Goal-driven Situation Awareness Process Based on Predictive Modeling

Yevhen Burov[1]

[1] Lviv polytechnic National University, 12 Bandera str, Lviv,79013, Ukraine

Abstract

The increasing complexity of information systems and the inherent limitations of the human mind give rise to the need to delegate the tasks of situation assessment to intelligent agents. Classical models of situation awareness process imply sequential, event-driven treating of situation awareness. However, the recent development in cognitive psychology suggests the central role of predictive, generative modeling in human situational awareness process, which confers advantages when compared with sequential process. This article proposes a goal-driven process and architecture of situational aware intelligent agent based on generative, predictive conceptual modeling. The main advantage is the ability to reuse the rich knowledge about previous experiences, which is constantly updated and kept logically consistent. Similarly to human cognition, such approach allows to reconcile the use of patterns from experience with the information coming from the environment and execution feedback resulting in the updates of those patterns and learning. Compared to the BDI proposed agent architecture adds the ability to dynamically react to the changes in the environment, prioritize those changes in the goal system, reuse and modify beliefs as a consistent pattern system in the knowledge base.

Keywords

Situational awareness, intelligent agent, artificial intelligence, goal system, conceptual modeling

1. Introduction

A highly dynamic world requires humans to quickly assess situations, adapt and use existing knowledge, make decisions, and perform actions coming from those decisions. Situational awareness, making predictions, building hypotheses, and checking them against available data are important parts of human cognition.

However, the increasing intricacy of the modern world and the inherent limitations of human mind in promptly and accurately making decisions in complex scenarios give rise to the need to delegate the task of situation assessment and decision-making to systems of goal-driven intelligent agents. The incorporation of situation awareness into such systems poses a noteworthy challenge in the realm of artificial intelligence.

The major factors, contributing to this challenge are:

- The need to use both prediction and perception of the environment, with reasoning and modeling the impact of possible actions.
- Being goal-driven while goals provide the agency and autonomy to intelligent agent, help to select the most important goal to follow in the moment, and actions which are furthering this goal.
- The need to implement focusing on the small part of the world, related to selected goal. Shifting attention rather than doing an explicit query and selection of related knowledge.
- Using contextual knowledge.
- The fuzzy nature of knowledge, where the ontology concept can be represented by multiple prototypes depending on the context. Prototypes are working as initial templates and

COLINS-2024: 8th International Conference on Computational Linguistics and Intelligent Systems, April 12–13, 2024, Lviv, Ukraine

yevhen.v.burov@lpnu.ua (Y. Burov)

0000-0001-8653-1520 (Y. Burov)

provide patterns and constraints. Although the mind constructs the actual knowledge model on top of this.

- The dynamic nature of the environment requires constant updating and validating the model.

The recent developments in the understanding of how human cognition works, using predictive modeling, provide an important insight into the possible organization of situation-aware and goal-driven agents. Existing models of situation – aware systems need to be updated taking into consideration those developments.

This article proposes and discusses the updated model of situation-aware system for goal-driven intelligent agent, centered around predictive conceptual modeling. It consists of introduction, background research analysis, main part, discussion and conclusion. In the background analysis part, the insights from cognitive psychology about situational awareness is analyzed. Likewise, the current understanding of how goals are organized and processed conceptually is discussed. The Belief-Desires-Intention framework as a classical approach to model intelligent agents and its application to situational aware systems is described. The background section is concluded with the analysis of situational aware system models.

In the main part of the article the architecture of goal-driven situation-aware intelligent agent is presented. The specific functional modules organization and interaction is discussed in more detail. In conclusion, the advantages of goal-driven and based on predictive modeling approach is highlighted along with the directions for further research.

2. Background research

2.1. Cognitive science about predictive situation awareness and conceptual modeling

The recent developments in the understanding of cognitive processes in the human mind could bring a valuable insight into the area of artificial intelligent systems. After all, this process was formed as a result of millennia of evolutionary process and represents the most efficient form of cognition we know now. The notion of concept occupies the central place in our understanding of cognition [1].

Concepts themselves are the result of grouping and finding regularities in the world done in our mind. But once formed we use concepts to build predictive models of the world. Without concepts we are experientially blind [2].

Concepts give meaning to the world and allow us to reason about it using the networks of related concepts. Concepts don’t have a fixed meaning or properties. The meaning of concept changes depending on the context and goal of the person using it. Prototype theory is used to represent multiple meanings of concept as typical instances of this concept in different contexts. [3,4]. The authors of [5] propose a method allowing to differentiate, retrieve and manage meanings of concept in different contexts.

Concepts correspond to the object in the real world, but also to the imaginary, abstract objects. The ability to manipulate abstract concepts is the powerful ability of the human mind, allowing us to overcome the limitations of our working memory size or information processing speed.

Therefore, conceptual modeling as the ability to build, and reason with conceptual models is an efficient way to represent and process information which holds promise also to be implemented in systems with artificial intelligence.

Predictive modeling is a promising and quickly growing area in intelligent systems area. Thus, the improved classification methods, based on predictive classification [6] or decomposition [7] are developed.

According to the current understanding of cognitive psychology [8,9], the human brain navigates and assesses the world using predictive modeling. Previously, the process of awareness was often represented as linear, starting with perception of environment, the interpretation of data readings, building the model based on those interpretations and available knowledge, and, finally, making decisions and acting on them.

Predictive models are taken from the memory about previous experiences as a structure of relevant patterns and dynamically re-constructed (updated) taking in consideration the current goals and environment characteristics accessible via sensor data. Without previous experience people are experientially blind and cannot understand the current situation.

The external data are perceived as a change in the world and this change is reconciled with predictive model into coherent whole. In the process of such reconciliation model could be changed. Such reconciliation happens on multiple levels of generality, starting from the most abstract, general principles and going down into details.

The use of predictive modeling creates several advantages including faster reaction to changes in environment and goals, the ability to reason and learn, constantly adapting the patterns to real-world experiences. The mind constantly creates hypothesis about current context and checks them against data coming from senses, other communication channels, and the results of reasoning.

The insights from the current understanding of human cognitive situation awareness process, centered around predictive modeling could be used to enhance the models of situational awareness process in intelligent agents.

2.2. Goals and goal systems in human cognition

The implementation of goal-driven behavior is essential for intelligent agents, because maintaining goal systems allows agents to be autonomous, flexibly prioritize their actions depending on context. According to dictionary definition [9] goal is “The result or achievement toward which effort is directed”. Such common definition excludes from the study of goal system in cognition the negative goals – the projected states of the world which intelligent agent is actively avoiding (such as injury, destruction, failure). Those kinds of states are structurally like goals, they are included in goal setting and goal following processes on par with ordinary goals but have negative motivation – instead of actively reaching the goal, intelligent agent plans and acts to avoid those states.

In [10] is proposed another definition of goal, stressing the anticipatory nature of goal and its influence on the behavior of agent. A goal is an “internal, mental representation that is anticipatory and can take various formats, and it is used as a set-point in a control-system to drive the external behavior of an agent for modifying the world”. A goal is not necessarily pursued. An agent can set a goal and observe passively how it is fulfilled in the world. We will consider goals as anticipated (desired or undesired) states of the world which intelligent agents strive to reach (or avoid) through their actions.

In goal-related research authors differentiate between abstract and concrete goals. Abstract goals are formulated generally, some of them could never be achieved. Abstract goals have no specified plan of achievement. However, they influence the motivation to reach other, dependent goals. Concrete, perceptual goals are focused on specific actions, often sensory-motor ones [8].

The author of [11] introduces the concept of abstract goals, which are not directly accomplished by existing web services but involve decomposition into achievable goals and non-deterministic choices by the user. It also presents the concept of Brokered Goals, which specify achievable goals from a system perspective and serve as the link to semantic web-services technology.

We can also differentiate between final goals, which are the terminal points of some kind of project and proximate goals, which specify the intermediary states on the path to final goal achievement. Intention [10] is defined as the next step to take on this path.

The usage of goals assumes the ability to check whether the specific goal was achieved and the means to assess how far the current state is from the goal-state.

With each goal is associated the measure of motivation [12], specifying how important this goal is in the current context. Motivation is used to select which goal should be acted on in the current circumstances. Motivation is defined dynamically based on the current situation, other goals, experiences, and the internal state of the agent. Motivation for a goal can be derived from other, dependent goals.

Intelligent agents have many interrelated goals, forming goal systems [13]. The goal system looks like an archipelago of goal structures. Some goals are context-dependent, and some configurations are called out within contexts and situations. Other goals are abstract, long-standing and are used in strategic planning, project selection, and following opportunities.

Goal systems are actively researched in psychology and computer science [14], aiming to develop modeling frameworks for better understanding goal setting and goal-following processes. In [15] a conceptual framework for goal-directed system is proposed.

Goals are often modeled with Ontologies. An example of such a model is [16]. The paper demonstrates how goal modeling can be approached starting from a problem domain model represented by an ontology. Ontological model and a goal model are used to represent requirements and domain formalization.

Planning is also part of the goal processing process. It happens dynamically, taking in consideration current context and goal system. Planning is based on previous knowledge about following similar goals in similar circumstances. It builds an anticipated trajectory of states from current state to final state through a sequence of intermediate states. The availability of perceived trajectory from current state to the other, important state, influences motivation. For example, an action could be perceived as harmful and avoided, if there's a perceived sequence of states leading from the results of this action to undesirable final state (such as injury).

Overall, the understanding of goal setting and processing process in human cognition provides valuable insight into the organization of goal handling by intelligent agents.

2.3. Modeling goal-driven intelligent agents with Belief-Desire-Intention framework

BDI (Belief-Desire-Intention) is the dominant framework in the modeling agency and implementing intelligent agents. The BDI agent model has been the basis for research on autonomous agents for the past 30 years. The BDI ecosystem is complex, with various agent architectures, languages, and platforms developed [17].

The BDI model emphasizes the notion that an intelligent agent's behavior can be modeled by examining how it processes information (beliefs), what it wants to achieve (desires), and how it chooses to act (intents).

Beliefs refer to the agent's perception of the world, including its understanding of the current situation, available information, and its own internal state. These beliefs are essentially the agent's model of the environment it operates in.

Desires encompass the agent's goals, objectives, or preferences. They represent what the agent wishes to achieve or accomplish in its environment. Desires are often described as a set of possible states of the world that the agent finds favorable.

Intents are the agent's planned courses of action to achieve its desires based on its beliefs. They represent the agent's decision on how to act in response to its current beliefs and desires. Intents are the bridge between an agent's internal cognition and its external behavior.

A BDI agent program consists of initial beliefs and plan-rules specifying when a plan can be used to achieve a goal or respond to changes in beliefs [18]. The execution of a BDI agent follows a deliberation cycle that involves updating events, beliefs, and intentions, and executing plans.

Various formalisms are used to represent beliefs in BDI implementations. Symbolic models such as models using propositional, first-order or modal logics are used to reasoning in well-defined environments. [19, 20] They are computationally efficient and easy to implement but may lack the ability to handle uncertainty. They can be too rigid and not well-suited for complex, dynamic environments.

Probabilistic models, such as Bayesian networks or Markov decision processes are used when the agent needs to reason under uncertainty or in stochastic environments. Beliefs are represented as probabilities. They are excellent for reasoning under uncertainty but can be computationally intensive. They may require a lot of data for accurate belief representation.

Apart from symbolic and probabilistic models, temporal models [21,22] are used. There are also approaches using fuzzy logic, ontological models, situational analysis [23, 11].

The research in BDI framework introduces several kinds of desires (goals). Test goals are used to check if a condition is true, and different agent programming languages have different approaches to handling false test goals. Achievement goals can be procedural (goals to do) or declarative (goals to be), and different agent programming languages support either procedural or declarative goals. Procedural goals are independent of the agent's beliefs, while declarative goals are related to the agent's beliefs [17]. Goals are often represented by simple terms or conjunctions of positive literals, depending on the programming language. The work [18] propose motives as extensions of BDI agent, expressing motives as an extension of goal concept. In [24] the graded approach to estimate beliefs, goal in intentions is developed.

Plans in BDI modeling languages consist of steps such as goals, belief update operations, and actions. Series-parallel interleaving allows plans to be built incrementally by sequentially and parallelly composing other plans. Some languages provide finer control over the ordering of steps, allowing them to be executed in any order or synchronized. Arbitrary interleaving allows for more fine-grained ordering of steps than series-parallel interleaving. True concurrency in some languages allows steps to be executed simultaneously, either interleaved or on different processors.

In [25] plans are modeled using object -oriented approach as activity diagrams, which are later translated into specific modeling language.

Research in BDI framework proposes a large number of developments, reflecting different aspects of intelligent agents modeling and implementation. However, it lacks the implementation of complex goal-systems, support of dynamic, contextual interplay of goals and beliefs. The BDI framework could benefit from the implementation of insights coming from cognitive psychology about human situational awareness and anticipated, predictive conceptual modeling.

2.4. Situation-aware systems modeling

According to the definition [26], situational awareness refers to the conscious comprehension of the immediate surroundings and the ongoing events within it. The concept of situational awareness encompasses the perception of the various elements present in the environment, the understanding of their significance and interconnections, and the prediction of their future states. The investigation of situational awareness falls within the broader domain of data fusion [27].

The phenomenon of situational awareness encompasses a range of operations, linked to cognitive ability, including the discernment of relevant stimuli in the surrounding environment, the identification and interpretation of patterns and objects, the recognition of familiar situations based on past experiences, the process of logical decision making, and the subsequent execution of those decisions, the evaluation of the success of actions taken, as well as the adjustment of knowledge and procedures. The primary objective of a system that is situationally aware is to make decisions and adjust the behavior of an intelligent agent in response to the dynamic environment, in accordance with the agent's objectives. Situation-aware systems have been recently introduced not only in autonomous driving but also in smart buildings and smart cities [28].

Several models have been developed to represent the process of situational awareness. These models can be categorized as process models, functional models, and formal models.

The early process models, such as John Boyd's Observe-Orient-Decide-Act (OODA) loop or the Predict-Match-Extract-Search loop [29,30] were developed as a generalization of real-world situational awareness processes in complex environments, such as the battlefield.

Functional models are exemplified by the Endsley model [31] and the JDL (Joint Directors of Laboratories)/DFIG (Data fusion information group) models [32,33].

There are also investigations that explore different perspectives in the situational awareness process using various formal frameworks, such as Category theory, generalized information theory, interpreted systems, ontologies, and specification languages. However, the most widely accepted framework for conceptualizing the situational awareness process is the functional

JDL/DFIG model. This model, like many other situational awareness process models, follows the structure of human cognition process.

The JDL/DFIG model divides the process of situation awareness into five levels [33]:

- level 0. The assessment of signals/features. At this level, signals from various sensors are gathered and interpreted as input data, representing attributes of measured entities. The signals undergo processing, and errors in measured data are evaluated.
- level 1. The assessment of entities. The acquired data is interpreted as attributes of entities from the ontology.
- level 2. The assessment of situations. The entities involved in the current context and their relationships are analyzed in order to construct a model of the context and detect situations within this context. This level operates with conceptual models of the environment, context, and situations.
- level 3. The assessment of impact. Planning actions based on the detected situations, making decisions, and analyzing the consequences of those decisions.
- level 4. The assessment of performance. Evaluating the correspondence between the current situation and the goals of the system, analyzing performance, providing feedback to lower levels of information fusion, and updating models.

The JDL/DFIG model is continually evolving and undergoing revisions. It is currently recognized as a component of the data fusion process, which involves integrating multiple data sources to generate more consistent, accurate, and useful information [34].

The classical models of situation-awareness process follow the paradigm of 'smart camera' – feedforward perception model, implying that information is first read from the sensors, then interpreted and built into the model of current context. In the next step this model is analyzed and decisions pertaining to it are made.

However, the current understanding of human situation-aware processes stresses the primary role of predictive modeling. Brain starts with building a model of context based on previous knowledge and updates it taking into consideration sensor inputs.

Thus, there's a need to update situation awareness process models according to the current understanding of corresponding human processes.

3. The model of goal-driven situation aware system

3.1. Modeling system architecture

We will model situation-aware intelligent agent as a set of interrelated, dynamically constructed conceptual models processed by corresponding functional modules. (fig. 1)

For the representation of those models, knowledge graph formalism [35] was chosen. not only because it is commonly used in conceptual modeling, but also because of the common, conceptual nature of all models used. Knowledge graph (KG) represents the local agent's knowledge, stored in local knowledge base. The vertices of this graph SV_{con} correspond to concepts in agent ontology On, and edges SE_{rel}– to relationships between those concepts:

$$Gr_{kn} = (SV_{con}, SE_{rel}) \quad (1)$$

To select part of knowledge graph relevant to current context we propose to use attentional mechanism. Each vertex v_i of Gr_{kn} has weight w_i that is dynamically recalculated depending on goals followed, situations detected, environment conditions available. Attentional mechanism automatically selects interrelated concepts into conceptual model Cm_{con} it works having weights above certain threshold Th, other concepts being ignored.

$$\forall v_i \in Cm_{con}: w_i > Th \quad (2)$$

The weight assignment function F_{wt} assigns weights to the groups of related concepts belonging to patterns Pt_{in} used in current goal or task.

$$F_{wt}: Pt_{in} \to \mathbb{R} \quad (3)$$

The system has following functional modules (fig.1):

- context processing module (CPM);

- external data processing module (EDPM);
- goal system module (GSM);
- situation detection module (SDM);
- execution module (EM)

Each functional module works with the part of knowledge graph relevant to the task it is performing. In this process it uses the knowledge patterns from knowledge base.

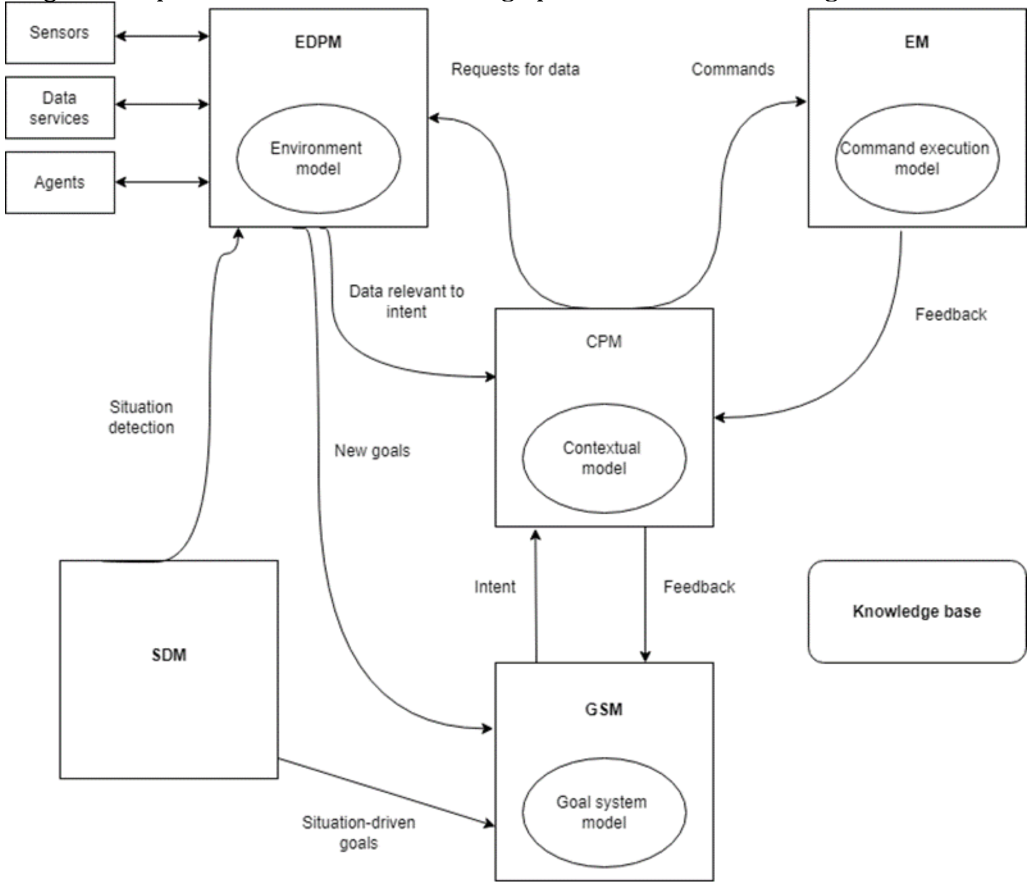

Figure1: Modeling system architecture

To avoid confusion, we will differentiate between the concepts of context and situation. Context is understood as a task/goal/intent followed in the current moment in the specific environment. While Situation is a possible condition/change/event which happens in the current context and requires an action from intelligent agent. For example, context could describe a person driving a car along the road. When a pedestrian starts crossing the street in the front of a car a situation is detected and immediate reaction from the driver is required.

The central place in the situation-aware intelligent agent model is taken by Contextual model Cm_{con}. Contextual models contain concepts and relationships relevant to the specific intent followed in current environment. It is dynamically constructed from the current Environment model, and intent, provided by Goal-system module using patterns of experience from the knowledge base. Contextual model is constructed by CPM and contains a part of conceptual model of environment $Cm_{env}^{int} \subseteq Cm_{env}$ with the elements of environment relevant to the current intent Gl_{int}, part of knowledge graph containing concepts and relationships relevant to the implementation of intent and deduced from patterns in knowledge base Cm_{int} and intent itself:

$$Cm_{con} = (Cm_{env}^{int}, Cm_{int}, Gl_{int}) \tag{4}$$

Contextual model is passed from one moment of time to the next one. In this way, the system continues to follow a goal from the previous moment, providing consistency and perseverance in following goals. However, the CPM also updates the Contextual model and can switch from one model to another if some unpredicted situation is detected or intention for the next moment changed, as indicated by Goal-system module.

Thus, CPM, acting on the input from GSM, constructs the contextual model, based on available knowledge from knowledge base. It fills in the missing data interacting with EDPM, and makes decision related to the next action, which is passed to EM. Execution module interacts with external services via corresponding APIs and sends feedback about the success/fail in the execution of command.

Situation detection module analyses the contextual and the model of environment for the cues about possible situations. The knowledge about such cues is taken from a knowledge base. In case a situation requiring reaction from IA is detected, SDM updates the goal model in GSM, which will influence the next goal processed.

Environment data processing module monitors the environment with sensors, interprets data coming from them, updates the Environment model. The Environmental conceptual model is reconciliated with Contextual model. For example, when a new object is detected by sensors, this object is added with high weight to contextual model. The new configuration is processed by SDM and GSM. If no important situations are detected or the change in the attended goals determined, the new object is ignored.

Otherwise, the system could construct the new contextual model based on the new specified goal.

On the other hand, EDPM follows the requests from CPM about getting additional information from external data sources. CPM can also change policies of gathering data from sensors, requiring more specific data, or prioritizing the collection of data for specific objects.

Goal system module maintains and processes the Goal models. It selects the goals relevant to the current environment, assesses dynamically the weight of each, selects the most important goal and builds the plans to reach it starting from the current context.

In the process of building the plan/intention it uses the knowledge of how similar goals were followed in similar environments previously. Goal module maintains predictive models for each followed goals- it can find the chains of intermediary goals, while following the more distant goal. Goal module updates the contextual model, taking into consideration the environment objects and relationships relevant to the most important goal and intent as a next step to reach this goal. It also adds to the contextual model objects which are not present in the environment, but important for following this goal/intent. Let’s consider each functional module and its interactions with other modules.

3.2. Maintaining the system of goals and developing current moment’s intent

Goal system module maintains the set of goals and their relationships for intelligent agent. In every time moment it selects the most important intent, which becomes a focus of attention and passes it to the CPM, that constructs the contextual model to support the execution of this intent in the current environment state.

Goal system is a set of goals with dependency relationships between them and motivation function F_{mt} which computes the motivations for each goal:

$$SuGl = (SGl, SRe_{gl}, F_{mt}) \tag{5}$$

Goal is formalized as the state in the world, with associated assessment function F_{ev} and weight w_{gl}. The state of the world in goal is described as conceptual model, including elements, belonging to this state Cm_{gl} and their status, derived from their properties values and described by a set of conditions SCd.

$$Gl = (Cm_{gl}, SCd, w_{gl}, F_{ev}) \tag{6}$$

Assessment function F_{ev} allows to evaluate whether in the current state, represented by Contextual model Cm_{con} the goal is attained:

$$F_{ev}: (Cm_{con}, Cm_{gl}, SCd) \to (true, false) \tag{7}$$

The metric of distance between two states/goals $F_{ds}: (Gl_i, Gl_j) \to \mathbb{R}$ is also useful when assessing the dependencies between goals.

With each goal and relationship weights are associated. The weight of the goal w_{gl}reflects its importance and is used to calculate motivation to reach this goal.

The weights of relationships w_{rlg}^{ij} reflect how closely dependent two goals gl_i and gl_j as states of the world are. The dependency relationship can reflect causal, probabilistic or pragmatic dependency between states. In this way proximate goals obtain their weight from the weight of the final goal.

Goals and relationships weights are dynamically recalculated and normalized with every change in the Environment model. The actual values of weights are assigned and adjusted in the process of learning.

Goals have different sources of provenance. There are abstract goals, set initially. Those goals cannot be reached, but they influence the weight (motivation) of other dependent goals. Abstract goals could have positive or negative motivation. In a goal system they work as general principles and values which influence the motivation for other, dependent goals. They can also reflect high-end, strategic goals. The example of such goals: attain high status, be punctual, avoid injury. Other goals come from external goal-setting sources or because of detecting important situations. Goals are removed once they are reached or deemed unreachable or unimportant.

Related goals form structures and patterns. One of such structures is the chain of proximate goals on the path to the final goal, representing a plan of reaching this goal.

$$Pl(g_i) = (g_{i1}, g_{i2}, \dots, g_{in}) \tag{8}$$

Plans are built using the knowledge of how similar goals were attained. However, in order to accommodate for different states of environment, there are multiple different variants of plans for each goal.

Another structure reflects the probabilistic relationship between two states, in which the weight of relationship depends on the probability of following state given the initial state.

The weights of goals are recalculated and normalized in every time moment. In the first step of selection all goals not related to the current Environment model obtain low weight. After that, only goals which can be acted upon in the current Environment are left. After this, the goal with maximum value of motivation function is selected. Motivation is calculated depending on goal weights. If the selected goal has multiple proximate goals, leading to it, then the proximate goal closest to the current state is chosen. Intention, as a next actionable state is derived from this nearest proximate goal.

The goal system keeps track of the history of progressing towards the specific goal, which helps to maintain perseverance and following up on the attained goals. GSM receives feedback from the context processing module about the success/fail of intent execution and updates accordingly plans and knowledge base.

3.2.1. Detecting situations in the current environment

Situation detection module functionally corresponds to the second level of DFIG model. It analyses the Environment model for cues and patterns related to situations, which could happen in current environment. For this it monitors the set of cues. Each cue is a condition (pattern) with weight, reflecting its importance.

$$Cue = (Cd_{cue}, w_{cue}) \tag{9}$$

Cues are ordered according to their weight. Cues leading to the situations with greater impact have more weight. The impact is deduced from the knowledge base. If an important cue is detected, SDM may ask the EDPM for additional diagnostics data, allowing it to confirm/decline the presence of a situation. If an important situation is confirmed, SDM updates the goal system with a new goal, having high weight and related to the reaction to this situation. GSM builds the plan and forms the intention to fix the situation.

SDM, while analyzing the causal chains leading from the current state to possible negative state in the future can predict the probability of this outcome and form a preventive intention to avoid such negative outcome. Likewise, SDM can predict positive opportunity as a chain of states starting from current state and having higher probability of realization. In this case it will also create a new goal in the goal system.

Thus, SDM works as the analysis module looking for events with negative consequences and for opportunities to further. SDM interacts with knowledge base to get information about cues and situation patterns.

3.2.2. Monitoring the environment and getting information

External data processing module monitors the environment state via available sensors. It detects the new objects in the environment and classifies them into specific classes, using local ontology. Thus, the set of EDPM functions correspond to zero and first levels of DFIG model.

Additionally, EDPM issues requests and obtains the information from the external services, processes and reconciliates the answers with agent's ontology and knowledge base. Therefore, external information services act as 'on-demand' sensors providing additional information for SDM and CPM.

A new goal is coming from external source is also processed first by EDPM, which conceptualize it using the local ontology concepts and relationships and passes to GSM.

EDPM maintains and modifies the Environment model, reflecting the objects present in the environment and their characteristics. Environment model is used by other modules. CPM constructs its Contextual model taking a part of Environment model and adding to it objects relevant to current intent. SDM monitors the Environment model for cues pointing to possible situations. Both CPM and SDM can issue requests for EDPM to get additional information from the environment or external information services.

3.3. Implementing the intent, performing actions, and getting feedback

The Context processing module has a purpose to transform the intent obtained from GSM into set of commands, passed to the Execution Module and implementing this intent. CPM maintains the Contextual conceptual model with concept instances and relationships, relevant to the task of following the stated intent in the current environment state. For this purpose, it copies the objects relevant to current task/intent from the Environment model.

CPM uses knowledge base patterns for information on how similar tasks were executed in similar environment state to construct the actual Contextual model. Alternatively, CPM can reuse conceptual models from previous experience and reconcile them logically with current state of Environment model.

The availability of models' sequence from previous experiences allows us to prepare and use models ahead of time. Contextual model, updated by applying patterns from knowledge base can have additional elements, not present in Environment model.

CPM fills the gaps in knowledge by addressing EDPM for additional information coming from sensors or external services. When contextual model has enough data, CPM makes decision about the right practice to apply to implement the intent. CPM obtains data from knowledge base about external services, commands and parameters needed to execute the commands implementing the intent. Additionally, the knowledge about how to test the success/fail conditions using services or Environment model is supplied.

CPM creates and sends commands to Execution Module, which selects and addresses corresponding external services. EM constructs a local conceptual Command execution model, containing knowledge about of how to execute command, the expected results, error conditions and processing. The feedback about success or failure of command is sent back to CPM or tested additionally following the changes in environment model.

4. Conclusions and discussion

The introduction of generative, predictive models of the world as a basis for intelligent agents' situational awareness confers several advantages compared to sequential, reactive, interpretational, and event-driven architectures. The main advantage is the ability to reuse the rich knowledge about previous experiences, which is constantly updated and kept logically consistent. Such knowledge typically comes from learning in the process of real-world task execution, and not in the form of externally imposed rules. Moreover, similarly to human cognition, such an approach allows to reconcile the use of the patterns from experience with the information coming from the environment using execution feedback resulting in the updates of those patterns.

Compared to the BDI proposed agent architecture adds the ability to dynamically react to the changes in the environment, prioritize those changes in the goal system, reuse and modify beliefs as a consistent pattern system in the knowledge base.

However, in order to implement the proposed model in practice several research problems should be resolved including the construction of conceptual models from pattern hierarchies in knowledge base and reconciliation of them with data coming from environment.

References

[1] Zhengyu Sha. "Concepts and Conceptual Representation," 2022, 103–88. https://doi.org/10.1007/978-981-19-8143-2_3.

[2] Barrett, L. F. "How Emotions Are Made: The Secret Life of the Brain," 2017. https://www.semanticscholar.org/paper/How-Emotions-Are-Made%3A-The-Secret-Life-of-the-Brain-Barrett/b54f2fd56ec084aa8e1a3b05dd24d93ecd5c945a.

[3] Marika C. Inhoff, Laura A. Libby, Takao Noguchi, Bradley C. Love, Bradley C. Love, and Charan Ranganath. "Dynamic Integration of Conceptual Information during Learning." PLOS ONE 13, no. 11 (2018). https://doi.org/10.1371/JOURNAL.PONE.0207357.

[4] Cuper, Alicja, and Małgorzata Cuper-Ferrigno. "A Few Remarks on Prototype Theory in Cognitive Linguistics." Language Culture Politics International Journal 1 (December 9, 2021): 57–67. https://doi.org/10.54515/lcp.2021.1.57-67.

[5] Burov, Yevhen, and Ihor Karpov. "Contextual Concept Meaning Alignment Based on Prototype Theory." In: Proceedings of COLINS-2023: 6th International Conference on Computational Linguistics and Intelligent Systems, 2023.

[6] Tekouabou, S. C. K., Cherif, W., Toulni, H., Abdelaoui, E. A., & Silkan,H. (2022). Using Class Membership based Approach to Improve PredictiveClassification in Customer Relationship Management Systems. International Journal of Computing, 21(2), 242-250. https://doi.org/10.47839/ijc.21.2.2593

[7] Mienye, I. D., Sun, Y., & Wang, Z. (2020). Improved Predictive Sparse Decomposition Method with Densenet for Prediction of Lung Cancer. International Journal of Computing, 19(4), 533-541. https://doi.org/10.47839/ijc.19.4.1986

[8] Clark, Andy. "Whatever next? Predictive Brains, Situated Agents, and the Future of Cognitive Science." Behavioral and Brain Sciences 36, no. 3 (2013): 181–204. https://doi.org/10.1017/S0140525X12000477..

[9] Goal. URL: https://www.dictionary.com/browse/goal

[10] Castelfranchi, Cristiano. "Intentions in the Light of Goals." Topoi 33, no. 1 (April 2014): 103–16. https://doi.org/10.1007/s11245-013-9218-3.

[11] Gugliotta, Alessio, Stefan Dietze, and John Domingue. "A Situations & Goals Semantic Model for Designing and Implementing Semantic Web Services-Based Processes." Services Computing. SCC '08. IEEE International Conference 2 (2008): 581–82.

[12] Motivation: Definition, Types, Theories, and How to Find It - Verywell Mind. URL:https://www.verywellmind.com/what-is-motivation-2795378.

[13] Kruglanski, Arie W, James Y Shah, Ayelet Fishbach, Ron Friedman, Woo Young Chun, and David Sleeth-Keppler. "A Theory of Goal Systems." The Motivated Mind, 2018, 207–50. https://doi.org/10.4324/9781315175867-6.

[14] Vancouver, Jeffrey B, Justin M Weinhardt, and Aaron M Schmidt. "A Formal, Computational Theory of Multiple-Goal Pursuit: Integrating Goal-Choice and Goal-Striving Processes." Journal of Applied Psychology 95, no. 6 (2010): 985. https://doi.org/10.1037/a0020628.
[15] Pezzulo, Giovanni, and Cristiano Castelfranchi. "Thinking as the Control of Imagination: A Conceptual Framework for Goal-Directed Systems." Psychological Research PRPF 73 (2009): 559–77. https://doi.org/10.1007/s00426-009-0237-z.
[16] Ribino, Patrizia, Massimo Cossentino, Carmelo Lodato, Salvatore Lopes, Luca Sabatucci, and Valeria Seidita. "Ontology and Goal Model in Designing BDI Multi-Agent Systems." WOA@ AI* IA 1099 (2013): 66–72.
[17] Silva, Lavindra De, Felipe Meneguzzi, and Brian Logan. "BDI Agent Architectures: A Survey." In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, 4914–21. Yokohama, Japan: International Joint Conferences on Artificial Intelligence Organization, 2020. https://doi.org/10.24963/ijcai.2020/684.
[18] Saadi, Adel. "A Further Exploration of the Natural Incorporation of Motives in BDI Architectures," 1–7. IEEE, 2021.
[19] Aiguier, Marc, Isabelle Bloch, Salim Nibouche, and Ramon Pino Perez. "Morpho-Logic from a Topos Perspective: Application to Symbolic AI." arXiv Preprint arXiv:2303.04895, 2023.
[20] Su, Yun, Yongqiang Dai, and Xiaohong Li. "Logical Model and Verification of Emotion Triggers for BDI Agents," 1135–40. IEEE, 2019.
[21] La Torre, Salvatore, and Gennaro Parlato. On the Model-Checking of Branching-Time Temporal Logic with BDI Modalities, in: Proceedings of AAMAS. 681–89, 2020.
[22] Alzetta, Francesco, Paolo Giorgini, Mauro Marinoni, and Davide Calvaresi. "RT-BDI: A Real-Time BDI Model." edited by Yves Demazeau, Tom Holvoet, Juan M. Corchado, and Stefania Costantini, 12092:16–29. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2020. https://doi.org/10.1007/978-3-030-49778-1_2.
[23] Buford, John, Gabriel Jakobson, and Lundy Lewis. "Extending BDI Multi-Agent Systems with Situation Management," 1–7. IEEE, 2006.
[24] Dunin-Kęplicz , Linh Anh , Andrzej Szałas "A Framework for Graded Beliefs, Goals and Intentions," 2010. https://doi.org/10.3233/FI-2010-263.
[25] Caillou, Philippe, Benoit Gaudou, Arnaud Grignard, Chi Quang Truong, and Patrick Taillandier. "A Simple-to-Use BDI Architecture for Agent-Based Modeling and Simulation," 15–28. Springer, 2017.
[26] APA dictionary of psychology, Situational awareness, 2022. URL: https://dictionary.apa.org/situation-awareness
[27] J. Bleiholder, F. Naumann. Data fusion. ACM computing surveys (CSUR) 41, no. 1 (2009): 1-41
[28] Grigore Stamatescu, Ioana Făgărăşan, and Anatoly Sachenko, "Sensing and Data-Driven Control for Smart Building and Smart City Systems," Journal of Sensors, vol. 2019, Article ID 4528034, 3 pages, 2019. https://doi.org/10.1155/2019/4528034.
[29] C. Richards, C. Boyd's OODA loop. Richards, 2020.
[30] E. Shahbazian, D. Blodgett., P. Labbé, The extended OODA model for data fusion systems. Fusion01. (2001)
[31] M C Wright, , J M Taekman, M R Endsley. "Objective Measures of Situation Awareness in a Simulated Medical Environment." Quality & Safety in Health Care 13 Suppl 1 (2004) 65–71.
[32] A.N Steinberg. C.L. Bowman, Revisions to the JDL data fusion model. In: Handbook of multisensor data fusion, CRC Press, 2008, pp. 65-88.
[33] E. Blasch, "One decade of the Data Fusion Information Group (DFIG) model." Commercial + Scientific Sensing and Imaging (2015)
[34] Foo, Pek Hui, and Gee Wah Ng. "High-level information fusion: An overview." J. Adv. Inf. Fusion 8, no. 1 (2013): 33-72.
[35] Ehrlinger, Lisa, and Wolfram Wöß. "Towards a Definition of Knowledge Graphs." SEMANTiCS (Posters, Demos, SuCCESS) 48, no. 1–4 (2016)