Detection of Hostile Aircraft Behaviors using Dynamic Bayesian Networks

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Abstract—Aircraft Combat Survivability in military air operations is concerned with survival of the own aircraft. This entails analysis of information, detection and estimation of threats, and the implementation of actions to counteract detected threats. Beyond visual range weapons can today be fired from one hundred kilometers away, making them difficult to detect and track. One approach for providing early warnings of such threats is to analyze the kinematic behavior of enemy aircraft in order to detect situations that may point to malicious intent. In this paper we investigate the use of dynamic Bayesian networks for detecting hostile aircraft behaviors.

Keywords—threat assessment, situation detection, situation recognition, behavior recognition, behavior detection.

I. INTRODUCTION

There are three main objectives for pilots in military air operations: (1) flight safety, (2) combat survival, and (3) mission accomplishment [1]. Flight safety is concerned with flying the airplane safely and involves monitoring e.g. weather, fuel level and other aircraft in the airspace, combat survival is concerned with not being shot down by e.g. enemy aircraft and enemy air defense, and mission accomplishment is concerned with carrying out the present mission, e.g. protection of assets, weapon delivery and reconnaissance [2]. These goals often stand in conflict with each other; fulfillment of the mission may lower combat survivability due to larger exposure to risks. Weighting between these goals can vary and in critical missions pilots may take larger risks thus decreasing combat survival while in less critical missions survival takes precedence. Maximum combat survival would be achieved by not flying at all. This is however not the goal, but rather, the goal is increased combat survivability while still allowing for mission accomplishment [2]. To increase combat survivability, a fighter pilot actively tries to avoid or counteract threats.

Threats in air combat can be defined as elements designed to inflict damaging effects, force undesirable maneuvers or degrade system effectiveness [3]. Two main types of threats that can affect the combat survivability of an aircraft can be discerned: enemy ground and sea based firing units and enemy fighter aircraft [4]. During e.g. reconnaissance missions, a pilot may be exposed to enemy air defense operating from either fixed locations or from mobile units. Information regarding these types of threats may be received through e.g. surveillance and intelligence information. Although enemy air defense may be mobile, they are relatively slow and can generally be avoided through navigation [4]. Undetected/unknown threats on the ground are however more complicated and may need advanced sensing technology, new analysis algorithms and additional intelligence information. In contrast to ground-based threats, enemy fighter aircraft are highly dynamic and cannot generally be avoided by changes in route [4]. They can however often be detected with the aircraft’s sensors systems or be made aware of through information received over link. Although both types of threats are important to consider, this paper focuses on threats in the air, i.e. threats posed by enemy aircraft.

Combat in the air domain is broadly divided in two categories, within visual range (WVR) combat and beyond visual range (BVR) combat [5]. In WVR combat opposing aircraft are within the visibility range of the pilots, and historically, WVR combat and regular guns have been the prevailing situation from the first world war until the 1980s [6]. In BVR combat, pilots are required to rely on sensors for detecting enemy aircraft and inferring the level of threat they pose. The threat of an enemy aircraft can be determined as a combination of two parameters: intent and capability [7] [8], where capability can be defined as an opposing agent’s ability to inflict injury or damage, and intent can be defined as the will or determination of an opposing agent to do so [8]. The capability of an enemy involves identifying the opposing platform and from this inferring its capabilities in relation to the own platform [7]. Intent on the other hand can usually not be observed directly and involves reasoning around the future behavior of the enemy platform based on signs that the enemy is carrying out specific actions or is involved in specific behavior [7].

Modern BVR missiles can be fired from very far away, more than 100km, and at such distances it can be very hard to detect them directly with the onboard sensors systems. To get early warnings of such threats, enemy behavior can be analyzed to possibly infer threatening behavior coupled to e.g. the action of firing long-range air-to-air missiles. Such behaviors can consist of e.g. a set of maneuvers that in relation to each other constitute a threatening behavior. An example of a complex situation from the air defense domain includes the hump

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dive attack [9]. In this situation, a bomb plane in its deployment phase approaches its destination, rises to a high altitude, starts to dive in an attack vector towards the target on the ground, it releases its bombs, and then makes evasive maneuvers. One reason for carrying out such an attack is to maximize the kinematic energy of the weapon, directed towards the target on the ground. Recognition of the hump dive attack is an example of detection of threats by reasoning around enemy intent, and it has been addressed using e.g. fuzzy inference [10].

Similarly to recognizing the hump dive attack, early warnings of long range air-to-air missiles can possibly be achieved by recognizing complex behavior expressed by enemy aircraft. This is essentially a situation recognition problem where a set of constraints are put on a domain of situations defined by a number of relations and objects in a universe of interest, in order to recognize situations of interest [11] [12]. Situations of interest may evolve over time and constraints may thus also need to be defined as a partial temporal order on relations. In its essence we need to define a number of relations that in sequence or in parallel define a situation type that is of interest and then try to identify instances of this situation type in an incoming stream of data.

A. Related work

The problem of recognizing complex patterns has been addressed using both deterministic and probabilistic methods. Deterministic approaches include the work of Dousson et al. [13] who presented an approach based on propositional reified logic and temporal constraint propagation for addressing the situation recognition problem within environment surveillance. In later work [14] [15] the focus shifted to recognizing chronicles in network surveillance applications and the terminology was changed accordingly to chronicle recognition. The use of chronicle recognition has also been investigated in air scenarios [16]. Also related is the work of Walzer [17] [18], who use a rule based approach for complex event recognition. In that work, the rete algorithm [19] is extended to allow for temporal constraints to be modeled using rules. The use of a rule-based approach has also been proposed for recognition of behaviors in maritime surveillance applications [20]. Deterministic recognition of complex behaviors has also been addressed using Petri nets, for e.g. complex event recognition in video surveillance [21] [22], for modeling plan and activity prototypes in automated scene recognition [23], and for multi agent activity recognition in basketball games [24]. Petri nets have also been investigated for situation recognition in surveillance scenarios [25] [12]. A main difference compared to the present work is that we here also focus on coping with uncertainty, something of high importance in the surveillance domain.

Probabilistic approaches for detecting complex behaviors include the work of Meyer-Delius et al., who use hidden Markov models (HMMs) and dynamic Bayesian networks (DBNs) in their work on recognizing situations in e.g. intelligent driving assistants [26] [27]. HMMs have also been used for dynamic behavior modeling in [28]. Also related is work using Markov random fields for e.g. doctrinal intent inference [29]. The use of Bayesian networks (BNs) is also popular in the surveillance domain, e.g. for detecting insider threats in information systems and terrorist threats in homeland security applications [30] [31], and for signature based detection of interesting maritime situations [32]. Highly related is also work on using and constructing DBNs for recognition in a variety of different scenarios [33] [34] [35]. Besides the use of graphical models recognition of interesting situations has also been addressed using fuzzy inference [10] and temporal fuzzy logic.

Work on threat evaluation in ground based air defense situations is also something that is related to this work. In threat evaluation, the objective is to estimate the level of threat that individual (enemy) objects pose to one's own defended assets [8]. Formally, a function is needed which maps each pair of defended asset and detected enemy object to a threat value that denotes the level of threat that the object is considered to pose to the asset [36]. The threat evaluation problem has been addressed using e.g. rule-based systems [37] [38], BNs [39] [36] [40], evidential networks [41], DBNs [42] [43] and fuzzy logic [44] [45] [46]. A main difference compared with this work, is that we here focus on explicitly representing specific situations that evolve over time.

B. Problem

The problem addressed in this paper is that of intent inference based on recognition of aircraft behavior that plays out over time. Early warnings of imminent threats can possibly be provided in this way. A number of requirements are identified.

- There can be many different types of situations of interest and there is thus an interest in making use of general methods for describing situations at an abstract level.
- Interesting situations can play out over time. This indicates that situations preferably are modeled using a representation in which temporal relations can be modeled.
- Sensors systems are seldom able to present a perfect view of the surrounding world and there is thus a need of coping with uncertain data. Moreover, there is also uncertainty related to the actual modeling of interesting behaviors.
- It is of interest to continuously get estimates that represent a likelihood, or similar, that an interesting situation is taking place, compared with waiting until the complete pattern has been recognized.

Probabilistic inference using DBNs seem to be a suitable choice, since they provide a general way of conceptualizing interesting situations, they allow for temporal causal relations to be modeled and they allow for uncertainty to be managed. In this paper we investigate the use of a DBN for recognizing one type of interesting situation in a BVR air combat scenario.

C. Outline

The rest of this paper is organized as follows. Section II provides preliminaries regarding BNs and DBNs. Section III presents a case of an interesting situation, a proposal for how it can be broken down into discrete variables, and for how it can be detected using a DBN. Section IV presents initial experimental results when attempting to detect the interesting situation using the proposed mechanism. Finally, section V concludes the paper and discusses future work.
A. Bayesian networks

In probability theory a domain of interest is modeled using a set of random variables \( X \) where each has a domain of values it can be assigned. A probability distribution \( P(x_i) \) is defined for every variable \( x_i \) in \( X \). A probability distribution is in the discrete case simply a vector, consisting of probabilities for every possible value in the domain of the variable, whose values sum to 1. Joint probability distributions can be formed for every subset of variables, e.g. \( P(x_1, x_2) \) denotes the joint probability distribution for the variables \( x_1 \) and \( x_2 \), and consist of a probability value for every combination of values that the variables in the distribution can take on. The complete model is described using a full joint probability distribution, i.e. a joint probability distribution consisting of all the variables in the domain, i.e. \( P(x_1, ..., x_{|X|}) \). Given the full joint probability distribution it is possible to calculate the probability for every possible combination of variables and outcomes by summing the corresponding probabilities. Probabilistic inference allows the calculation of posterior probabilities of variables given the full joint probability distribution and observed evidence. Using the full joint probability distribution for inference quickly becomes intractable as the number of random variables increase. Moreover, it is also unnatural and difficult to define the full joint probability distribution in its entirety [47].

A BN [48] enables for a compact representation of a full joint probability distribution. A BN is a directed acyclic graph (DAG), where nodes represent random variables and where edges denote conditional dependence between variables. For each node, a joint probability distribution is formed together with its direct ancestors. These joint probability distributions are referred to as conditional probability tables. BNs can be seen as representing cause and effect relations amongst nodes, and given evidence for some variables that have been observed, the posterior probability distributions for other variables can be determined. Variables that can be observed are often referred to as information variables while unobservable variables are referred to as hypothesis variables. Figure 1 illustrates an example of a simple BN.

The example depicts five random variables for reasoning around the causes of an alarm, e.g. was it raised due to a burglary or due to an earthquake. The available information is who of your two neighbors that called in the alarm. One of the main strengths of probabilistic approaches is that they allow for reasoning and inference with uncertain and incomplete data. BNs do however not allow for modeling temporal dynamics.

II. BACKGROUND

A. The interesting situation

A typical BVR air-to-air missile launch can be divided into three phases, denoted A, B and C in figure 3. The purpose of the first phase (A) is to move the launching aircraft (a/c) to be within weapon range with respect to its target. The range of the weapon is highly dependent on the velocity of the carrier. Therefore, to maximize weapon range the velocity of the launching a/c must be aligned, at least horizontally, with line-of-sight to hit point. The hit point is where the target will be located when the missile arrives. The next phase (B) begins shortly after launching the missile. During this phase the launching a/c turns to decrease the opponent’s weapon range while maintaining radar to missile data link communication. It is important to uphold communication with the missile to continuously transmit target data since the missile is not capable at this distance to track the target by itself. The field of view of the radar sets the limit for how large the bank angle can be during the turn. The last phase (C) starts when the heading has changed to such a degree that radar field of view limit is reached. Turning more would yield loss of radar to missile communication.

B. Dynamic Bayesian networks

A DBN [49] on the other hand allows for modeling dynamic systems. DBNs are a generalization of HMMs and BNs which allows for causal time dependencies to be modeled. In a DBN a set of time slices is depicted. In addition to conditional dependencies to other nodes in the same time slice, nodes are in DBNs also able to have dependencies to nodes in previous time slices (not necessarily restricted to only the previous time slice). Figure 2 illustrates an example of a simple DBN, where the mobility of a road is modeled. The mobility is affected by the type of road and on the weather, and the mobility affects the average speed on the road. Continuous raining over several time steps may have a different effect on mobility compared to only a shorter period of rain. Such aspects can be captured using DBNs.

Fig. 2. Illustration of a simple DBN modelling the mobility on roads (adapted from [50]).

III. THE GIMBAL TURN

A. The interesting situation

A typical BVR air-to-air missile launch can be divided into three phases, denoted A, B and C in figure 3. The purpose of the first phase (A) is to move the launching aircraft (a/c) to be within weapon range with respect to its target. The range of the weapon is highly dependent on the velocity of the carrier. Therefore, to maximize weapon range the velocity of the launching a/c must be aligned, at least horizontally, with line-of-sight to hit point. The hit point is where the target will be located when the missile arrives. The next phase (B) begins shortly after launching the missile. During this phase the launching a/c turns to decrease the opponent’s weapon range while maintaining radar to missile data link communication. It is important to uphold communication with the missile to continuously transmit target data since the missile is not capable at this distance to track the target by itself. The field of view of the radar sets the limit for how large the bank angle can be during the turn. The last phase (C) starts when the heading has changed to such a degree that radar field of view limit is reached. Turning more would yield loss of radar to missile communication.
To recapitulate, the interesting situation is described using three phases with respect to the enemy a/c: (A) move into firing position, (B) turn to minimize the opponent’s weapon range with respect to the own a/c while still keeping both target and missile in radar cover, and (C), guidance of missile. To model this situation using a DBN, three tasks need to be carried out: (1) define which random variables to use, (2) define a DBN which represents the interesting situation (graphical structure as well as conditional probability tables), and (3) define how the random variables are extracted from available data (our own position and radar track data of the enemy aircraft). In the following, these three tasks are carried out, starting with task 1 and 3 in section III.B, to then define the DBN (task 2) in section III.C.

B. Random variables and discretization

Two criteria can be put on the first phase of the situation: the enemy aircraft should have the target within its missile range and the enemy aircraft should have a future interception point with the target close to zero, but based on the velocity of the weapon. In the present case, weapon range is considered to be 100km. The condition for having the target within missile range can thus be calculated as the Euclidean distance between the enemy aircraft and the target (the own a/c). A random variable can be constructed for this, named $\text{WithinWeaponRange (WWR)}$ and it has a Boolean domain and can be defined as:

$$\text{WWR} = \begin{cases} \text{True} & \text{dist}(S,T) < 100000 \\ \text{False} & \text{otherwise} \end{cases},$$

where $\text{dist}(x,y)$ is the Euclidean distance between two objects $x$ and $y$, $S$ denotes the own a/c, and $T$ denotes the enemy platform.

The second criterion in the first phase is that a weapon fired from the present position of the enemy a/c should have a future interception point with the target close to zero, but based on the velocity of the weapon. In the present case, weapon range is considered to be 100km. The condition for having the target within missile range can thus be calculated as the Euclidean distance between the enemy aircraft and the target (the own a/c). A random variable can be constructed for this, named $\text{WithinWeaponRange (WWR)}$ and it has a Boolean domain and can be defined as:

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The second criterion in the first phase is that a weapon fired from the present position of the enemy a/c should have future interception point with us. An important proximity parameter often used within threat evaluation applications is the closest point of approach (CPA) measure [51] [52]. CPA denotes a future point where two objects in a Euclidean space are closest to each other given their present positions and velocities. The CPA metric is illustrated in figure 4.

A closely related parameter is the time until CPA, TCPA. A third related parameter is the distance at CPA (DCPA). This parameter denotes the distance between the two objects at their CPA given their present positions and that they keep their present velocities. Let $v_r$ be the relative velocity of two objects (our velocity subtracted from the velocity of the enemy), then TCPA can be calculated as

$$\text{TCPA} = \begin{cases} \frac{p_2 - p_1 - v_r \cdot t}{|v_r|} & v_r \cdot v_r > 0 \land |v_r| > 0 \\ \infty & \text{otherwise} \end{cases},$$

where $p_1$ is our position and $p_2$ is the position of the enemy. Given CPA, DCPA can be calculated using as the Euclidean distance of the two objects’ future positions given their present positions and velocities, as

$$\text{DCPA} = \text{dist}(p_1 + v_1 \text{TCPA}, p_2 + v_2 \text{TCPA}).$$

As stated, we are interested in knowing a future interception distance between us and a weapon fired from the enemy platform. This can be calculated by normalizing the velocity of the enemy platform and then multiplying with the assumed weapon speed. We define a random variable, $\text{WeaponInterceptionDistance (WID)}$ as

$$\text{WID} = \begin{cases} \text{Short} & \text{DCPA} < 500 \\ \text{Medium} & \text{DCPA} < 5000 \\ \text{Large} & \text{otherwise} \end{cases},$$

where DCPA is calculated using equation (3), but with the speed of the assumed weapon instead of the speed of the enemy platform.

Measuring if an assumed fired weapon is within radar coverage is difficult. This involves, for every possible firing location, projecting the position of the missile and then calculating the relative angle from the platforms heading to a vector formed from the platforms position and the projected weapon position. For a single consecutive update, the calculation can be carried out as illustrated in figure 5.
However, if the platform continues to turn over a number of consecutive updates, then we need to, as stated, take into account multiple possible firing locations and the present location. Although this could be used to calculate if a possibly fired weapon is within radar coverage, it is not feasible since it requires probability calculations external to the DBN. In this initial study we therefore consider a missile to be within coverage in case we are in coverage of the enemy a/c, which is the second requirement in the guidance phase.

The second requirement in the guidance phase is that our a/c should be in the radar coverage of the enemy a/c. In case this is not true, then it is not possible to guide a missile towards our location. A parameter describing if we are in the coverage of the enemy radar can be calculated as the relative angle ($RA$) between a vector created from the enemy position and our position, subtracted from the heading of the enemy, as

$$RA = \cos^{-1}(p_2 - p_1 \cdot v),$$

(5)

where $p_1$ is our position, $p_2$ is the position of the enemy and where $v$ is the velocity of the enemy. Based on the relative angle, a random variable $InRadarCoverage (IRC)$ can be defined as

$$IRC = \begin{cases} 
    \text{Inside} & RA < 45 \\
    \text{OnEdge} & 45 \leq RA \leq 65 \\
    \text{Outside} & \text{otherwise}
\end{cases}$$

(6)

It is also the case that not all types of aircraft are able to carry all types of weapons, or even have the capability of guiding them. Another important parameter is thus the type of platform of the target. Moreover, this observation is also true regarding different kinds of long-range air-to-air weapons, as well as the actual capabilities of the radar systems on different platforms.

C. Detection using DBN

In the previous section we defined three information variables, i.e., variables for which we can gather evidence: $WithinWeaponRange$, $WeaponInterceptionDistance$, and $InRadarCoverage$. In addition to this, two suitable hidden variables have also been identified: $MissileLaunched$ and $MissileInAir$. $MissileInAir$ is our main hypothesis variable. This is what we want to calculate the likelihood of since it indicates the probability of the situation taking place. The $MissileLaunched$ variable is used for separation of the different phases. As it turns out, we actually do not have to model the third phase explicitly, since it is captured by the domains of the random variables that have already been defined.

A missile is only assumed to be launched when the enemy has the friendly platform within weapon range and when the projected distance at closest point of weapon approach is close to zero. Thus, if a missile has been launched, these variables are true and low, respectively, and two dependencies can be created. Moreover, a long range missile cannot be fired from all types of platforms, yielding yet another dependency. Moreover, if a missile is in the air, then it needs to have been launched, yet another dependency. If a missile is being guided, then the enemy a/c needs to have us and the weapon that is guided within its radar cover. Optimally a little short of the radar edge so as to maximize the future distance towards us, but still keeping safe from losing our track. The graphical structure of a DBN can now be designed. This is illustrated in figure 6.

IV. EXPERIMENTAL RESULTS

A. Experimental setup

Two situations have been simulated using Matlab, one in which the interesting behavior occurs and another where only parts of the interesting situation occurs. The two situations are 90 seconds long and they are illustrated in figure 7.
Two experiments have been carried out using the two simulated scenarios. In the first experiment, the simulated data for the two situations is used directly as input to the discretization system (written in Java). The output from the discretization has been used as input to the DBN which has been defined using Geenie [53]. The likelihood of $MissileInAir$ given the data has been calculated. In the second experiment, the simulated data is not used directly as input to the discretization step. Instead, a measurement model which adds noise has been applied on the data. The noisy measurements are then used as input to the discretization, whose output is used in Geenie to calculate the likelihood of $MissileInAir$ data, as in the first experiment.

B. Detection using ground truth data

The result of the first part of the first experiment is shown in figure 8. Here the DBN is applied on the simulated situation.

As can be seen in the figure, the first indication of the situation taking place occurs at around time 16. At this point the likelihood rises a little. After this it however drops for a while. This is possibly connected to the phase where the enemy a/c starts turning away. Due to the CPTs that have been used, this is what is promoted. Around time 20, the likelihood rises drastically. The probability of missile in air is thus considered high. The second part of the first experiment consisted in applying the DBN on the non-gimbal turn situation, figure 9.

The likelihood behaves similarly to the true gimbal turn however; at around time 55 the likelihood drops drastically. This is where the enemy a/c in the simulated scenario turns too much. It does not have radar coverage with our a/c anymore.

C. Detection with noisy data

In the second set of experiment, a measurement model has been applied on the simulated data before feeding it to discretization and recognition. The results of applied the DBN on noisy data from the true situation are shown in figure 10.

As can be seen in the figure, the likelihood estimate is similar to the case without noise. It can be seen that the noise affects the shape of the curve. Between time 50 and 80 the likelihood varies to some extent. However, noise also appears to eliminate the drop in likelihood between time 19 and 24. The
results show that the DBN is able to handle noise to some extent. Around time 40, however, the likelihood starts to drop a little. Perhaps the probabilities in the CPTs affected by the inside radar cover needs to be adapted. Lastly, the second part of the second experiment involves using the DBN on noisy data from a situation that does not represent the air-to-air missile guidance situation. The results are shown in figure 11.

As seen in the figure, initially the curve is similar to that of the true turn. However, at around time 20, the increase in likelihood is not as large as for the true turn, and at around time 65 the likelihood drops. There is also a drastic drop around time 30. This is however quickly recovered. As it seems, the DBN actually better separates the gimbal turn from the other situation when noise is present. When applied on the noise free data the two curves are very similar until the point when the enemy a/c over turns. In the noisy data, however, there is a clear difference from time 20 and onwards.

V. CONCLUSION

The ability of getting early warnings could mean the difference between life and death in BVR air combat situations. If an enemy missile is left undetected for too long, its chance of reaching our no-escape zone is increased. Early warnings of such threats can be important for carrying out evasive maneuvers sooner, possibly increasing combat survivability. In this paper we have investigated the use of DBNs for inferring enemy intent with regards to one type of interesting air situation, the gimbal turn.

Our initial results have shown that DBNs can be used for successfully recognizing interesting air-to-air combat situations. However, it is necessary to carry out more experiments in order to understand how the technique is affected by noisy data. Our future work thus includes continuing our investigations into the task of recognizing interesting situations in the air domain. In this paper we have used crisp border for discretization of the random variables used in the DBN. One way of possibly coping better with the uncertain data is to not use crisp border. Future work thus also includes investigating this. Finally, in this paper we have not at all regarded uncertainty with respect to the modeled situation. This is important too.

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