Predictive Modeling of Interacting Agents

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Abstract

A model for characterizing communications behaviors has been generalized to a probabilistic model for intentional behavior. A representational scheme and processing architecture enable process models of agents’ actions to be generated. Responsive actions are decomposed into measurement, inference, planning and control components and are predicted as a function of the estimated capability, opportunity and intent of given agents to perform such component actions. Applications include Technical and Operational Intelligence.

1. MODELING ADAPTIVE RESPONSE

A key problem in many military, intelligence and commercial applications is the need to adapt to unanticipated behavior of interacting purposeful agents; e.g. of adversaries, competitors, customers, partners, or subordinates. Factors in assessing situations or threats can include unanticipated goals, tactics and capabilities of such agents. It can also involve unanticipated opportunities for agents’ actions to be successfully performed, as well as agents’ unanticipated perceptions of such opportunities.

There is a need, therefore, to be able to
(a) create predictive models of behaviors that a purposeful agent might exhibit and
(b) determine the distinctive observable indicators of those behaviors.

In many practical problems of interest the specific behaviors that must be predicted are unprecedented and unexpected. As argued below, this will require a shift in paradigms: construing the inference problem as one of model discovery, rather than model recognition. That is to say, the information system will have the job of explaining the data, rather than merely that of recognizing known patterns of interest.

A. Open Communications and Open Interactions Networks

Our framework for characterizing interacting purposeful agents is that of an Open Communications Network [1]. As depicted in Figure 1, this is an unconstrained network of agents that may interact on the basis of diverse capabilities, motives and allegiances. Interactions within such a network may be

- Intentional; e.g. by point-to-point or broadcast communications or publication); or
- Unintentional; e.g. by presenting active or passive signatures; reflective cross-sections, electromagnetic or thermal emissions, or other detectable physical interactions with the environment.

Agents can interact with one another and with non-purposeful elements of their environment in complex ways. As illustrated in Figure 1, when we function as a node in a network of interacting agents, our understanding of received data requires the characterization of proximate sources and, recursively, of their respective sources; i.e. of the pedigree of our received data.

A previous paper [1] discussed a representational and processing scheme for such problems in communications, as in Network-Centric Operations. We now broaden this notion of an open network of communicating agents to encompass all types of interactions among entities. Actions in general can be thought of as involving one or more actors (or “agents”) communicating with one or more objects acted upon (“targets”). Agents can “communicate” by such diverse means as weapons or financial exchange, as well as by signals or symbols.

To recognize and anticipate other agents’ actions, a node in a net-centric information exploitation process must implicitly or explicitly model such agents’ actions in response to a world state or world state history.

B. The MIPC Response Model

We suggest that such a response model can be decomposed into four process models:

- **Measurement model**: \( p(Z^k_M | X, w) \); probabilities that agent \( w \) will generate measurement sets \( Z \) in world states \( X \);
- **Inference model**: \( p(\hat{X}^k | Z^k_M) \); probabilities that agent \( w \) will generate world state estimates \( \hat{X} \), given measurement sets \( Z \);
• Planning model: \( p(\hat{A}_s^k \mid \hat{X}_x^k) \): probabilities that agent \( w \) will generate action plans \( \hat{A}_s \), given world state estimate \( \hat{X} \);
• Control model: \( p(A_{C_s}^k \mid \hat{A}_s^k) \): probabilities that agent \( w \) will generate actions \( A_C \), given action plans \( \hat{A}_s \).

These process models can generally be assumed to be conditionally independent, arising from mutually independent system components. Thus, they can be modeled serially per Figure 2, which also shows representative performance factors for each component (indices have been suppressed for clarity).

\[
A^*_t = h_t^b(\beta_C, \hat{A}_s^k) + v^*_t
\]

where terms are defined as follows:
- \( Z_M^k \): Measurement set as of time \( k \);
- \( \hat{X}_M^k \): Estimated world state;
- \( \beta_M, \beta_1, \beta_P, \beta_C \): Systematic bias terms, respectively, for measurements, inference, planning and control;
- \( v^*_M, v^*_1, v^*_P, v^*_C \): noise components, respectively, of measurement, inference, planning and control (generally non-Gaussian).

The transforms \( h \), particularly those for Inference and Planning, can be expected to be highly nonlinear. Equation (4) is the control model dual of (1), with explicit decomposition into random and systematic error components. Equation (3) is a planning model, which – as argued by Bowman [3] – has its dual in data association:

\[
\hat{Y}_s^k = h_s^l(\beta_M, Z_M^k) + v_s^k
\]

for association hypotheses \( \hat{Y}_s^k \in 2^{\hat{C}} \).

Of the four constituent models, Measurement and Control are familiar territory in estimation and control theory. In contrast, Inference and Planning model processes that are not directly observable. They are also the provinces of information fusion and automatic planning. These are “higher-level” in the old dualistic sense that human inference (i.e. perception and cognition) and planning are considered “mental” processes, whereas “measurement” (sensation) and motor control are “physical” processes. The former are certainly less well understood and, therefore, less amenable to predictive modeling.

By decomposing actions into constituent elements, and these into random and systematic components, we could isolate those components that are difficult to model. If so, we would – at the very least – be able to assess the sensitivity of our behavior model to such factors.

Our ability to predict the performance of fusion and robotic systems is relatively primitive compared to Measurement and Control, to say nothing of our ability to predictively model human cognition or behavior. As shown, each of the four models can involve both random and bias error components. However, note that only Planning can involve intentional error components.

Intentionality occurs specifically as factors in the planning bias term \( \beta_P \). This term, then, is the focus for assessing an agent’s intentional reporting biases, as well as any other intentionally-directed patterns of behavior.

The non-intentional elements – Measurement, Inference, Control, and aspects of Planning – impose constraints on the subject agent’s actions, however intentioned. Once again, such constraints enable the intelligence analyst to select among the constrained set of behaviors.

\[1\] It is well recognized that human perception (inference) is often driven by expectations and desires; i.e. by prior plans and inferences concerning their expected outcomes. These factors are modeled as feed-back in the MIPC loop.
2. INFERRING HUMAN INTENT

Intent can be estimated and predicted, at least to some extent, as a function of an agent’s state.

Philosophers of the mind have worked surprisingly hard to explicate the relationships among (i) willing an action, (ii) causing an action, and (iii) performing an action [4-7]. There is the issue of crediting an agent with an action when that action was unintended or when it was fortuitously achieved by an ineffective plan. Davidson [5], for example, argues that a person’s actions comprise only intended events, not unintended consequences; that is to say, intent is a necessary condition for action.2 Of course, predicting agent behavior must consider the ways in which intents affect actions, intended or not. More people fall to their deaths intending to fly than those who actually fly.

Fortunately, we needn’t fully understand the causal relationship between intent and action – Descartes’ paradox of the ghost in the machine – in order to be able to estimate or predict an agent’s intentions as a component of the likelihood of various actions (performed or caused) by that agent. A predictive model need not incorporate an explanatory model (although the latter can help validate the former – cf. [8], pp. 72ff).

As Waltz [9] notes, inferences can concern not only the physical states of entities, but their informational and psychological states as well. Information states largely involve the availability of information to a sentient being, while the cognition, perception, interpretation, evaluation of – and the intended response to – information are aspects of the being’s psychological state. In the MIPC/COI model discussed in Section 3, the former maps into “Opportunity”, the latter into “Capability” and “Intent”.3

The problem of inferring such psychological states differs from such physical state inference problems as target recognition or target tracking in at least the following three ways:

a) Observability: psychological states are not directly observed but must be inferred from physical indicators, often on the basis of inferred physical and informational states;

b) Complexity: the causal factors that determine psychological states are numerous, diverse and interrelated in ways that are also numerous and diverse;

c) Model Uncertainty: these causal factors are not well understood, certainly in comparison with the mature physical models that allow us to recognize and predict target types and kinematics.

Nonetheless, however complex and hidden human intentions and behaviors may be, they are not random. Methods for representing, recognizing and predicting these are presented in the following section.

3. “MIPC/COI” MODEL FOR AGENT CHARACTERIZATION

The MIPC model presented in Section 1.B can be used not only in planning “our” actions but also in inferring those of other agents; e.g. in Operational Net Assessment.

These models can be incorporated in a game-theoretic structure for operational planning and prediction among interacting agents. This MIPC response model can be inserted into the loosely-coupled network of agents discussed in Section 1.A. Figure 3 (using OODA-loop terminology) illustrates generalized exchanges among agents having diverse motives, allegiances and means of interaction. Note that an agent can observe and be affected by one another only via the latter’s “Acts”. The hidden components (Observe, Orient, Decide) must be inferred.4

One potentially useful method for exploiting such interactions is that of Stimulative Intelligence; meaning the systematic stimulation of agents or their environment to elicit information [10]. Once again, such stimulation can be physical (e.g. imparting energy to stimulate a kinetic, thermal, or reflective response), informational (e.g. providing false or misleading information), or psychological (e.g. stimulating perceptions, emotions or intentions). Such techniques can play a role in eliciting indicators of physical, informational and psychological (e.g. perceptual) states. Consider, for example, the technique

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2 Of course, whether it is a necessary condition for action (or even for intentional action), intent is clearly not a sufficient condition. As discussed in the next section, capability and opportunity for the action are also required.

3 In the MIPC model, Inference and Planning are activities that can affect cognitive (i.e. psychological) states. These activities need not themselves be performed by cognitive entities, but may involve automation. They also may be performed sub-consciously by human or other biological organisms.

4 If the exchange is between agents, rather than within one agent, specifically physical acts are required (barring such paranormal phenomena as extra-sensory perception or telekinesis). Of course not all physical stimuli are the result of activity of responsive, much less, purposeful, agents.
familiar from old cowboy movies of hiding behind a rock and raising one’s hat on a stick to draw an adversary’s gunfire. This is done to elicit information concerning that adversary’s physical state (location and weapon capability, etc.), as well as his state of awareness and hostile intent.

The use of intentional stimulation to gather intelligence presumes the availability of predictive models of responsive entities such as purposeful agents. While physical stimulation techniques to infer physical states are very mature – think of conventional radar, active sonar and seismic mapping – stimulation to infer psychological states is rather more art than science. This is due to the attendant observability, complexity and model uncertainty problems cited above.

The MIPC model of intentional action can be integrated into our earlier Threat Assessment model developed by Little and Rogova [11,12] and extended by Steinberg [13,14]. In this “COI” model, actions are characterized, predicted and recognized in terms of the indications and constraints on agents’ actions imposed by their capability, opportunity and intent to carry out various actions.

a) Capability is the availability of resources sufficient to undertake an action of interest;
b) Opportunity is the presence of an operating environment in which potential targets of an action are present and are susceptible to being acted upon;
c) Intent, of course, is planned or willed action.

Accordingly, the data structure for threat hypotheses given in [13,14], etc., can be generalized to a predictive model of agent behavior per Figure 4. The model involves constituent models of an agent’s capability, opportunity and intent to carry out various actions. Taking these to be necessary conditions for intentional behavior, these constituent models interact to generate the five probability matrices shown in the figure, characterizing, respectively:

a) feasibility of various specific actions;
b) attendant constraint satisfaction;
c) opportunities for actions against potential targets;
d) probabilities of actions against potential targets;
e) probabilities of possible outcomes of such actions.

A Capability Model, as seen in the figure, is an influence diagram that relates the factors that determine an agent’s capability to conceive of, plan (or design) and implement actions of various types. For example, if the concern is about an agent’s capability to develop weapons technologies, the model involves factors for the design (e.g. possessing the concept, underlying theory and enabling technology); development (e.g. materials, factories and skills); and deployment or delivery of such weapons.

Similarly, an Intent Model is an influence diagram that decomposes an agent’s high-level objectives (e.g. national or personal strategic goals) to networks of sub-goals and finally to assessment of possible state changes in various “targets” that could be conducive to these sub-goals.

It is important to note that an intention is neither a desire to do something nor the perception of its value. Rather it is the determination to do it. However, intent assessment involves inferring such determination on the basis of models of desires and perceptions. These can include evaluation of the agent’s informational and cognitive state; such as his assessment of the consequences of his action (e.g. the likelihood of achieving desired goals, of secondary effects such as collateral damage or stimulated reaction by other agents) and the expected cost of the action. In other words, this is a model of the agent’s internal Utility/Probability/Cost assessment, by which he estimates the utility of particular states, the probability of attaining such states given various actions and the cost of such actions [15].

An Opportunity Model concerns the presence of situational factors necessary for such actions to occur. In general, such a model is an influence diagram in which agent/target relations are evaluated. Depending on the types of action involved, factors can include the agent’s access to a target within the constraints imposed by the action (e.g. within a weapon’s effective radius) and the vulnerability of a target to such actions.

Threat Assessment involves evaluating each of these components from two directions. Top-down Intent assessment decomposes agents’ assessed high-level goals (i.e. desired world states) into specific target state changes that would be conducive to these goals. Intent can also be assessed from the bottom up, to explain observed investments of effort, money, time, etc.

Capability assessment is performed both in terms of the inherent capabilities of the technology/action class, and in terms of observed designs and developments.

Opportunity assessment addresses both the maturity (i.e. the operational availability) of the design/development and the availability of the enabling infrastructure.

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5 This is a change to previous versions of the COI model [1,2,4], in which the evaluation of an agent’s perception of opportunity and outcome was construed as elements of Opportunity Assessment.
Capability/Opportunity/Intent models of actions can be combined to represent complex activities; e.g. to represent recursive refinement of an agent’s responses.

Characterizing an agent’s behavior can involve the fusion of the following four categories of information:

- **Internal Evidence** (evidence from the agent itself):
  - Explicit declarations
  - Information completeness and consistency
- **Prior Evidence** concerning agent performance:
  - Assessed Capabilities, Opportunities (e.g. readiness and access to targets) and Intent
- **Situational Evidence** (expected biasing factors):
  - Ambient operating conditions
  - Emotional stressing conditions
- **External Evidence** (agent’s relationships):
  - Consistency of reporting with other sources;
  - Consistency of behavior with other agents.

These evidence types can be used for characterizing biases in reporting as well as in other types of action. As in sensor registration or calibration, evidence of the above types is used to align and calibrate the agent behavior characterization.

Classical sensor registration/alignment methods apply: Absolute Alignment methods are applicable to aligning internal evidence. Relative Alignment methods are applicable in aligning commensurate data concerning an agent across multiple information sources. Common Model methods are applicable in associating non-commensurate behavior factors [2].

### 4. MAPPING COI INTO MIPC

Table 1 indicates how COI factors provide necessary conditions for the MIPC processes. As noted above, Intent is only relevant in the Planning process, although all four processes are subject to control. The resulting expanded MIPC process diagram is shown in Figure 5.

**Table 1: COI CONDITIONS FOR MIPC ACTIONS**

<table>
<thead>
<tr>
<th>ACTION PROCESS</th>
<th>CONDITION</th>
<th>CAPABILITY</th>
<th>OPPORTUNITY</th>
<th>INTENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEASURE (Observe)</td>
<td>Sensor Resources/ Techniques</td>
<td>Ambient Energy (Signal and Noise)</td>
<td>N/A (Measurement Controls)</td>
<td></td>
</tr>
<tr>
<td>INFER (Orient)</td>
<td>Data/Info Processing Techniques; (including Info Fusion)</td>
<td>Measurement and Calibration Data</td>
<td>N/A (Inference Controls)</td>
<td></td>
</tr>
<tr>
<td>CONTROL (Act)</td>
<td>Control Techniques</td>
<td>Plans and Resources</td>
<td>N/A (Control of Controls)</td>
<td></td>
</tr>
</tbody>
</table>

A processing architecture for inferring agents’ capability, opportunity and intent has been discussed in previous publications [1,10,13,14] and is summarized here for completeness. The architecture was originally developed as part of a general framework for performing Situation and Threat Assessment [13,14]. That work involved developing theoretical and ontological foundations for the representation and recognition of relationships, situations and, specifically, of threat situations.

Such applications require the system to exploit a wide range of evidence and a wide range of entity and aggregate behavior models. This is certainly the case in the many situations of interest that involve estimating and predicting human individual and group behavior.

Adapting to unanticipated behavior of interacting agents requires an ability to create predictive models of behaviors that a purposeful agent might exhibit and determine the distinctive observable indicators of those behaviors.

Often, however, the specific behaviors that must be predicted are unprecedented and unexpected; i.e. unsuitable for template-driven recognition methods. This drives a need to shift from the model recognition paradigms familiar in automatic target recognition to a model discovery paradigm.

Under such a paradigm the system will be required to compose models that explain the available data, rather than simply to recognize pre-existing models in the data.

A processing architecture for adaptively building and refining models to account for the data is shown in Figure 6. The architecture extends one developed for model-based scene understanding and target recognition.

This adaptive process for model discovery iteratively builds and validates Interpretation Hypotheses, which attempt to explain the available evidence. A Feature Extraction process searches available data for indicators (i.e. supporting evidence) of situation types of interest (e.g. movements of weapons, forces or other resources related to threat organizations).
Hypothesis Generation develops one or more Interpretation Hypotheses, which have the form of labeled directed graphs (illustrated at the bottom of the figure). In the present application, Interpretation Hypotheses concern the capability, opportunity and intent of agents to carry out various actions. These conditions for action are decomposed into mutually consistent sets and evaluated against the available evidence.

The process closes the loop by means of a Response Management function that nominates information acquisition actions. A UPC model is used to predict the cost-effectiveness of such actions in terms of (a) the predicted utility of particular information, (b) the probability of attaining such information given various actions and (c) the cost of such actions [15]. Utility is calculated in terms of the expected effectiveness of specific information to refine hypotheses or to resolve among competing hypotheses as needed to support the current decision needs (i.e. to map from possible world space to decision space) [13].

Information acquisition actions can include the intentional stimulation of the information environment to elicit information. Stimulation to induce information sources to reveal their biases requires an inventory of models for various classes of behavior [10]. A key research goal is the development and validation of methods for the systematic understanding and generalization of such models – the abductive and inductive elements of Figure 6.

6. SUMMARY

The problem of predicting agents’ actions is decomposed into components that can be solved separately and combined consistently and systematically. A general probabilistic model for characterizing intentional behavior is presented, based on a model for characterizing information sources. Responsive actions are decomposed into measurement, inference, planning and control components. Intentional actions are predicted as a function of agents’ estimated capability, opportunity and intent to perform relevant actions. This representational scheme enables the generation of process models for characterizing and predicting such activities as capabilities development (e.g. in Scientific and Technical Intelligence) and tactical operations (in Operational Intelligence).

REFERENCES