generated by a simulation developed in the STATOR project at the Royal Netherlands Naval College. This file contains information about:

- Target track;
- IFF on board?
- IFF mode;
- Vesta on board?
- Link 11 on board?
- ESM signature;
- Situational a priori information.

III. Pre-processing

In the real situation the decision making process is done by humans, they are experts in deriving facts from given information. In our model rules are necessary to do the same. Not all information which is necessary for the classification and identification of a target is directly given by the sensors. Sensors give basic information like the input given to this system.

We want to derive facts out of this basic input by combining this information in the right way together with a-priori knowledge. We want to divide these facts into three types, facts concerning position, facts concerning identity and facts concerning behaviour:

a) Concerning the position:

- Adherence to airlane
- Adherence to air co-ordination order(ACO);
- In military speed/altitude domain;
- Flying in formation;
- Manoeuvring;
- Inside identification safety range (ISR).

b) Concerning the identification:

- Visual identification friendly/hostile;
- ESM friendly/hostile;
- IFF.

c) Concerning behaviour evaluation:

- Hostile act;
- Hostile intent;
- Performs identification.

IV. Reasoning

The reasoning model is split up in two divisions, classification and identification. The modeling is done in two steps, first a global overview of the reasoning processes is given, followed by a detailed reasoning model using Bayesian belief networks.

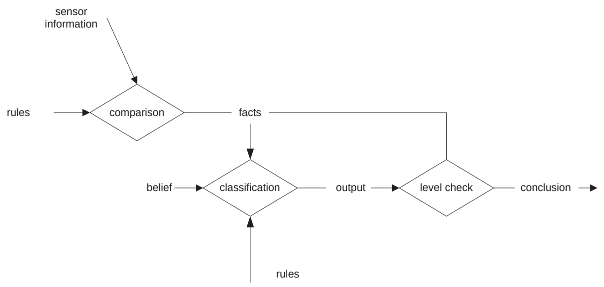

Fig. 3. An overview of the classification reasoning process

A. Classification

The classification is done in three layers using iterative deepening. This can be seen in Figure 5. First we determine if the target is most likely an air target or a surface target. If the probability of an air target is the highest we search in that branch of the tree and examine whether the target is a weapon or a weapon carrier. And finally we determine what kind of weapon or weapon carrier the target might be.

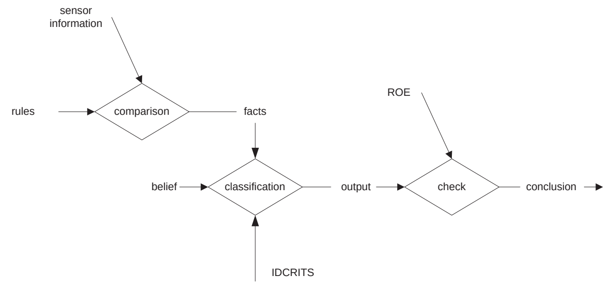

Fig. 4. An overview of the identification reasoning process

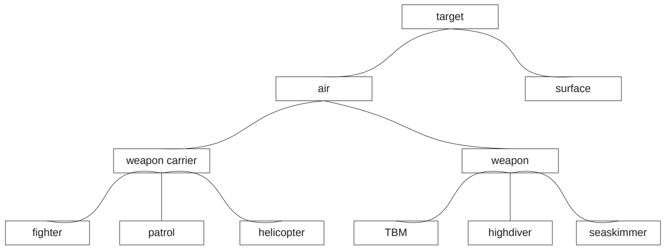

Fig. 5. Classification

The Bayesian belief networks for the different layers use facts that can be used to distinguish between the different groups. Information about these distinguishing features were gathered by interviewing experts at the OPSCHOOL (operational school). In Figures 6 one of the Bayesian belief networks for the first layer is given. The numbers displayed in the figures are gathered by interviewing several experts at the OPSCHOOL. The interviewed experts gave similar beliefs to the same relations, these answers were combined into the used values. The information is combined using *noisy and* and *noisy or* gates [6].

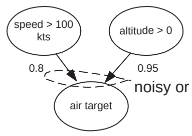

Fig. 6. Bayesian belief model of an air target

In Figure 6 we can see that the speed and altitude are distinguishing features for an air target. In Figure 7 we can see that more information is needed in the network to decide whether the target is a weapon carrier or a weapon, than to decide whether the target is an air or a surface target.

B. Identification

Identification is done similar to the classification process but we have just one layer with 6 mutually exclusive decisions. Before we have any information about the target we identify the target as unknown, this identity is kept until we receive enough information to identify the target with one of the following 5 identities. A target can get 3 real identifications:

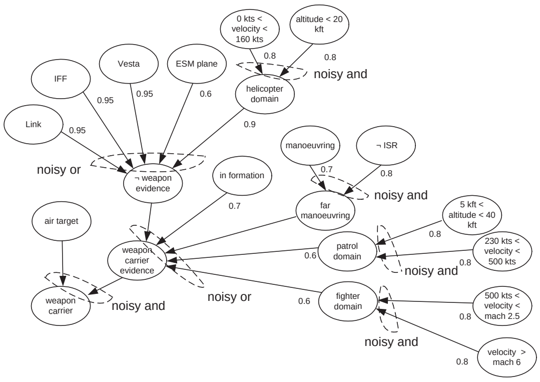

Fig. 7. Bayesian belief model of a weapon carrier

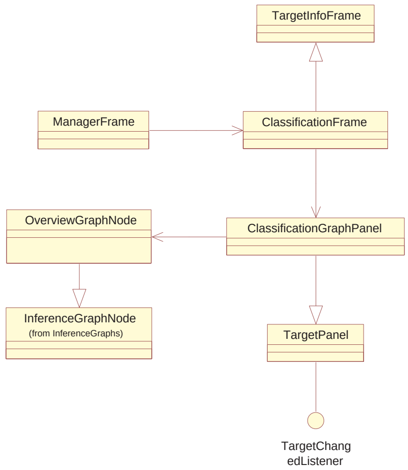

Fig. 9. Class diagram of the gui

friendly, neutral or hostile. But before we are able to identify the target definitely we can assign pending identities to the target: assumed friendly and suspect. In Figure 8 we see that a lot of information is needed to get an identity for a target. All facts in the figure reinforce the belief of the target being a suspect target.

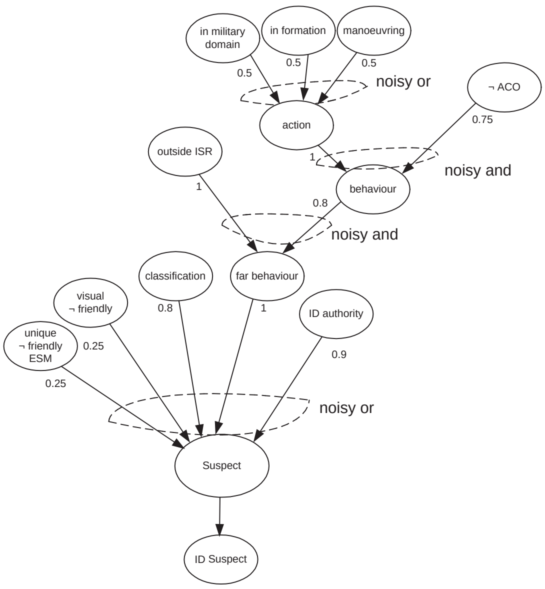

Fig. 8. Bayesian belief model of a suspect target

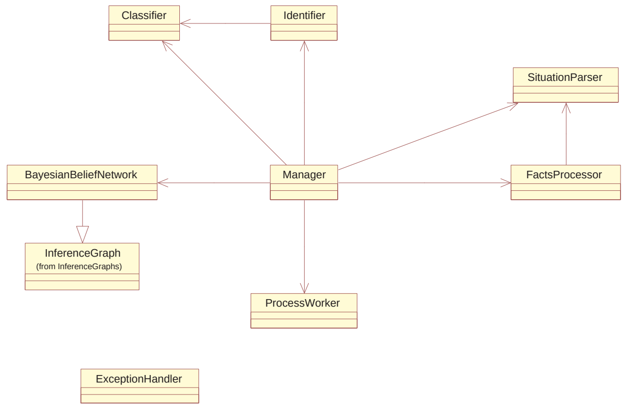

Fig. 10. Class diagram of the main model

V. System

Based on the set of rules and the reasoning models for the classification and identification the complete system was implemented using JAVA. The class diagrams of the user interface and the main model can be found in Figure 9 and 10.

A full class diagram may be difficult to interpret because it gives a lot of information about the contents of the classes from which the functionality of the class is not directly evident. Therefore a class diagram with empty classes is created. Also some Class, Responsibility and Collaboration (CRC) cards that describe the responsibilities of the classes in natural language have been created. These CRC-cards can be seen in Figures 11.

Now we know the overall structure of the system we take a new look at the input. The input is an XML file which contains all available information at different timepoints. In the Target Identification and Classification (TIC) program we implemented the rule base and the Bayesian belief networks. These are ordinary Bayesian belief models without a temporal aspect. The temporal aspects are discussed in the next section, but we first wanted to examine the models in a simple way and if they work the temporal relations can be added afterward. The program makes a decision for each timepoint independently based on the sensor data available at that timepoint. By looking at the decisions in time we might already see some temporal relations.

VI. Temporal aspects

There are a couple of processes in which temporal reasoning may offer additional information. These processes are:

- Getting sensor data;
- Deriving information;

Manager	
Responsibility	Collaborators
This class updates all the information about the target.	SituationParser FactsProcessor Classifier Identifier BayesianBeliefNetwork ProcessWorker

SituationParser	
Responsibility	Collaborators
This class parses all necessary values out of an XML file. Values that are not available are if possible replaced by initial values.	

FactsProcessor	
Responsibility	Collaborators
This class derives per target facts from the information gathered by the SituationParser.	BayesianBeliefNetwork SituationParser

ProcessWorker	
Responsibility	Collaborators
This class updates all nescessary information for the classification and indentification of the target.	Classifier Identifier ManagerFrame FactsProcessor

BayesianBeliefNetwork	
Responsibility	Collaborators
This class adds information to the Bayesian belief network and reads information out of the bayesian belief network.	InferenceGraphNode

Classifier	
Responsibility	Collaborators
This class combines all available influencing facts into a conclusion about the target's classification.	BayesianBeliefNetwork

Identifier	
Responsibility	Collaborators
This class combines all available influencing facts into a conclusion about the target's identification	BayesianBeliefNetwork Classifier

ManagerFrame	
Responsibility	Collaborators
This class manages all possible actions in the user interface.	Manager

InferenceGraphNode	
Responsibility	Collaborators
This class represents a node in the Bayesian belief network	

ExceptionHandler	
Responsibility	Collaborators
This class handles exceptions	

Fig. 11. The CRC cards

- Decision making.

The benefits and problems of temporal reasoning in these processes are evaluated.

First the sensor information, in a lot of civil situations it is obvious that sensor information will give information about the target. At an airport for example, the incoming planes would like the air traffic controller to know exactly what kind of plane is coming and in which position the plane is at the moment. Because there is a limited set of possible approaches to each landing strip we expect to see a pattern in the sensor readings. While the plane is coming closer more detailed information can be given and one of the approaches gets more probable in time. In military situations we expect a little different situation. In a military environment we expect very limited information about approaching targets. Hostile forces will try to give as little information as possible about themselves and sometimes try to give false information to mislead their opponents. Furthermore as long as we do not know what kind of target is approaching there are no strict rules about how the target will approach for example. So sensor readings will not be very predictable in time and temporal reasoning will not add much information in this process.

Second the process of deriving and combining information. As explained before sensor data can be used to obtain more detailed information. For example, the heading and speed of a target may be derived from positions of the target in time. Therefore we have to take a look at each derived fact and determine if it is possible to use temporal reasoning. Most of these facts are partially related in time, but others can't be evaluated at one timepoint, an example of such a fact is *manoeuvring*. It is obvious that we are not able to tell whether a target is moving according to one position. The partially temporal related facts become more certain when they occur often. Finally there are also some facts which can be derived from other facts in time, like the heading and speed can be derived from the positions of a target in time, but which can also be obtained directly from the sensor data. This means that these facts can also be derived if the sensors are malfunctioning or have been switched off.

The way a target moves (its behaviour) is the most distinctive feature between different sorts of targets. From the list above it shows that the behaviour of a target is time related, thus it may be useful to evaluate the behaviour in time.

Finally the decision making, the decision will get more reliable in time because there will be more information available when the target has been followed for some time or the target has come closer. The decision process will take care of the processing of this information into a proper decision, in which the process could take the decision at an earlier time point into account. In comparison to the benefits of temporal reasoning in the evaluation process the benefits in the decision process is expected to be quite small.

To model these temporal relations we could use dynamic Bayesian networks (DBN). DBN is a term which can be explained in many different ways.

1 Some say a dynamic Bayesian network is a network which is dynamic in time [7], so the actual structure of the network may change over time.
2 Others say a dynamic Bayesian network is a regular Bayesian network in which some nodes have connections to nodes in another timeslice [1] and [4], as depicted in Figure 12.
3 Some state that a dynamic Bayesian network is a regular Bayesian network where some nodes have a temporal character [5] see Figure 13.

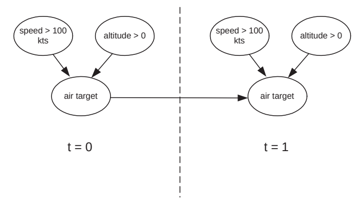

Fig. 12. An example of intertimeslice connections in a DBN

The last two explanations can directly be projected into our model. If we take another look at the first part of this section we learn that these two sorts of temporal relations are seen frequently. As an example of the first: if an altitude is measured once we can say that in the next time slice it is very well possible that the target has approximately the same altitude again and will still be an air target. As an example of the second temporal information like the target is manoeuvring is injected into a node.

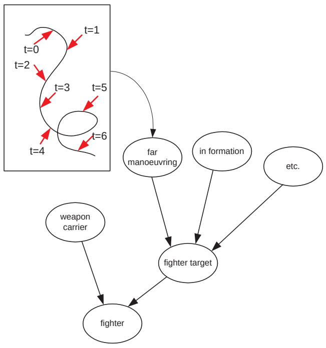

Fig. 13. An example of temporal input in a DBN

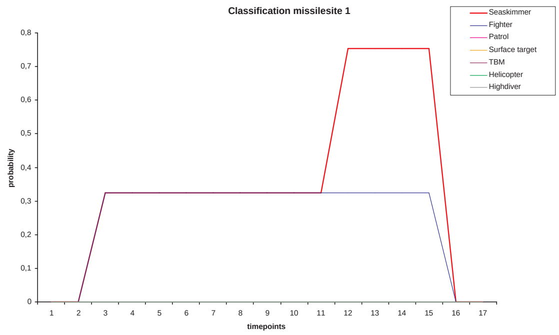

Fig. 14. The probability distribution over the possible decisions for missile site 1

VII. Results

The system was tested by executing a scenario in which a ship may encounter all sorts of targets in a way that has been designed to test the program, to see if the program produces good results and satisfies its requirements. The scenarios that were used are described in Section VII-A, after which the test results are given and explained in Section VII-B.

A. The test scenario

The model that was used in this test scenario was developed in the STATOR project at the Royal Netherlands Naval College. This program gives an XML file as output in which all information from the ship's sensors about targets in the neighbourhood are given.

In this scenario a ship sails a certain track in which some targets may approach the ship. In our scenario the ship first reaches a missile site which fires four sea skimming missiles, second the ship reaches a missile site which fires two sea skimming missiles with way points and in the end an airliner flies across the ship in an airlane. This will be split up in three separate scenario's.

B. The test results

1) Scenario 1: The ship reaches the first missile site and encounters four seaskimming missiles. In Figure 14 the probability distribution in time can be seen. Here the first of four missiles is approaching the ship. In the figure the evolution of evidence in time can be seen, first the sensors give information about the altitude and velocity of the target. For the range of altitude and velocity of this target there are two sorts of targets which are equally likely, namely a seaskimming missile and a fighter. The decision displayed will be *airtarget*, because the probability of *weapon* and *weapon carrier* are equally likely too. Some time later, the target switches its radar on. This new information makes it possible to decide that the target is probably a seaskimming missile.

2) Scenario 2: The ship reaches the second missile site and encounters two seaskimming missiles with waypoints in their track. In Figures 15 and 16 the probability distribution in time can be seen. The difference between these two figures is the database used to determine what platform may use the detected radar. In the first figure the radar is thought to be of a seaskimming missile, in the second figure the radar is thought to be of a highdiving missile. In the last case there is some conflicting evidence, the target is moving with a velocity and in the altitude range of a seaskimming missile but regarding the radar it could be a highdiving missile.

In these figures we see first two pop ups before we continuously detect the target, that is because of the sort of radar which is used. In this scenario we have a priori knowledge about the position of a missile site along the track. We expect a threat out of that direction and use a special radar to check for a longer range with smaller bundle in that direction once in a while. So we are able to detect the missiles before they enter our air surveillance radar range.

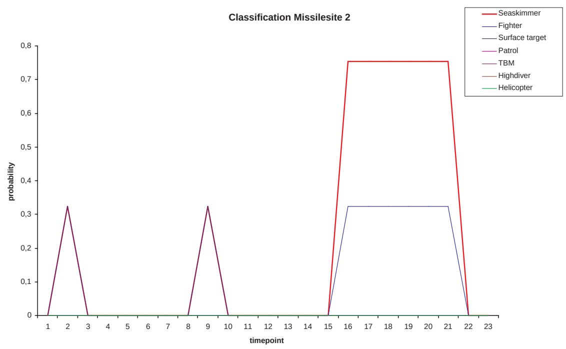

Fig. 15. The probability distribution over the possible decisions for missile site 2

3) Scenario 3: The ship encounters an airliner which is flying in an airlane. The classification of this target can be seen in Figure 17. This aircraft transmits an IFF signal in mode 3. This makes us able to identify the target this can be seen in Figure 18. In the first two scenario's we see no identification figures, because we are not able to identify a target based on velocity and altitude only.

VIII. Evaluation of the test results

During the execution of the test scenario's we realised that the TIC program was able to classify most of the targets correctly if there was enough information available. First we tested the program using the velocity, altitude and heading of each target. We saw that the program was not able to make

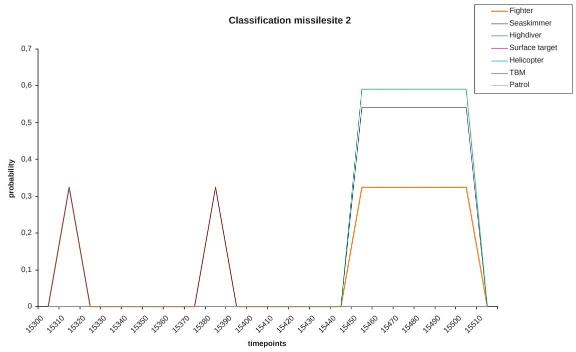

Fig. 16. The probability distribution over the possible decisions for missile site 2 with conflicting evidence

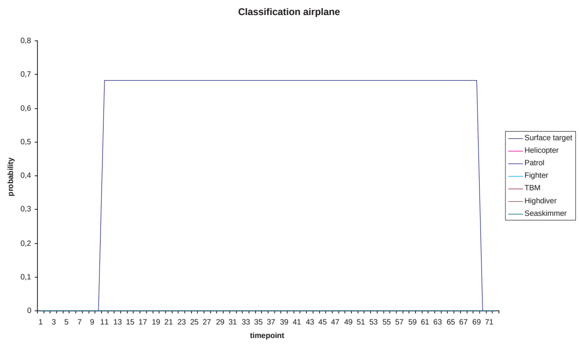

Fig. 17. The probability distribution over the possible classification decisions for the airplane

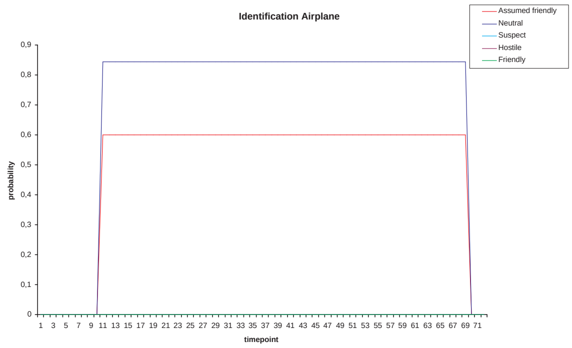

Fig. 18. The probability distribution over the possible identification decisions for the airplane

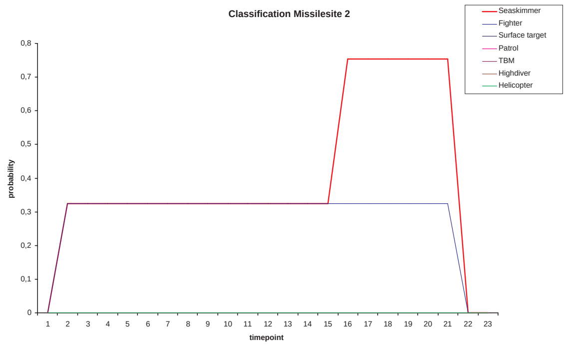

Fig. 19. The probability distribution over the possible decisions for missile site 2 with temporal relations

a correct decision. Because the velocity and altitude domain of a fighter and a seaskimming missile are almost identical, the probabilities of both options become equal. The program decides with a maximum likelihood theorem, and then displays the decision *air target*, because that is the only thing that is certain. If the program gets some more specific information like a radar that switches on during the approach the program becomes able to draw the right conclusion. The same can be seen in the third scenario, the airliner has a slightly higher velocity than we would expect of a patrol aircraft so the probability stays quite low. The decision is made based on the ESM signature which is obviously a civil one.

It became clear that the identification needs more information than the classification to make a good decision. This could be directly deduced from the BBN. Therefore we only see a proper identification in the third scenario. In that case we have an IFF transmission and we know the target is flying in an airlane and we have an ESM signature of the target which is obviously a civil one. This leads to a *neutral* identity, because of the IFF mode 3 we see a lower probability for an *assumed friendly* identity.

In the second scenario a number of situations occur where temporal reasoning could improve the results. We already discussed the first two peaks, but if we add the temporal relation that the belief is kept if no contradicting new information is received, the figure would look smoother, we expect the figure to look like Figure 19 in stead of Figure 20.

IX. Conclusion

This paper shows that it is possible to design and implement a model that is able to make a decision about the classification and identification of an air target based on sensor data in a maritime environment.

To improve the simulated decision process better knowledge about the way classification and identification is done on board combat vessels was necessary; this knowledge was gathered at the OPSCHOOL. Further information about how to model uncertainty was very important. A global study of the most common approaches showed Dempster-Shafer and Bayesian belief networks were promising possibilities. A deeper study into these two theorems showed Bayesian Belief Networks best for this problem. Finally a study was done to investigate the possibilities of temporal reasoning in the model. The most commonly used methods were investigated and Dynamic Bayesian networks showed to be useful for this model.

To design reliable Bayesian belief networks expert knowledge was necessary, which was again gathered at the OPSCHOOL. Based on this knowledge a system is designed which can be split into two complementing parts: the classification and the identification.

The Bayesian belief models were implemented using JAVA. In this implementation the temporal aspect is not taken into account. To test the models some challenging scenario's were carried out. These tests show that for a proper classification of the target more information is needed than the velocity

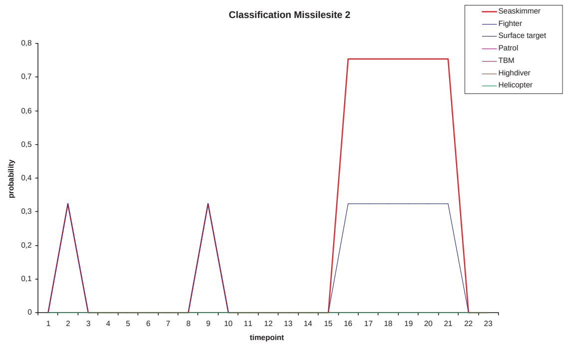

Fig. 20. The probability distribution over the possible decisions for missile site 2 without temporal relations

and the altitude of the target. For the identification of a target even more complex information is needed about the target's behaviour. These tests showed that temporal reasoning may have a smoothing effect on the decision.

It is important to build a prototype which takes the temporal aspects into account and to perform tests to determine the real benefits of temporal reasoning.

This model may be used in several applications:

- In a naval combat simulation;
- In a threat evaluation program;
- As a decision support system on board combat vessels.

For this last application some changes have to take place in the situation on board combat vessels. Most operators do not trust automatic systems. This model should be used as a support to make the right decision, not to make decisions on its own. But before the system is ready to be used in such a critical environment a lot of tests should be done to guarantee the reliability. In some cases the model might need some fine tuning.

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