A Behaviour Model as Extension for the Object-Oriented World Model

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Abstract

This report focuses on extending the object-oriented world model by a behaviour model for its representatives. The world model in general is used as a foundation for fusing multiple sensor sources into one coherent picture. It should enable other services to access the stored information for further processing, e.g. for recognizing suspicious situations in surveillance tasks. While the base model is able to capture the real world entities by translating them into representatives while incorporating background-knowledge in form of concepts, it is not able to predict the behaviour of these representatives. Here, a concept based on intelligent rational agents is introduced.

1 Introduction

Given the humongous amount of heterogeneous data generated by the multitude of sensor sources (e.g. RADAR, cameras, ...), as well as the complex and demanding task itself, due to its time pressure, inconsistencies, imperfect and in general quite uncertain information, surveillance tasks, e.g. in the maritime domain, are quite challenging for human operators. Therefore automatic system are created to assist and support the operators during decision making processes.

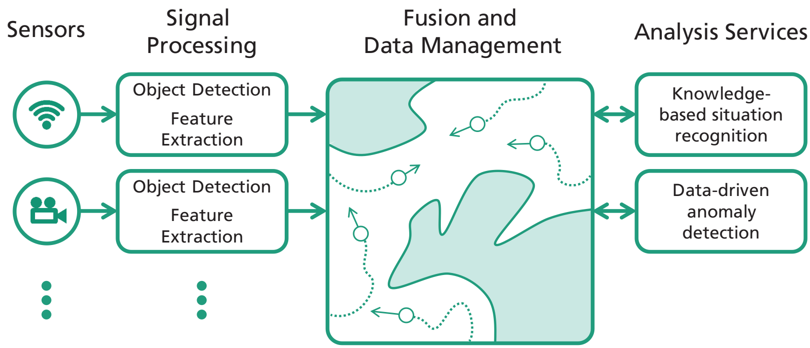

Figure 1.1: General structure for situation analysis task in surveillance applications.

Such an automatic system shall infer the existence of situations $\mathcal{S}$ by observing all entities $\mathcal{E}$ in the real world while incorporating the available background knowledge for the given application domain. The inference of the existence of a situation is called situation analysis.

The incoming data from the sensor systems will be processed and object are detected and their features are extracted. This information is the base for different situation analysis algorithms, either knowledge-based or data-driven. Figure 1.1 gives an overview of the whole task: Sensors will capture the entities translate them to objects in the fusion and data management system, which will be used as foundation for the analysis services. In order to utilize this information a model for representing it is needed. Here, the Object-Oriented World Model (OOWM) is used.

2 Object-Oriented World Model

The OOWM was first introduced by Gheta et al. in [GHB08]. It is the foundation for reasoning of autonomous systems [BGB$^+$10, GHBB10, GBB$^+$10, BKFB12, Bel15]. This approach has a fixed background knowledge. In [Kuw10, Kuw12a, Kuw12b] first steps towards an adaptive open-world modelling are given. This was further described and elaborated in [KB13a, KS13, KB13b, KB14, KGHB15, KB16]. For surveillance tasks, it is used in [KFEPB12, Fis16].

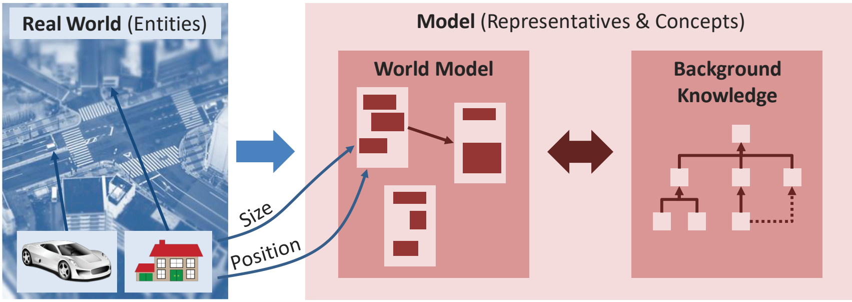

Figure 2.1: Schematic structure of the OOWM.

Here, the formalization of the OOWM stated by Kuwertz and Beyerer in [KB16] is adopted.

The OOWM is a computational representation of the real world. Its main components are shown in Figure 2.1. It is generated by using the information acquired by sensor observations. This model is then considered a consistent representation of the current state. It can act as the foundation of higher level data fusion services in order to assess a situation at hand, support the decision making process, and improving thus the situational awareness. In order to improve the model, background knowledge in form of conceptual models relevant for the application domain are incorporated.

The model builds representatives for all entities $\mathcal{E}$ in the real world, which are observed by the available sensors (and relevant for the application domain).

Definition 3 (Representative)**.** *A representative $R \in \mathcal{R}$ is given by the set of attributes $\mathcal{A}_R = \{A_1, \ldots, A_n\}, n \in \mathbb{N}$.*

Definition 4 (Attribute)**.** *An attribute A_i is represented by the probability distribution $p_{A_i}(a)$ (Degree of Belief (DoB) in attribute values). This distribution $p_{A_i}(a)$ is either discrete or continuous.*

The representative R are given by the joint probability distribution

$$p(R) = p(\mathcal{A}_R) = \prod_{i=1,\ldots,n} p_{A_i}(a) \; .$$

In order to map the entities $\mathcal{E}$ with the corresponding representatives $\mathcal{R}$, an association mechanism is needed. For further readings into this topic, relate to the work by Baum et al. in [BGB$^+$10].

The background knowledge is given in form of concepts $\mathcal{C}$. These concepts consist of a set of attributes which can be used as a prototype for representatives in the world model.

Definition 5 (Concept)**.** *A concept $C \in \mathcal{C}$ s given by the set of attributes $\mathcal{A}_C = \{A_1, \ldots, A_m\}, m \in \mathbb{N}$. A concept C may be represented by the joint probability distribution $p(C) = p(\mathcal{A}_C) = \prod_{i=1,\ldots,m} p_{A_i}(a)$.*

Definition 6 (The Association probability of representative R to concept C)**.**

$$p(C \mid R) = \frac{1}{z} \cdot p(C) \cdot \prod_{A_i \in \mathcal{A}_R} \left(\int_{\mathbb{R}} p_{A_i}(a) \cdot p_{A_c}(a) \, \mathrm{d}a \right)$$

with A_c as corresponding attribute of the concept C for the attribute A_i of R and z as normalization parameter.

3 Situation

The formalization of a Situation is in line with [Fis16]. According to Ye et al. [YDM12],

> ”A situation is defined as an external semantic interpretation of sensor data. Interpretation means that situations assign meanings to sensor data. External means that the interpretation is from the perspective of applications, rather than from sensors. Semantic means that the interpretation assigns meaning on sensor data based on structures and relationships within the same type of sensor data and between different types of sensor data.”

Following the definitions in section 2, the entities $\mathcal{E}$ in the real world are described in the OOWM as representatives $\mathcal{R}$. As a situation S is not necessarily depending on all representatives, the subset of relevant ones are given by $\mathcal{R}^r \subseteq \mathcal{R}$.

Definition 7 (State space of a situation)**.**

$$\Omega_S := \bigtimes_{R \in \mathcal{R}^r} R \times \mathbb{T} = \bigtimes_{R \in \mathcal{R}^r} \bigtimes_{A_i \in \mathcal{A}_R} A_i \times \mathbb{T}$$

$\mathbb{T}$ *represents the time domain. A point in time* $t \in \mathbb{T}$ *can either be continuous* $\mathbb{T} = \mathbb{R}_0^+$ *or discrete* $\mathbb{T} = \mathbb{N}$.

Definition 8 (Situation at a point in time)**.** *A situation* S_t *is defined for the time* t *as the mapping*

$$S_t \colon \Omega_S \to \{0, 1\} \; .$$

Where $S_t = 0$ *or* $\bar{S}_t$ *denotes, that a situation does not exists, and* $S_t = 1$ *or* S_t *that the situation exists.*

For the time t an element of the state space is given by $\omega_t \in \Omega_S$. A trajectory through the state space is then defined for a time interval $d = \{t_1, t_2, \ldots, t_k\}$ by the elements $\omega_d = (\omega_{t_1}, \omega_{t_2}, \ldots, \omega_{t_k})$.

Definition 9 (Situation over a time interval)**.** *A situation* S_d *given the time interval* d *is defined as*

$$S_d \colon \bigtimes_{i=1}^{k} \Omega_S \to \{0, 1\} \; .$$

The existence of a situation at time t (analogously for time interval d) can be described by probabilistic means. Hence, the situation S_t can be interpreted as a binary random variable:

- Σ_S is a sigma-algebra on Ω_S, thus a subset of the power set of Ω_S.
- p is a probability measure on (Ω_S, Σ_S).

Definition 10 (Existence of a situation)**.** (Ω_S, Σ_S, P) *is a probability space and* p *a distribution for* S_t *with the existence probability given by*

$$p(S_t = s), \text{ with } s \in \{0, 1\} \; .$$

So far, the existence of a situation can be inferred by using the trajectory ω_d. But ω_d depends on the behaviour of the entities $\mathcal{E}$ and their interactions with each other. Integrating the specific behaviour of each entity might have a huge impact on the situation analysis, as it might give explanations for valid and righteous behaviour even though at first glance it seems to be just erratic. This arises the question about ”how to model the behaviour?”.

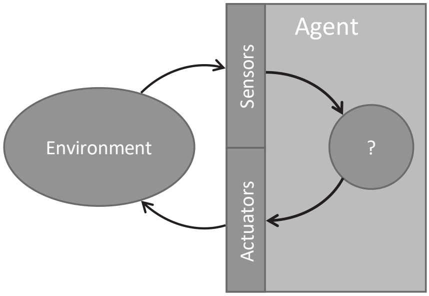

Figure 4.1: Intelligent Agent. [RN95]

4 Expending the OOWM with Agents

Not all entities will have a dedicated behaviour relying on a reasoning process, e.g. inanimate entities like a cup. For all others, the assumption of an agent model seems to be a fitting choice, as Russell and Norvig state in [RN95]:

> ”An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors.”

As seen in Figure 4.1, such an agent is able to perceive the environment using its sensors, resulting in a subset of representatives in the OOWM $\mathcal{R}^p \subseteq \mathcal{R}$. Further the agent can carry out actions $\mathcal{B}$ with its actuators, which will effect the environment. These actions will influence the attributes of the entities in the real world.

An intelligent agent will use some reasoning process to decide on the action to take. Thus results the characterization for an ideal rational agent by Russell and Norvig [RN95] as follows:

> ”For each possible percept sequence, an ideal rational agent should do whatever action is expected to maximize its performance measure, on the basis of evidence provided by the percept sequence and whatever built-in knowledge the agent has.”

This can be adapted to the formalization for situations as follows: For the observation made by the entity E, the resulting state space is given by

$$\Omega_E \coloneqq \bigtimes_{R \in \mathcal{R}^r} (R, \mathcal{C}_R^r) \times \mathbb{T}$$

and $\mathcal{R}^r \subseteq \mathcal{R}^p$ is the set of all observed representatives, which are relevant for a decision. Further, $\mathcal{C}_R^r$ denotes all relevant concepts for the representative R.

The behaviour H of an agent over a time interval $d = (t_1, \dots, t_k)$ is the mapping of the state space Ω_E to an action $B \in \mathcal{B}$:

$$H\colon \bigtimes_{i=1}^{k} \Omega_E \to B$$

The set of possible mapping is denoted with $\mathcal{H}$.

This implies, that some of the representatives in the OOWM will behave like a rational agent. Thus, the background knowledge needs to be extended by the set of behaviour models:

Definition 11 (Behaviour in the OOWM)**.** *The set of possible behaviour mappings $\mathcal{H}$ is part of the background knowledge. A representative may follow a specific behaviour $H \in \mathcal{H}$ based on the given concept C.*

Definition 12 (Association between representative and behaviour)**.** *The association between the behaviour H and a representative R is given by*

$$P(H \mid C), \forall H \in \mathcal{H}, \forall C \in \mathcal{C}, \text{with } P(C \mid R) > 0 \,.$$

These definitions allow each representative to follow a behaviour based on its associated concepts. For the next step, the behaviour needs to be filled with a model for actually choosing an appropriate action given all the available information.

5 Behaviour model

Following Russell and Norvig [RN95], there are multiple models for an agent to make a decision. One of these is a utility-based agent as shown in Figure 5.1. This agent will perceive its environment and build a representation of the world. It is able to infer the effects of its own actions on the environment. A utility function is then used to decide on the one action which will maximize the gain for the agent. This action will be carried out by its effectors.

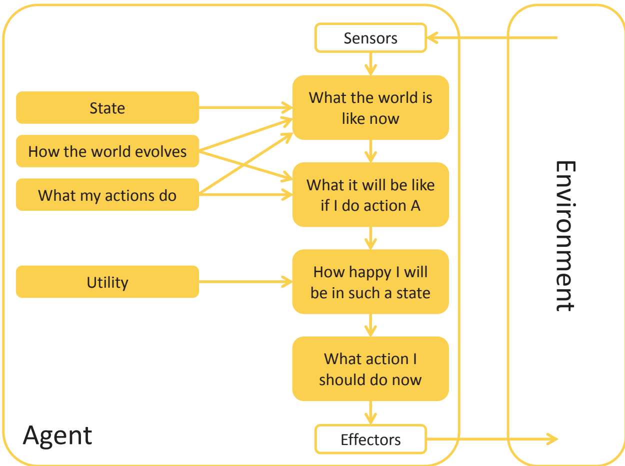

Figure 5.1: Utility-based agent. [RN95]

Another concept for an agent is given by Rao and Georgeff in [RG95]. It is called an BDI agent:

- Beliefs: Observed knowledge of the agent about himself and the world.
- Desires: States that solve a problem.
- Intentions: Possible plans or strategies for achieving the objectives.

An addition to this model is given by Broersen et al. in [BDH$^+$01]. The idea is to include obligations, which will hold values, norms and rules applicable to all agents.

While this models define a general concept about how to decide on an action, it is still unclear, how the goals are defined and how exactly decisions are made. A famous example of this issue is given by Lewis Caroll in his novel Alice's Adventures in Wonderland:

> ”Alice: *Would you tell me, please, which way I ought to go from here?*
> The Cheshire Cat: *That depends a good deal on where you want to get to.*
> Alice: *I don’t much care where.*
> The Cheshire Cat: *Then it doesn’t much matter which way you go.*
> Alice: *... So long as I get somewhere.*
> The Cheshire Cat: *Oh, you’re sure to do that, if only you walk long enough.*”

Therefore, without a valid objective in mind, it is quite impossible to decide on the right action, or any action would be ok.

The decision theory is the study of analysing the choices made by agents. It splits into two branches: normative and descriptive decision theory.

> ”The distinction between normative and descriptive decision theories is, in principle, very simple. A normative decision theory is a theory about how decisions should be made, and a descriptive theory is a theory about how decisions are actually made.” [Han94]

A major drawback of decision theory is, that it is only concerned with the choices made by a singular agent. Closely related is the field of game theory. In game theory, the choices of agents, which actions will interfere with each other, are analysed.

Thus, ”[g]ame theory can be defined as the study of mathematical models of conflict and cooperation between intelligent rational decision-makers” [Mye07]. The decision making is described in form of games:

Definition 13 (Game)**.** *A (non-cooperative) game Γ consists of a set of players $\mathcal{N}$, a set of strategies $\mathcal{B}$ and the utility function u:*

$$\Gamma = (\mathcal{N}, \mathcal{B}, u)$$

Definition 14 (Players)**.** *Each representative $R \in \mathcal{R}$ with a behaviour H can be interpreted as a player in a game Γ. The set of players is given by*

$$\mathcal{N} = \{1, \ldots, n\} \; .$$

Definition 15 (Strategies)**.** *A strategy B of a player $i \in \mathcal{N}$ corresponds to an action $\mathcal{B}_i$ each representative R_i can choose of. Thus, the set of all strategies is given by*

$$\mathcal{B} = \bigtimes_{i=1}^{n} \mathcal{B}_i \ .$$

Definition 16 (Utility function)**.** *A utility is mapped to all players for each strategy combination:*

$$u \colon \mathcal{B} \to \mathbb{R}^n \ .$$

There are solution concepts for this kind of games like the Nash equilibrium [Nas51]. Such a game is a model for a non-cooperative situation, that means, that the agents will try to maximize their own utility, but they will not try to increase the gain for each other. Going back to the surveillance task, this often does not apply, because the agents might want to work together to increase the overall utility. To counter this challenge, cooperative games were designed, e.g. a bargaining game:

Definition 17 (Bargaining game)**.** *An extension of a game Γ by a conflict point c is called a (cooperative) bargaining game*

$$\Gamma_B = (\mathcal{N}, P, c) \ ,$$

whereas P denotes the payoff space with all the feasible utility results

$$P = \{u(B) \mid B \in \mathcal{B}\} \ ,$$

and the conflict point $c \in P$ is the utility gained by the players, if they do not agree on a solution.

This kind of game will allow solution concepts like the Nash bargaining solution [Nas53] to follow specific axioms, which define a fair and reasonable outcome for all players in a bargaining situation.

Following the OOWM's concepts, the behaviour of each agent should be depending on their type. One game to follow this notion, is a Bayesian game [Har68], in which each player will be assigned a specific type influencing the utility. The type will be chosen by nature (modeled as a special player).

Definition 18 (Bayesian game)**.** *A game with incomplete information extended by types for the players is given by*

$$\Gamma_{\mathit{Bayesian}} = (\mathcal{N}, (\mathcal{T}_i, \mathcal{B}_i, u_i, p_i)_{i \in \mathcal{N}}) \,.$$

The nature will assign randomly the types for the players. The players only know their own type.

The type $\mathcal{T}$ of a player will define its preferences (utility) and strategies. Before any player can act, the nature will choose the type $T_i \in \mathcal{T}_i$ for each player $i \in \mathcal{N}$. Compared to the general game, the utility function needs to be adjusted. It has to assign a value not only to the combinations of strategies, but also for the types:

$$u \colon \mathcal{B} \times \mathcal{T} \to \mathbb{R}^n \,.$$

The belief p_i of player $i \in \mathcal{N}$ is a probability distribution for the types.

Translating a Bayesian game to the OOWM will result in the following mapping:

- Players are representatives: $\mathcal{N} \to \mathcal{R}$
- Types are concepts: $\mathcal{T} \to$ concepts $\mathcal{C}$
- Beliefs in the types are probability distribution over the assigned concept for each representative: $p_i \to p(C \mid R)$ for $R \in \mathcal{R}^p$

For solving a game, many solution concepts were introduced over the course of time. For non-cooperative games this includes: rationalizability and iterated dominance, Nash equilibrium, Bayesian Nash equilibrium. The Nash equilibrium was for example used by Anneken in [Ann16] as a solution concept to estimate the behaviour of ships. Some solution concepts for cooperative games are the core, Nash bargaining solution and Kalai-Smorodinski bargaining solution. The Nash bargaining solution was used by Anneken et al. in [AFB17] to estimate the behaviour for multiple cooperating vessels in the maritime domain.

6 Situation analysis

The main idea here is to use the extended OOWM for situation analysis in surveillance tasks. Thus $\mathcal{R}$ are all representatives of the entities $\mathcal{E}$ of the real world.

There is an observer responsible for the surveillance task. This observer is an entity itself: $E_O \in \mathcal{E}$. The corresponding representative is given by $R_O \in \mathcal{R}$. Each observer has its own background knowledge, which includes the concepts $\mathcal{C}_O$ and behaviour models $\mathcal{H}_O$. The observer R_O can perceive a subset of the entities which results in the following set of representatives $\mathcal{R}_O^p \subseteq \mathcal{R}$.

Each of the observed representatives $R \in \mathcal{R}_O^p$ will base its action $B_R \in \mathcal{B}_R$ on other representatives perceived by it $\mathcal{R}_R^p \subseteq \mathcal{R}$, the concepts $\mathcal{C}_R$ and the behaviour model $\mathcal{H}_R$.

The observer will base his anticipations regarding the behaviour of the representatives $\mathcal{R}_O^p$ on his background knowledge $\mathcal{H}_O$ and on each of the perceived representatives. The entities in the real world will base their behaviour H on their own observations. In case, that the observer is able to perceive the same relevant part of the world as the representative, the expected behaviour and the actual behaviour should be the same. It will deviate, if the concepts $\mathcal{C}$, the behaviours $\mathcal{H}$, or the observed representative $\mathcal{R}_O^p$ do not match.

By comparing the predicted behaviour with the actual, it is possible to make a statement about the possibility $p(H_O \mid H_R)$. This has been done e.g. in [AFB16a, AFB16b] by geometric comparisons of movement patterns using the Hausdorff metric or dynamic time warping. Another approach was shown in [Ann16, AFB17], where a utility function was developed, which was in turn used to participate a behaviour. The utility by the actual behaviour is than compared with the one from the estimated strategy.

The information gained about the probability $p(H_O \mid H_R)$ can then be used for the mapping between the entities and the situation $S \in \mathcal{S}$ at hand: An entity, which behaviour deviates, can be considered an anomaly, while at the same time the probability for an expected illegal action can be estimated by modelling it as possible behaviour.

7 Conclusion and Future Work

A concept for integrating a behaviour model into the OOWM was introduced. This model is based on a game theoretic approach. While the OOWM is already incorporating methods for associating real world entities with the computational representatives based on background-knowledge in form of concepts, it is not able to predict behaviour or give inside into the decision process of entities. The addition of utility based intelligent agents, which will make a decision based on the results of a Bayesian game, will address this shortcomings. This will allow a surveillance system to support an operator with even more inside.

Additional to the introduced extension, the next steps will include further research into a prototype, the estimation and prediction of actions, and based on this the detection of anomalies or suspicious behaviour. One important step will be the design of the utility function.

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