Sequential Bayesian Classification Decisions for Mobile Sensors

Baro Hyun, Pierre Kabamba, Weilin Wang, and Anouck Girard

Abstract—This work is motivated by the U.S. Air Forces Intelligence, Surveillance and Reconnaissance (ISR) mission, where an Unmanned Aerial Vehicle (UAV), or an agent, is to fly over a number of unidentified objects within a given search area, collect information using onboard sensors, and classify the objects. The problem is challenging because the mission time is limited, the agent is only provided with partial a priori information, and the amount of information that the sensor can measure is dependent on the range and the azimuth of the explorer with respect to the object. A sequential decision problem (path planning) is posed that incorporates the potential loss of the classification outcome that is made by an autonomous moving agent. The problem is solved using stochastic dynamic programming. The resulting path exploits the interaction between the agent kinematics, informatics, and classification. Numerical simulation results that validate the concept are presented.

I. INTRODUCTION

A. Mission Overview

There are a number of objects of interest in a given area, and the properties of the objects are unknown. An agent equipped with sensors is to collect information with respect to the objects and classify their properties based on the gathered information. The onboard sensors are imperfect in that the information collection rate decreases as the range between the sensor and the object increases. The agent is constrained with time due to limited fuel and has a priori information of how many targets could be in the area provided by intelligence. The objective is to generate a path that provides optimal classification.

B. Literature Review

Much work has been done previously under the broad topic of probabilistic decision making in UAV operations. In [15], the authors investigated the use of human operator feedback for target recognition in an ISR scenario where a team of Micro Aerial Vehicles (MAVs) is assigned to fly over a number of objects of interest and the operator must decide whether the object is a target or not. In [14], the authors presented decision making strategies under uncertainty and adversarial action for the Cooperative Operations in Urban Terrain program (COUNTER), where stochastic dynamic programming was employed to optimize the resource allocation. In [1], the problem of path planning for UAV in the presence of radar-guided surface-to-air missiles was investigated. The radar model was formulated probabilistically, and the optimal strategy obtained in this work confirmed the standard flying tactics such that an aircraft should “deny range, aspect, and aim”.

With an information-theoretic measure, one can quantify information, which is an abstract concept, using the probabilities associated with the outcomes of the situation at hand. In [12], the author investigated the use of Shannon’s information [16] in performance and requirement estimation in multisensor fusion application. A set of heuristics was developed to relate the information content and recognition performance of a sensor system by using Johnson’s criteria [6]. In [13], optimal sensor parameter selection in a static visual system was studied with the optimality criterion as the reduction of uncertainty in the state estimation process using Shannon’s mutual information. In [2], sensor management in a dynamic environment was examined where the authors used an active sensing approach that combines particle filtering, predictive density estimation, and relative entropy maximization.

C. Original Contribution

The original contributions of this work are two-fold, such that

1) A sequential decision problem (path planning) is posed that incorporates the potential classification outcome that is made by an autonomous moving agent.

2) The problem is solved using stochastic dynamic programming (SDP). The resulting path exploits the interaction between the agent kinematics, informatics, and classification.

D. Paper Outline

The remainder of the paper is as follows. In Section II, the modeling for kinematics, informatics and classification are presented. In Section III, the risk function is formulated with the notion of confusion matrix. In Section IV, a dynamic optimization problem that minimizes the risk is formulated and the risk function for different outcomes of the action variable is derived. Also, loss function candidates for interesting mission scenarios are presented. In Section V, numerical simulation results are given. Conclusion and future work are discussed in Section VI.

II. MODELING

The agent is comprised of three relevant subsystems: kinematics, informatics, and classification. In this section, we present the model for each subsystem. For more details, see [17].
A. Kinematics

We assume that the physical world that the agent explores is the Manhattan gridded space. The area of interest is represented by a grid made from the intersection of horizontal and vertical lines with equal spacing. An agent is located on the intersection of the lines (vertex) and it moves along the lines of the grid (edges). There are four choices of movement direction which are up, down, left, and right. The agent moves from one vertex to another adjacent vertex depending on the direction it chooses.

Let us define a decision variable $\phi$, which describes the agent’s action on the direction it chooses to go. There are five possible outcomes for $\phi$, which are up, down, left, right, and stay. Abstracting each action with its first character, i.e. $u$ for up, $\phi$ is defined as

$$\phi \in \{u, d, l, r, s\}.$$ 

B. Informatics

We define two events which are the property of the object (X) and the measurement type (Y), respectively. For the object property, $X \in \{T, NT\}$ where $X = T$ denotes an event that an object of interest is a target while $X = NT$ denotes the object being a non-target. For the measurement type, $Y \in \{Y_0, Y_1, Y_2\}$ and Table I shows the summary of the events. Feature-type ($Y_2$) is an attribute of a target while non-

<table>
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</tr>
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<td>$Y_0$</td>
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</tr>
</tbody>
</table>

feature-type ($Y_1$) is an attribute of a non-target. An object possesses several attributes, which are recognized visually by the agent. These attributes are categorized by either one of the three outcomes shown in the table by using statistical pattern recognition techniques [17].

1) Property of Object: The probability of the object being a target and the probability of the object being a non-target are defined as

$$P(X = T) = p, \ P(X = NT) = 1 - p.$$  

These are the a priori probabilities in Bayes’ sense. In practice, this information is given by intelligence obtained prior to the mission.

2) Likelihood Functions & Constraint: Given the two events, $X$ and $Y$, the conditional probability of $Y$ given $X$ is formulated as follows.

$$P(Y = Y_i|X) = \sigma_iX$$  

where $0 \leq \sigma \leq 1$ and $i \in \{0, 1, 2\}$.

Based on fact that the sample space probability must equal to one, i.e. $P(\Omega) = 1$, one can derive the following equation using the product rule.

$$p(\sigma_{0T} + \sigma_{1T} + \sigma_{2T}) + (1 - p) (\sigma_{0NT} + \sigma_{1NT} + \sigma_{2NT}) = 1$$  

This is a constraint that the likelihood functions should satisfy in order to be proper functions.

3) Modified Performance Prediction Model: A performance prediction model for Electro-Optical (E-O) sensors is used as the measurement model for the agent. The modified performance prediction model for E-O systems is given as the product of the target transfer probability function and the cross section probability.

$$P_{MPPM} = P(r)P_c(\theta)$$  

$P(r)$ is the target transfer probability which describes the probability of successful discrimination (detection, recognition, or identification) as a function of the range between the sensor and the object to be classified.

$$P(r) = \frac{(N/N_{50})^E}{1 + (N/N_{50})^E}$$  

$E = 2.7 + 0.7 (N/N_{50})$ is obtained by fitting field test data, $N_{50}$ is the minimum resolution constant that gives 50% success rate of the chosen discrimination task (from Johnson’s Criteria [6]), $N = \rho d_c/r$ is the actual resolution of an object shown in the image plane. Here, $\rho$ is the maximum resolvable spatial frequency, $d_c$ is the characteristic target dimension, $r$ is the range from the sensor to the object. As the range between the sensor and the object shortens, the actual resolution of the object ($N$) increases, thus the probability of successful discrimination approaches 100%, i.e. $r \to 0, N \to \infty, P(N) \to 1$, and vice versa. The performance is shown in Fig. 1. One important aspect to point out is that depending on the chosen motion of the agent, the relative range to object(s) will vary, so the probability of successful discrimination will vary as well. Exploiting this aspect is the foundation of our approach to designing optimal control/decision strategies.

The probability of successful discrimination is not only dependent on the range, but also on the orientation of the object. An object can be observed via various viewpoints, but only through the vantage point can the proper feature that classifies the property of the object be seen. This is analogous to observing dice from sideways where some of the sides have an ordinary pattern (non-feature) while the others have some particular ones (feature). Since the orientation of the object is unknown a priori, this aspect needs to be taken

Fig. 1. Probability of discrimination tasks with respect to range.

<table>
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</tr>
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<td>$Y_0$</td>
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</tr>
</tbody>
</table>
into account in the model. The cross section probability $P_c$ is defined as

$$P_c(Y = Y_1 | X) = \frac{\theta_{Y_1|x}}{2\pi}$$

(6a)

$$P_c(Y = Y_2 | X) = \frac{\theta_{Y_2|x}}{2\pi}$$

(6b)

with $0 \leq \theta \leq 2\pi$ where $\theta$ is the visible angle parameter (vantage point) at which the agent can observe the corresponding measurement type. This parameter may vary depending on the size of the target and the sampling rate of the measurement.

The completed modified performance prediction model describes the probability of successful discrimination as a function of the range ($r$) and the object property ($X$). We formulate the likelihood functions that were defined earlier, using the performance prediction model. The likelihood of measuring $Y_0$ is the probability of no detections, and it is identical regardless of the object property. On the other hand, the likelihood for measuring $Y_1$ and $Y_2$ correspond to the recognition level of a discrimination task and they are also functions of the object property. The following set of equations summarize the likelihood functions.

$$\sigma_0 = 1 - P(r) = \frac{1}{1 + (N/N_{50})^E} \text{ with } N_{50} = N_{50,\text{detection}}$$

(7a)

$$\sigma_{1X} = \frac{\theta_{Y_1|x}}{2\pi} \left( \frac{N/N_{50})^E}{1 + (N/N_{50})^E} \right) \text{ with } N_{50} = N_{50,\text{recognition}}$$

(7b)

$$\sigma_{2X} = \frac{\theta_{Y_2|x}}{2\pi} \left( \frac{N/N_{50})^E}{1 + (N/N_{50})^E} \right) \text{ with } N_{50} = N_{50,\text{recognition}}$$

(7c)

These likelihood functions are known functions obtained by calibration prior to the mission.

C. Classification

a) Snapshot: The Bayes theorem gives the posterior probability of an event (hypothesis) given evidence that supports the hypothesis. The posterior probability of an object being a target given some measurement $Y$ is

$$P(X = T | Y) = \frac{P(Y | X = T)P(X = T)}{P(Y)}$$

(8)

where $P(X = T)$ is the a priori probability, $P(Y | X = T)$ is the likelihood function and $P(Y) = P(Y | X = T)P(X = T) + P(Y | X = NT)P(X = NT)$ by the theorem of total probability [9]. Note that

$$P(X = NT | Y) = 1 - P(X = T | Y)$$

(9)

b) Subsequent measurements: The Bayes theorem still holds for sequences of evidence. Assuming that evidence is conditionally independent to evidence at other instants given $X$, we get

$$P(T | Y^1, Y^2, \ldots, Y^l) = \frac{P(Y^1, \ldots, Y^l | T)P(T)}{P(Y^1, \ldots, Y^l)}$$

(10)

where the superscript on $Y$ denotes the evidence order with a total of $l$ number of evidences. This is also known as the naive Bayes classifier.

Suppose that among the total $l$ measurements, there are $l_0$ number of $Y_0$ measurements, $l_1$ number of $Y_1$ measurements, and $l_2$ number of $Y_2$ measurements, i.e., $l_0 + l_1 + l_2 = l$. Substituting Eq. (7) yields,

$$P(T | Y_0^{1:l_0}, Y_1^{1:l_1}, Y_2^{1:l_2}) = \frac{\theta_{Y_1|T}^{l_1}\theta_{Y_2|T}^{l_2}P}{\theta_{Y_1|T}^{l_1}\theta_{Y_2|T}^{l_2} + \theta_{Y_1|NT}^{l_1}\theta_{Y_2|NT}^{l_2}(1 - p)}$$

(11)

Fig. 2. Block diagram of interconnected subsystems

D. Interaction between Subsystems

The agent is comprised of three subsystems: kinematics, informatics, and classification. The kinematics subsystem describes the physical representation of the agent in the actual physical world that has several objects of interest in it. The important information that the agent gets from this subsystem is the relative distance, or the range, between the agent and the object of interest. Also, the agent decides which direction to go in this subsystem, and the time history of these decisions creates the path of the agent. The informatics subsystem describes how the agent extracts information out of the object of interest. The extracted information is abstracted by three levels of measurement characteristics, denoted as $Y_0$, $Y_1$, and $Y_2$, that are distinguished qualitatively. Based on this information, the classification subsystem decides the property of the object of interest either being a target or a non-target. The overview of the subsystem interconnection is shown in Fig. 2.

Kinematic decisions affect the classification result because the likelihood functions, Eq. (7), are dependent on the range between the agent and the object and the posterior probability, Eq. (8), is a function of the likelihood functions. The classification results affect the kinematic decisions, i.e., if the agent classifies an object with high certainty it is likely that the agent will not approach the object closer, but seek a different one.
III. BAYES RISK

In this section, we define Bayes risk which is the cost function for the dynamic optimization problem. First we define the confusion matrix, which is shown in the following table (OOI : Object Of Interest). There are four possible outcomes.

<table>
<thead>
<tr>
<th>Classifier says OOI</th>
<th>OOI in data</th>
<th>No OOI in data</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Positive (TP)</td>
<td>L_{TN}P_{TN} + L_{FP}P_{FP}</td>
<td></td>
</tr>
<tr>
<td>False Positive (FP)</td>
<td>L_{FP}P_{TP} + L_{FN}P_{FN}</td>
<td></td>
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The probability and the loss function corresponding to each outcome is defined as $P_{outcome}$ and $L_{outcome}$.

Given the probabilities and the loss functions, one can define the risk function, $R$. The risk function takes two forms depending on the outcome of the random variable $X$.

\[ R(X = NT, \delta) = L_{TN}P_{TN} + L_{FP}P_{FP} \] \hspace{1cm} (12a)

\[ R(X = T, \delta) = L_{FP}P_{TP} + L_{FN}P_{FN} \] \hspace{1cm} (12b)

where $\delta \in \{NT, T\}$ is the decision variable. The first equation is the potential risk of making a decision when $X = NT$ while the second one is the case for $X = T$.

Without loss of generality, let $L_{TN} = L_{TF} = 0$, i.e. there is no loss for correct decisions. Also, let

\[ P_{FP} = P(X = T|Y) \] \hspace{1cm} (13a)

\[ P_{FN} = P(X = NT|Y) \] \hspace{1cm} (13b)

Then the risk function takes the form of

\[ R(X = NT, \delta|Y) = P_{FP}P(X = T|Y) \] \hspace{1cm} (14a)

\[ R(X = T, \delta|Y) = P_{FN}P(X = NT|Y) \] \hspace{1cm} (14b)

This is called the conditional risk function. Note that the risk function varies depending on the type of observation, $Y$.

Bayes risk is the averaged risk function over the distribution of the random variables $X$ and $Y$. Bayes risk with a single observation can be formulated as

\[ R_B(\delta) = E_Y \{E_X\{R(X, \delta|Y)\}\} \]

\[ = \sum_{i=0}^{2} \{P(NT)L_{FP}P(T|Y) + P(T)L_{FN}P(NT|Y)\} P(Y) \] \hspace{1cm} (15)

where $R_B$ denotes Bayes risk and $E_X$ denotes the expectation operator over random variable $X$. Note that the random variable representation in the probability mass function was omitted for simplicity, i.e. $P(T) = P(X = T)$.

IV. STOCHASTIC DYNAMIC PROGRAMMING

In the path planning, there are two decision problems at hand which are

- Whether to stay (and complete the mission) or to move (and take another observation).

1) If the agent decided to stay, what hypothesis to choose.

2) If the agent decided to move, which way the agent should go.

We approach this decision problem with Bayes decision theory and solve it with stochastic dynamic optimization.

A. Dynamic Optimization Problem

We formulate the cost function, $V$, as the Bayes risk with two decision variables, $\phi$ (action) and $\delta$ (hypothesis). For one-stage optimization, $V_1 = R_B(\delta_1, \phi_1)$, and $V^* = \arg\min_{\phi, \delta} V_1$, where the subscript denotes the stage. SDP can be solved recursively using the optimality equation [18]. For $N$-stage optimization:

\[ V_N = \arg\min_{\phi, \delta} \left\{ R_B(\delta_1, \phi_1) + \sum_{k=1}^{N-1} V_{k-1} \right\} \] \hspace{1cm} (16)

where $N$ is the time constraint (mission time).

B. Decided to Stay

Suppose we are in the case where the agent decided to stay, i.e. $\phi = s$. Now the agent faces a problem of deciding which hypothesis $(X = T \text{ or } X = NT)$ is true based on the up-to-date observations. In Bayes decision theory, this is formulated as Bayes’ test for simple hypothesis [19]. Basically, the decision variable $\delta$ is a mapping between the observation set $Y$ and the object property $X$, i.e. $\delta : Y \rightarrow X$. Let us define

\[ S_{NT} = \{Y|\delta: Y \rightarrow NT\} \],

\[ S_T = \{Y|\delta: Y \rightarrow T\} \],

with

\[ S_{NT} \cup S_T = Y, S_{NT} \cap S_T = \emptyset. \]

Now the problem is to identify the sets $S_{NT}$ and $S_T$.

Reformulating the Bayes risk (Eq. (15)), it is given as (X and $\phi$ are omitted for notational simplicity)

\[ R_B(\delta, Y) = P(NT)L_{FP}P_{FP} + P(T)L_{FN}P_{FN}. \] \hspace{1cm} (17)

The probability of false positive and false negative can be defined with their probability distribution function.

\[ P_{FP} = P(\phi(Y) = T|NT) \]

\[ = E_{NT}\{\phi(Y) = T\} \]

\[ = \sum_{j} F(Y_j|NT) \] \hspace{1cm} (18)

and

\[ P_{FN} = 1 - P(\phi(Y) = T|T) \]

\[ = 1 - E_T\{\phi(Y) = T\} \]

\[ = 1 - \sum_{j} F(Y_j|NT) \] \hspace{1cm} (19)

where $F(Y|X)$ is the probability distribution function of $Y$ conditioned on $X$ such that

\[ \sum_{j} F(Y_j|X) = P(Y|X). \]
Substituting these into the Bayes risk formula gives
\[ R_B(\delta, Y) = P(T)L_{FN} + \sum_{j} \right \}
\]
\[ = \frac{P(NT)L_{FP}F(Y_j|NT) - P(T)L_{FN}F(Y_j|T)}{P(T)L_{FN}} \]
\[ = P(T|\bar{Y}^{1:t}, Y^{t+1}) \frac{P(T|Y^{1:t})}{P(Y^{1:t}|T)} \]
Now using this formula, we want to find the set \( S_T \). Suppose \( S_T = \emptyset \), then
\[ R_B(\delta, Y) = P(T)L_{FN} \]
If there exists any \( Y \) that satisfies
\[ P(NT)L_{FP}F(Y_j|NT) < P(T)L_{FN}F(Y_j|T) \]
the integrand in Eq. (20) will be negative, thus giving a smaller risk than \( P(T)L_{FN} \). Rearranging the condition, we get
\[ S_T = \left\{ Y : \frac{F(Y_j|T)}{F(Y_j|NT)} > \frac{P(NT)L_{FP}}{P(T)L_{FN}} \right\} , \]
\[ S_{NT} = Y/S_T. \]

C. Decided to Move

The Bayes risk for the case where the agent decided to move is formulated as
\[ R_B(\delta, \phi \neq s, Y) = P(T)L_{FN} + \left\{ P(NT)L_{FP} - P(T)L_{FN} \right\} P(T|Y). \]
The expected risk over the measurement \( Y \) is
\[ R_B(\delta, \phi \neq s) = E_Y \left\{ R_B(\delta, \phi \neq s, Y) \right\} = P(T)L_{FN} + \left\{ P(NT)L_{FP} - P(T)L_{FN} \right\} \sum_{i=0}^{2} P(Y_i|T)P(T) \]
where the second equation is obtained by using Bayes' theorem. There are four cases for the expected risk over the measurement, \( Y \), each corresponding to different actions.

1) Multiple Observations: Bayes risk for multiple subsequent observations is formulated in this section. Here we introduce more notation: \( \bar{Y} \) is the sampled observation and the superscript indicates the sampled time instant. For instance,
\[ \bar{Y}^{1:t} = [Y_1^{1}, Y_2^{1}, \cdots, Y_t^{1}] . \]
The Bayes risk of measurement at time \( t+1 \) with sampled observation up to time \( t \) is
\[ R_B(X, \delta, \phi \neq s, \bar{Y}^{1:t}, Y^{t+1}) = P(T)L_{FN} + \left\{ P(NT)L_{FP} - P(T)L_{FN} \right\} P(T|\bar{Y}^{1:t}, Y^{t+1}) \]
Taking the expectation value over \( Y^{t+1} \) yields
\[ E_{Y^{t+1}} \left[ R_B(X, \delta, \phi \neq s, \bar{Y}^{1:t}, Y^{t+1}) \right] = P(T)L_{FN} + \left\{ P(NT)L_{FP} - P(T)L_{FN} \right\} \sum_{i=0}^{2} P(T|\bar{Y}^{1:t}, Y^{t+1})P(Y_i^{t+1}|\bar{Y}^{1:t}) \]
Since \( Y^{1:t} \) is conditionally independent of \( Y^{t+1} \) given \( X \), i.e., \( P(Y^{t+1}|T) = P(Y^{t+1}|T, Y^{1:t}) \), the Bayes' Theorem can be rewritten as
\[ P(T|\bar{Y}^{1:t}, Y^{t+1}) = \frac{P(Y^{t+1}|T, Y^{1:t})P(T|Y^{1:t})}{P(Y^{t+1}|Y^{1:t})} \]
Substituting this into the Bayes risk equation gives
\[ E_{Y^{t+1}} \left[ R_B(X, \delta, \phi \neq s, \bar{Y}^{1:t}, Y^{t+1}) \right] = P(T)L_{FN} + \left\{ P(NT)L_{FP} - P(T)L_{FN} \right\} \sum_{i=0}^{2} P(Y_i^{t+1}|T)P(T|\bar{Y}^{1:t}) . \]
This is the expected loss when the agent decides to move to some direction. The actual risk may be larger or smaller depending on the sampled measurement. Supposing that we know the likelihood function, the risk can be determined.

D. Loss Functions

There are several ways of posing the loss function. Depending on the loss function, the resultant paths are likely to be in one of two categories:

1) Strong emphasis on classified target being an actual target. In this case the loss function for false positive (FP), or false alarm, should be larger than the one for false negative (FN), i.e.
\[ L_{FP} \gg L_{FN} . \]

2) Opposite situation in which the emphasis is on the classified non-target being an actual non-target. In this case the loss function for false positive (FP), or false alarm, should be smaller than the one for false negative (FN), i.e.
\[ L_{FP} \ll L_{FN} . \]

V. Simulation Results

In this section, we present simulation results that were obtained by solving the SDP numerically. MATLAB® was used as the simulation environment.

An agent is to classify a single object. The parameter values are chosen as the following.
- \( P(T) = P(NT) = 0.5 \)
- \( N = 20 \)

Two scenarios with different set-ups are illustrated in Fig. 3 and Fig. 4. Fig. 3 shows the Bayes risk time history and the agent movement in the physical world for the case when the object is a non-target (NT) and the loss functions are \( L_{FP} > L_{FN} \). Notice that the risk for staying (blue dashed line) is always greater than the risk for moving (green solid line) in this particular scenario, so the agent stops when the mission time is reached. Also notice that as the agent approaches the object, it moves back and forth between two alternate locations (shown as thick blue stars) as the consequence of the risk. This suggests that an additional stopping criteria is needed when there is no improvement in the risk. However,
this may not be a problem when there are multiple objects with a stringent time constraint, as the agent will run out of time before examining all the objects.

Fig. 4 shows the Bayes risk time history and the agent movement for the case when the object is a target (T) and the loss functions are $L_{FP} < L_{FN}$.

VI. CONCLUSION & FUTURE WORK

In this paper, we present a sequential decision problem that takes the classification risk into account. The problem is solved using SDP. As future work, we are investigating several avenues which are 1. inclusion of azimuth-dependent measurement model, 2. online estimation of the likelihood function, and 3. mathematical definition of target “deception”.

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