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SITUATION ANTICIPATION AND PLANNING FRAMEWORK FOR INTELLIGENT ENVIRONMENTS

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ABSTRACT

Context. Situation anticipation, prediction and planning play an important role in intelligent environments, allowing to learn and predict the behavior of its users, anticipate maintenance and resource provision needs. The object of study is the process of modeling the situation anticipation and planning in the situation-aware systems.

Objective. The goal of the work is to develop and analyze the ontology-based framework for modeling and predicting the situation changes for intelligent agents, allowing for proactive agent behavior.

Method. This article proposes a framework for anticipation and planning based on GFO ontology. Each task or problem is considered a situoid, having a number of intermediate situations. Each task or problem is considered a situoid, having several intermediate situations. The framework is focused on the analysis of changes between situations, coming from anticipated actions or events. Contextually organized knowledge base of experiential knowledge is used to retrieve information about possible developments scenarios and is used for planning and evaluation. The framework allows to build and compare trajectories of configuration changes for specific objects, situations or situoids. The planning and anticipation process works in conditions of incomplete information and unpredicted external events, because the projections are constantly updated using feedback from sensor data and reconciliating this information with predicted model.

Results. The framework for reasoning and planning situations based on GFO ontology, allowing to model spatial, temporal and structural data dependencies.

Conclusions. The situation anticipation framework allows to represent, model and reason about situation dynamics in the intelligent environment, such as intelligent residential community. Prospects for further research include the elaboration of contextual knowledge storing and processing, reconciliation and learning procedures based on real-world feedback and the application of proposed framework in the real-world system, such as intelligent security systems.

KEYWORDS: GFO, situational awareness, anticipation, situation analysis, situoid.

ABBREVIATIONS

GFO is a General formal Ontology;

ISFO is an Integrated System of Foundational Ontologies;

IFDAO is an Integrated Framework for the Development and Application of Ontologies;

GOL is a General Ontological Language;

DFIG is a Data Fusion Information Group;

UFO is an Unified Foundational Ontology;

DCIM is a Data Collection and Interpretation Module;

SMA is a Situation modeling agent;

GMM is a Goal management module.

NOMENCLATURE

Tsk is a task;

t_{st}, t_{end} is a starting and ending times of task or situoid;

Su is a situoid;

$Sit_{st}^{su}, Sit_{end}^{su}$ are the starting and ending situations in situoid;

Ch is a chronoid;

Cf_{t_1} is a configuration in the time moment t_1;

$Gl_{\text{int},ti}$ is an agent's intention in moment t_i;

Cm is a conceptual model;

$Cm_{env,ti}$ is a conceptual model of environment in moment t_i;

$Cm_{con,ti}$ is a conceptual model of context in the moment t_i;

F_{sim} is a function measuring the distance between two contexts;

Pl is a plan;

Ac is a specification of action;

F_{sel} is a function for selecting the situation trajectory using criteria Cr;

TP is a true positive;

FP is a false positives;

FN is a false negatives;

TN is a true negatives detections;

$T_{responce}$ is a time of response;

$T_{analysis}$ is a time of analysis;

T_{action} is a time of action execution;

$S(t)$ is a current situation at time t, described by the parameters of the environment;

A is a set of available agent actions;

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ε is a set of possible external events that affect the situation;

K is a contextually organized knowledge base that contains data on previous situations and scenarios of their development;

$P(S_i, a, e)$ is a model of transition between situations that determines the probability of transitioning from a situation;

From S_i to S_j for actions $a \in A$ and events $e \in E$;

σ is a set of sensor data updated in real time;

τ is a trajectory of changes in situations $S(t_1), S(t_2), S(t_n)$ for a given period of time;

π is an optimal action plan of the agent $a_1, a_2, ... a_k$ to achieve a given goal;

$S(t)$ is a predicted situation at a given time t_t.

INTRODUCTION

The recent progress in information technology and artificial intelligence fueled by further growth of computation capacities creates many opportunities in all areas of economy and research. The scientific and technological area of intelligent ambience follows the age-old vision of intelligent environments helping humans to live fulfilled lives [1]. It is a recurrent theme in literature on smart homes and ambient intelligence [2, 3]. Situational awareness is a required feature for agents implemented in the intelligent environment, because it permits to discover potentially dangerous situations, guess and follow user's intents and act proactively [4, 5]. Situational awareness, in turn requires the ability to model and reason about situations and actions leading from one situation to another. Such ability is also linked to the implementation of goal-driven behavior of agents. The purpose of this article is the development of a conceptual framework for situation anticipation and planning analysis based on General Formal Ontology (GFO).

The object of study is the process of modeling the situation anticipation and planning in the situation-aware systems.

The implementation of such a process is a necessary condition for the development of fully autonomous intelligent agents. However, existing models, such as DFIG model [6] don't support it.

The subject of study is the frameworks and methods for modeling the situation development in intelligent agents.

The purpose of the work is to develop and analyze the ontology-based framework for modeling and predicting the situation changes for intelligent agents, allowing for proactive agent behavior.

1 PROBLEM STATEMENT

Let us assume that we have:

Input variables: $S(t)$, A, ε, K, $P(S_i, a, e)$, σ.

Output variables: τ, π, $S(t)$.

Optimization criterion:

The task of forecasting and planning is to minimize the loss function $L(\tau, \widehat{\tau})$ where $L(\tau, \hat{\tau}) = \sum_{t=1}^{n} d(S(t), \hat{S}(t))$, where $d(S, \hat{S})$ measure of deviation from the real situation $S(t)$, $S(\hat{t})$ from the predicted.

Limitation

$\forall a \in A,\ e \in E \div P(S_i, a, e) \in [0,1]$.

Trajectory τ must be achievable in the situation $S(O)$.

Forecasting and planning must work in conditions of incomplete information $\sigma(t) \neq S(t)$, where $S(t)$ is a complete description of the environment that is not available due to limited sensors

Problem statement:

The task of developing a framework for predicting situations and planning in intelligent environments is to construct an optimal trajectory τ and action plan π based on transition models $P(S_i, a, e)$, knowledge K, current sensor data σ and ensuring proactive agent behavior when fulfilling optimization criteria $L(\tau, \hat{\tau})$ in conditions of uncertainty and limitations.

Knowledge base Knb is organized around tasks, which are represented as situoids Su and agent's intents, and stores the information about situations dynamics in the form of intermediary situations Sit and actions Ac leading from one situation to another:

$$\left(Sit_i, Gl_{int,k}, Ac\right) \rightarrow Sit_j.$$

The problem is to build a reasoning framework, allowing to represent and model the situational dynamics in the form of a sequence of situations $S(t_1), S(t_2), S(t_n)$, using the knowledge from knowledge base Knb and similarity function F_{sim} evaluating the similarity between current context $Cm_{con,tc}$ and contexts from knowledge base.

Suppose given the original sample as a set of precedents (instances) $<x, y>$, where $x = \{x^s\}, x = \{x_j\}, x^s = \{x^s_j\}$, $y = \{y^s\}, s = 1, 2, ..., S, j = 1, 2, ..., N$.

For a given sample of precedents $<x, y>$ the problem of model synthesis can be presented as the problem of finding $<F(), w>: y^{s*} = F(w, x^s), f(F(), w, <x, y>) \rightarrow opt$, where the model structure $F()$ usually specified by the user in practice, and the set of controlled parameters w is adjusted based on the training sample.

In turn, the problem of subsample formation from a given sample $<x, y>$ is to find such a set of $<x', y'>: x' \subset \{x^s\}, y' = \{y^s \mid x^s \in x'\}, S' < S, N' = N$, wherein $f(<x', y'>, <x, y>) \rightarrow opt$.

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2 REVIEW OF THE LITERATURE

The integration of situational awareness into intelligent agents presents a significant challenge within the field of artificial intelligence. The primary factors that contribute to this challenge include:

– The necessity of incorporating both predictive abilities and environmental perception, alongside the reasoning and evaluation of potential actions.

– Being focused on objectives while utilizing goals to empower intelligent agents with agency and autonomy, aiding in the selection of the most crucial goal to pursue at any given moment, and taking actions that align with this goal.

– Concentrating on a specific area of the environment relevant to the chosen goal, emphasizing shifting attention rather than explicitly querying and selecting related information.

– Utilizing contextual knowledge effectively.

The ambiguous nature of knowledge, where ontology concepts may have multiple meanings depending on context.

The ever-changing environment necessitates continual updates and validation of the model.

In the same time the ability to represent situation related information and reason about it remains the major requirement for autonomous intelligent agents [7].

The recent advancements in our comprehension of cognitive mechanisms in the human mind have the potential to offer valuable insights into the realm of artificial intelligence systems. This cognitive process has evolved over millennia and stands as the most effective form of cognition known to us presently [8].

The notion of concept is foundational in our understanding of cognition. Concepts emerge from the act of categorization and identification of patterns within our mental constructs. Once established, concepts are utilized to construct predictive frameworks of the environment. Devoid of concepts, our experiential perception would be limited [9].

Concepts serve to provide meaning to our environment, enabling us to engage in rational thinking through interconnected concepts. The fluid nature of concepts entails that their meanings evolve based on the context and intentions of the user. Prototype theory is used to explain the diverse interpretations of concepts across varying scenarios [10, 11].

Concepts not only mirror tangible entities in the real world, but also extend to abstract and imaginative constructs. The capacity to manipulate abstract concepts showcases the human mind's potent ability, enabling us to transcend constraints imposed by working memory capacity and processing speed.

Hence, conceptual modeling, characterized by the proficiency in developing and reasoning with conceptual frameworks, proves to be an effective method for information representation and processing. This approach holds promise for integration into artificial intelligence systems.

According to contemporary comprehension within cognitive psychology [12], the human brain engages in the navigation and evaluation of the surrounding environment through the utilization of predictive modeling. Formerly, the concept of consciousness was depicted as a sequential progression, commencing with the perception of the environment, followed by the interpretation of data readings, the construction of a model based on said interpretations and existing knowledge, and ultimately, the process of decision-making and subsequent action.

The predictive models derive from recollections of past encounters, serving as a framework of pertinent patterns that are continuously reconstructed (updated) while considering the prevailing objectives and environmental attributes accessible through sensor data. Individuals without prior experiences are essentially deprived of such experiential knowledge and thereby struggle to comprehend their present circumstances.

The external information is perceived as alterations within the environment, which are then reconciled with the predictive model to form a cohesive entirety. Throughout this reconciliation process, the model itself may undergo modifications. Such process occurs across various levels of abstraction, beginning with overarching, fundamental principles and gradually delving into specific details.

The usage of predictive modeling yields multiple benefits, such as enhanced responsiveness to environmental and objective changes, the capacity for logical reasoning and knowledge acquisition, along with the continual adjustment of patterns based on real-world encounters. The mind persistently generates hypotheses regarding the current context and subsequently checks them against sensory input, various communication mediums, and the outcomes of logical deliberation.

The insights derived from the existing comprehension of the human cognitive process of situational awareness, which revolves around predictive modeling, could be leveraged to refine the models pertaining to situational awareness within agents operating in intelligent environments.

Predictive and anticipation computing are integral to enhancing the functionality and user experience of intelligent environments. These technologies leverage data analytics, machine learning, and artificial intelligence to create smart environments that respond proactively to user needs.

However, there's a difference between predictive and anticipatory computing [13]. Anticipatory computing involves awareness of past, present, and future, enabling proactive responses to changing conditions. This approach allows for a more dynamic and responsive intelligent environment, where systems can anticipate and adapt to various scenarios. In contrast, predictive computing focuses more on forecasting future events based on historical data. Both predictive and anticipatory computing are used in resolving multiple problems and accomplishing tasks in intelligent environments. They are integral to enhancing the functionality and user experience of intelli-

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gent homes. These technologies use data analytics, machine learning, and artificial intelligence to create smart environments that respond proactively to user needs.

The analysis of literature shows that the application of predictive computing in intelligent environments, such as intelligent homes is happening in such areas:

– Personalized user experience involves analyzing user behavior and preferences, and smart home systems can adapt their operation to individual needs. For example, artificial intelligence algorithms can learn a user's daily routine and adjust lighting, heating, and entertainment systems accordingly. This personalization increases comfort and convenience, making homes more intuitive and responsive to the lifestyle of their residents [14–17];

– Energy management is predictive analytics and can optimize energy consumption by analyzing usage patterns. Smart devices can adjust heating and cooling systems in real time, resulting in significant energy savings and cost reductions. For example, systems can adjust settings in advance based on predicted occupancy or weather changes [17, 18];

– Predictive maintenance involves performing predictive calculations that can predict potential failures in devices and systems, allowing for proactive maintenance. By monitoring device performance and usage data, smart home systems can alert users to problems before they lead to breakdowns, thus extending the life of devices and minimizing downtime [17, 19];

– Improved security, as smart security systems use predictive analytics to detect unusual patterns that may indicate security threats. For example, AI-powered cameras can recognize familiar faces and alert homeowners to strangers, providing real-time security updates and automated responses to potential breaches [20]. Another application of machine learning and predictive analytics is risk assessment using AI. AI can analyze historical security data to identify patterns and predict future risks. This allows for more robust security protocols tailored to the specific threats a household faces [21];

– IoT integration provides predictive computing that enables seamless integration of a variety of smart devices in the home. This interconnection allows devices to exchange data and information, creating a cohesive intelligent environment that enhances user experience. For example, a smart thermostat can communicate with security systems to adjust heating when the home is empty, optimizing both comfort and energy efficiency [22].

3 MATERIALS AND METHODS

The important precondition to building knowledge-based system for intelligent agents is selecting the underlying conceptual constructs used to build the framework model. This task is crucial to the research, because on its result depend such properties of framework as expressibility, the ability to communicate and process knowledge. In our research is used the method of ontological modeling, based on formal foundational ontology.

Such an ontology provides the logically non-contradictory set of interrelated conceptual constructs which are well-grounded in reality. Foundational ontologies, such as Unified Foundational Ontology (UFO) [23], General Formal Ontology (GFO) [24] supply the basic sets of elements, the vocabulary and syntax rules to build the anticipation framework upon them. Both UFO and GFO are rich in details and are well developed.

However, the important additional requirement for a framework working with anticipated situations is the support of spatial and temporal conceptual constructs. As a foundation of our modeling framework, we have selected GFO (General Formal Ontology) which is 4d ontology [25], supporting spatial and temporal conceptualizations.

GFO is a foundational ontology that provides a systematic framework for describing forms, modes, and views of existence across different levels of abstraction and granularity. It combines methods from mathematical logic, philosophy, artificial intelligence, and linguistics.

GFO is a component of ISFO (Integrated System of Foundational Ontologies). ISFO is a part of an Integrated Framework for the Development and Application of Ontologies (IFDAO). Besides ISFO the system IFDAO includes the subsequently developed modules: a Library of Ontology Languages, and a System of Development Tools. This system of tools supports the development of domain oriented and generic ontologies.

One of the main philosophical principles of GFO is foundational ontology should allow for different, even logically inconsistent conceptualizations, reflecting the variety of perspectives in different contexts. Foundational ontology is represented as partial order if logical theories, some of which may be inconsistent with theories not situated on the same partial ordering path [26, 27]. Therefore, ISFO represents an integrated and evolutionary system of foundational ontologies.

The important part of ISFO is GOL (General Ontological Language) used to express ontological concepts and relationships [28]. It provides a formal means for defining and structuring knowledge within ontologies. GOL allows otologists to create axiomatic theories and specify the semantics of concepts. While GFO represents the foundational principles, GOL serves as the linguistic vehicle for expressing those principles. GOL enables the development of domain-specific ontologies by providing a standardized way to describe entities, properties, and their interconnections.

Let's consider the components of GFO related to the representation of changes in the state of the world, being important for modeling predictions. The existence of an object in time is described with three interrelated concepts: presential, persistent and perpetuant. Presentials are individuals which are fully present in time-point. Presential is a state of an individual in specific time moment. Persistent is a universal, which instantiates presentials. This instantiation comes in every time moment. Persistant

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corresponds to an individual that can change and preserve its identity (it is a collection of presentials in multiple time moments. Perpetuant is an individual, instantiated by persistant and describes a specific individual which changes over time. For example, a Person is a Persistant; John is Perpetuant; John in specific time moment is Presential.

Topoid is a basic ontological category in GFO that represents a connected, bounded region of space. It is used to model spatial locations and can be thought of as a generalized spatial region that can vary in its dimensionality (e.g., points, lines, surfaces, volumes). Each topoid is characterized by its spatial extent, dimensionality and boundaries. Spatial Extent describes where entities are located.

The concept of topoid is flexible in terms of dimensionality, allowing for the representation of different kinds of spatial entities:

– 0D Topoid: a point;
– 1D Topoid: a line or curve;
– 2D Topoid: a surface or area;
– 3D Topoid: a volume or solid region.

Topoids are characterized by having clear boundaries, making them distinct from other spatial regions. Topoids play a crucial role in GFO's spatial ontology [29], providing a foundational element for representing spatial aspects of reality. They can participate in various spatial relations such as containment, adjacency, overlap, and separation. Topoids are integrated with other ontological categories in GFO, such as objects and processes, to provide a comprehensive model of reality. For example, in the case of intelligent residence topoid can represent its location and territory, the locations of specific buildings, the trajectories of moving objects.

The concept of chronoid is central to how GFO models the temporal dimension of reality. A chronoid is an ontological category that represents a connected, bounded region of time. It is used to model temporal intervals and periods, providing a way to describe when events and processes occur. A chronoid is characterized by its temporal extent and boundaries. Temporal Extent means that each chronoid occupies a definite duration in time. Boundaries allows to distinguish between different chronoids and temporal regions.

Chronoids are important in GFO's temporal ontology, allowing for the representation of time-related aspects of reality [30]. They can participate in various temporal relations such as precedence, overlap, containment, and succession. Chronoids are integrated with other ontological categories in GFO, such as objects and processes. In the context of intelligent residence chronoid, for example, could be used to represent a schedule for cleaning and maintenance.

A configuroid is an ontological category that represents structured configurations or arrangements of entities. It is used to model the specific way in which entities are organized or related to one another within a particular structure.

Configuroids have such key characteristics: Structural arrangement, Composite nature and relational properties, identifying connections between parts in the structure. Configuroids can participate in various structural relations, such as part-whole relationships, adjacency, and connectivity. In the context of intelligent home configuroid could be used to represent the structure of computer network.

However, it is important to differentiate between terms "configuration" and "configuroid". A "configuration" refers to a particular arrangement or setup of components within a system. It emphasizes the state or condition of being arranged or structured in a specific way. Configuration is state-oriented and describes the specific structure state in specific time moment. Configuration is contextual, often implying the context or circumstances under which entities are arranged. For instance, the configuration of a machine might refer to how its parts are assembled and how it operates under specific conditions. Configurations can change over time as entities are rearranged or modified.

A configuroid is an ontological category used to represent structured configurations or patterns in a more formal and abstract manner. It serves as a higher-level concept that captures the essence of structured arrangements.

In the GFO, a situoid is a concept used to represent situations or contexts [31]. It is an essential component for modeling the contextual and situational aspects of reality within ontology.

Situoids exhibit following characteristics:

– Contextual complex due to situationoids are used to capture the entire context or situation, including all relevant entities and their relationships;

– Temporal and spatial boundaries are the constraints on the situationoid in both time and space, i.e. it exists within a specific time range and spatial region;

– The dynamic nature of situationoids, as they can change over time as entities and their relationships evolve within the context.

Situoid is a unit of comprehension. Comprehension here refers to the act of understanding or grasping the meaning of something, whether it is the experience, the formation of concepts, or the recognition of objects.

In the context of situoids, comprehension plays a crucial role in making sense of the events or elements that make up a situoid. It involves considering these events or elements together in a single mental act before they can bear any meaning. Comprehension in situoids comes before inference or judgment and involves considering the events or elements as a whole, rather than focusing on individual steps or relations. Theoretical comprehension of a situoid involves being able to find a universal category that the situoid is an instance of which includes the finding of similar situoids in experiential knowledge.

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Situoid can be defined by the goal or task and considered as a movement between two bounding situations, current and the target one. Situoids integrate with other ontological categories in GFO, such as objects, processes, topoids (spatial regions), and chronoids (temporal regions), to provide a comprehensive model of reality. Each situoid has associated topoid, chronoid and configuroid. It means that it happens in space and time and the world is undergoing structural change during its existence.

Situations are situoid configuration in specific time moments. We can consider them as slices of situoids in the time points. Situoid is bounded with situations and can have a number of situations inside. Each situation, like a situoid can be considered as a whole, but also analyzed structurally.

For example, a medical emergency in a hospital can be represented as a situoid. This situoid would include patients, doctors, nurses, medical equipment, and their relationships and interactions during the emergency. It captures the specific spatial region (e.g., an emergency room) and the temporal duration (e.g., the time during which the emergency unfolds).

The proposed framework model explores the situational dynamics with ontological models of situoids and situations using topoids, chronoids and configuroids to specify spatial, temporal and structural aspects of situations and allow to model each situation development process as a whole.

4 EXPERIMENTS

Intelligent residential community systems need predictive mechanisms and anticipative analysis to deduce and follow user needs and behavior, make decisions and plan, look for possible issues and understand their consequences. On the other hand, the software agent working in intelligent residence has a limited set of tasks and problems; its activity is constrained both in time and space, which makes the implementation and functioning of such agent less resource intensive.

We consider the anticipatory and planning framework from the perspective of intelligent agent with situational awareness, which uses it. In [32] is shown that prediction and modeling feature constitute the central function of intelligent agent. This article also proposes the structure of such an agent as a set of interacting functional modules.

Let’s define the core assumptions and requirements for the anticipation and planning framework:

– The basic building blocks of this framework are provided by GFO ontology;

– The planning and modeling will be represented as situational dynamics within situoids;

– The predictions and models in framework will use experiential knowledge about situational dynamics in similar situations and situoids;

– Knowledge and modeling are organized contextually, a context being defined as specific task/goal being achieved in specific environment;

– Therefore, only relevant to context elements will be included in situation specification;

– The framework should support planning for the execution of tasks and reaching goals. But it should also allow us to model the development of situations when an agent is idle;

– Knowledge models are updated from comparison of predicted situations with real ones. The information about parameters of real state comes from the sensors;

– Framework will support different levels of granularity and specificity in planning. This will allow us to counteract the lack of information and incremental self-correcting movement towards the goal;

– It will also allow for multivariate modeling, considering different scenarios of situations development in the future;

– Historical information about past situations will be used to detect patterns and make decisions.

To understand the functioning of the proposed anticipation framework we need first to describe its place within the larger system of intelligent residential community. For the purpose of this article, we will use the simplified version of agent architecture from [32] (Fig. 1).

Sensors are in the agents, local to specific devices, placed in different parts of intelligent residential community. A separate functional module, Data Collection and Interpretation Module (DCIM) collects data from devices, interprets it according to agent’s ontology and stores them in database. Using data obtained from sensors DCIM builds the Environment model which contains data about found objects and their parameters dynamics. DCIM also uses the Environment model to detect patterns in data indicating known or threatening developments to timely counteract them. Environment model is a conceptual model, storing the dynamics of objects tracked in intelligent community over time. It is represented as a temporal knowledge graph [33].

DCIM interacts with Situation modeling agent (SMA) populating the models of situations with relevant objects information. Situation modeling-agent may ask DCIM for additional information and formulate the data collection task. DCIM also performs searches in the external databases and web upon the request of SMA. Goal management module (GMM) provides the current task and intent for intelligent agent. SMA uses experiential knowledge from knowledge base and updates it in the process of learning. Contextual model is used to constrain the situation model taking into consideration the current goal and agent’s environment.

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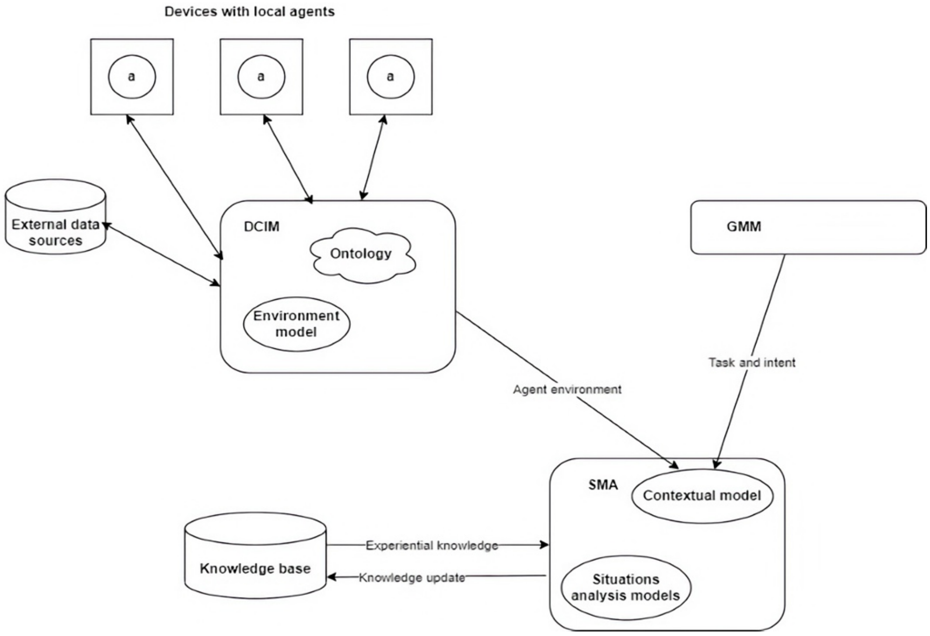

Figure 1 – The structure of intelligent residence system

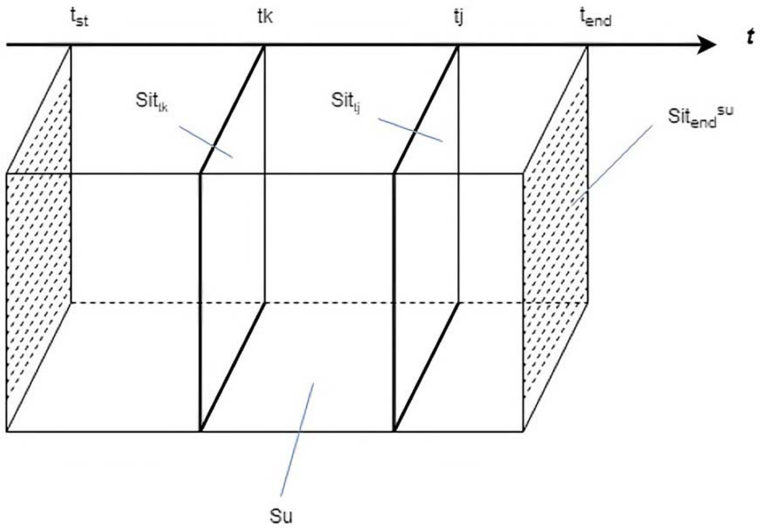

Figure 2 – The representation of situational dynamics in a situoid

5 RESULTS

Intelligent agent in every moment of time executes a task T_{sk}. This task is done in time and space, and therefore has a start t_{st} and completion moments t_{end}. Even if such an agent is doing nothing, it is aware of this and performs the observation of environment, predicting the natural changes happening in the observed environment.

Since the purpose of this article is to describe the planning and anticipation framework, we will omit the analysis of space dimension changes, described by corresponding topoid, unless it is involved in the detection of behavioral patterns in the intelligent community.

SMA can work with multiple tasks and problems in parallel. However, for the sake of simplicity we will exclude from our analysis the coordination of different tasks and focus on the predictions and planning within a single task.

Situoid GFO object is suitable for the representation of such task, because the dynamics of task execution and the prediction of future states can be represented as a sequence of situations inside the situoid. Each situoid Su is bounded by situations. The starting situation Sit_{st}^{su} corresponds to the state when the task was issued. The ending situation Sit_{end}^{su} corresponds to the state when the task is completed or abandoned. Starting and ending situations are projected onto chronoid *Ch*, in this case – a timeline, where situations are placed. Between the starting and ending situations in situoid exist a number of intermediate situations $(Sit_{t1}, Sit_{t2}, ..., Sit_{tk})$, which are also attached to the timeline (Fig. 2). Only the situations which represent

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some interest in anticipation or planning process are considered.

Apart from task, situoid can be created to reach the specific goal or resolve the detected problem. The process of modeling situations in all cases is similar. Each situoid created is considered as a whole within the context of task execution in the current environment.

Context for the situations is provided by the current state of environment and current intent $Gl_{int,tc}$ in task executed in it. The agent's environment model $Cm_{env.tc}$ is provided by DCIM as a part of *Environment model* $Cm_{env.tc} \supseteq Cm'_{env.tc}$ for the current time t_c. Context constrains and limits the number of elements included in the model of situation to only relevant to the intention in current time moment

$$Cm_{con.tc} = (Cm'_{env.tc}, Cl_{\text{int}.tc}, t_c). \qquad (1)$$

The process of task execution is modeled as a sequence of situations (Sit_{t1}, Sit_{t2}, …. Sit_{tn}), and corresponding sequence of configurations (Cf_{t1}, Cf_{t2}, .. Cf_{tk}), . Each configuration in sequence is represented as knowledge graph:

$$Cf_{li} = (SV_{con}, SE_{rel}, t_i), \qquad (2)$$

where SV_{con} is a set of nodes, corresponding to objects and SE_{rel} is a set of relationships used in situation specification. Both objects and relationships are classified according to the system's ontology. Specific configurations in (2) can be different, which reflects the situation configurations dynamics in the process of task execution.

Each situoid created is considered as a whole within the context of task execution. In each situoid we can specify the current situation, past situations, and the number of projected situations. All those situations are taken into account in making decisions for task execution.

Past situations are stored sparingly. They are usually linked to important events or changes in the process of task execution. Everything else in between is restored/approximated at need using available situational knowledge. The reason to preserve historical information is to be able to detect patterns in historical data, which can influence decisions and projections.

System creates only one version of the current situation. It is formed as an update of projected situation with *Environment model* data. This data introduces corrections into projected model, obtained from experiential knowledge.

However, there are multiple projected future situations. One of them describes the task completion (ending situation Sit^{su}_{end}). There are situations, specifying milestones or intermediary states placed between current and end situation. And there's the projection of the next situation, which is seen as a result of the implementation of agent intention in the dynamic environment.

As a basis for projections the experiential knowledge is used. This knowledge is stored contextually, that is a key for retrieval is context similarity. When a system looks for information in knowledge base it looks for the knowledge about the execution of similar task in similar environment. When similarity is established, the system makes a mapping between situation and knowledge pattern. In this way access to knowledge represented by patterns is provided.

Therefore, a function F_{sim} measuring the distance between the current context (1) and the key-context $(Cm^{kb}_{env}, Gl^{kb}_{\text{int}})$ from the knowledge base should be implemented. In the process of searching the value of this function should be minimized:

$$F_{sim} : ((Cm'_{env,tc}, Gl_{\text{int},tc}), (Cm^{kb}_{env}, Gl^{kb}_{\text{int}})) \rightarrow \min \qquad (3)$$

Knowledge is stored in the form of loosely organized patterns. For each pattern the information about its usage conditions is provided, including exceptions, variations depending on environmental conditions. Patterns are organized as Pattern Language, where patterns are linked in larger configurations of patterns or clusters. That allows them to be used together. Patterns are formulated on higher abstraction level, so one pattern could be used for a host of similar situations with the variation of parameters.

Knowledge patterns are represented as conceptual models in the form of weighted temporal knowledge graphs. The weights in knowledge graph are used to manage importance/relevance of specific parts of graph in specific situation. The temporal dimension of graphs will help to project the application of knowledge in future and place them on the situoid's timeline.

Modeling the transitions between the situations is an essential part of predicting future situations. These transitions involve changes in parameters, produced by different causes. Transitions could be natural and happen without the agent's intervention or they can be planned, including the proactive agent actions.

We model the basic anticipation of change as two situations and change leading from one to another (Fig. 3).

The source situation $Sit_{src,ti}$ is considered as a starting point for change, the target situation $Sit_{tg,tj}$ is the ending point of change. There's no limitation on how far in time the target state is located. The sole constraint is that it should be after the source situation $t_j > t_i$. After the specification of source and target situation, the system specifies the action, process or event from its experiential knowledge which can change the source state to the target state. This action or process we will summarily designate as a plan *Pl*. This anticipation of change could be considered as a situoid *Su*` fully contained within the initial situoid $Su : Su \supseteq Su'$ It is represented as a tuple

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$$Su' = (Sit_{src,ti}, Sit_{tg.tj}, Pl, Cm_{con}) \tag{4}$$

where Pl is a plan. In case of a situoid Su' representing the atomic change reflecting the current intention, instead of plan we specify the action Ac. Contextual information, reflecting the dependency from the environment and goal is represented by Cm_{con}.

At task creation the anticipation operation is first done between the starting and ending boundaries of situioids. The modeling system looks for processes executing similar tasks in the past. Such knowledge provides the plan, intermediary states and the confirmation of the task feasibility. Next, the situoid is split by intermediary situations using the available knowledge. In this way a plan Pl for reaching the goal, specified by the ending situation is built. This plan can be represented by a complex graph, like Gantt chart, including multiple intermediary situations.

Alternatively, a system could specify only starting and ending situations, and mark some intermediary states, without the detailed plan elaboration. This could be required in conditions of limited computational resources or reaction time, or if there are too many unknowns and random factors influencing the reaching of the goal. This is not unlike the flexible development process.

However, every time the anticipation includes consideration of basic transition between the current situation and the next situations. Such change can be envisioned as the result of the natural course of events (all changes are produced by natural causes, no action from agent is done) or some specific set of external events, or some actions performed by intelligent agent. A modeling system can create and analyze several future situations, compare them and select the most appropriate course of actions for agent.

The changes between the situations can be represented as transitions between points in multi-dimensional space of object parameters in conceptual space [34]. They can be also specified as changes in configurations between situations, highlighting the configurational dynamics. In the process of projecting and planning it could be useful to track trajectories of parameter changes. In the proposed framework we envisage such trajectories:

– A trajectory for a specific object or its parameters involves changing the parameters (configurations) of the object or its connections between several intermediate situations. For example, such a trajectory can reflect the movement of a person on a campus;

– A situation trajectory considers the situation as a single whole, as a holistic model. A situation trajectory tracks changes between situations and is used to predict multivariate development of situations within a single situationoid. It is necessary to develop several situation trajectories in order to adapt to possible external events that occur and to create contingency plans. Another use case for multivariate situation analysis is to predict and compare the consequences of the actions of different agents (Fig. 4);

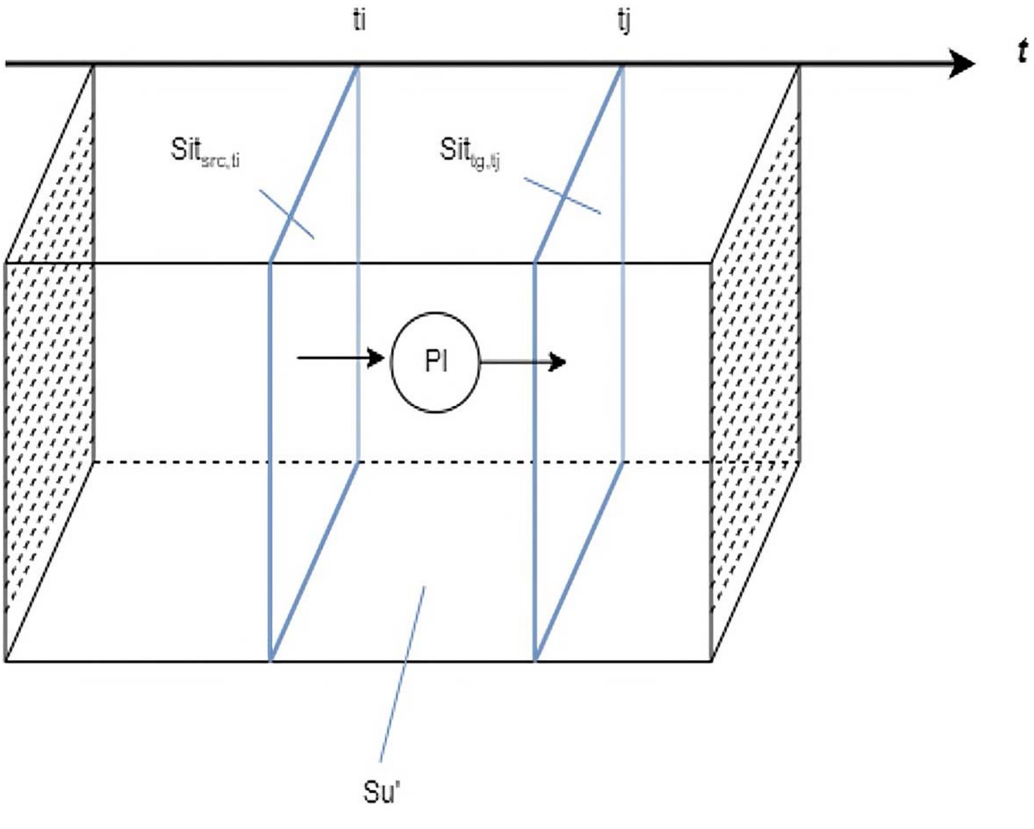

Figure 3 – Modeling changes between situations

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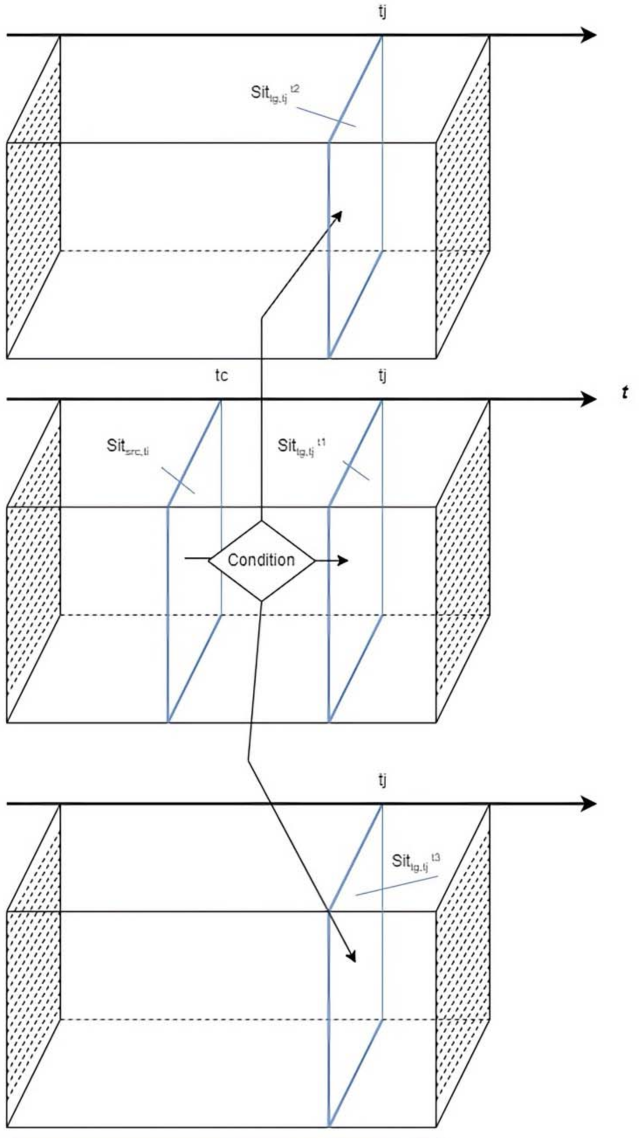

Figure 4 – Multivariate situation analysis with situation trajectories

– A situationoid trajectory is used when the execution of a task generates other tasks that are not related to or are not contained in the parent task and situationoid. In this case, the agent operates on dependent projects and tasks, each represented in its own situationoid.

The system builds several anticipation models and gains useful information when comparing them. The first such model is the Observer model. It implies no actions from the intelligent agent, just following the natural flow of events. What will happen if nothing is done. Another model is the Intention model, representing the result of immediate agent's action. What will be the expected result of such an action? Intention models are always built before an actual action is done, to anticipate the action's consequences and outcomes. Long-term planning models have intermediary situations and goals. They are often not specified in detail at start and are modified during the task execution.

The current situation model is built based on the anticipated model. This model is updated using data from Environment model provided by DCIM. In this operation only differences between anticipated configuration and real configuration are passed from DCIM. This allows us to reduce data traffic and increase performance (Fig. 5).

Next, the system defines the Intention model Sit_{tg} for the next situation and looks in knowledge base for possible actions leading to this situation. In this stage several models $SSit_{tg} = \{Sit_{tg}\}$ can be built including the *Observer model* or different variants of Intention models using different actions. The consequences of such actions are projected in the form of situation trajectories. Next, the most effective and efficient action variant is chosen and implemented using selection function F_{sel} and selection criteria Cr:

$$F_{sel} : (SSit_{tg}, Cr) \to \min \quad (5)$$

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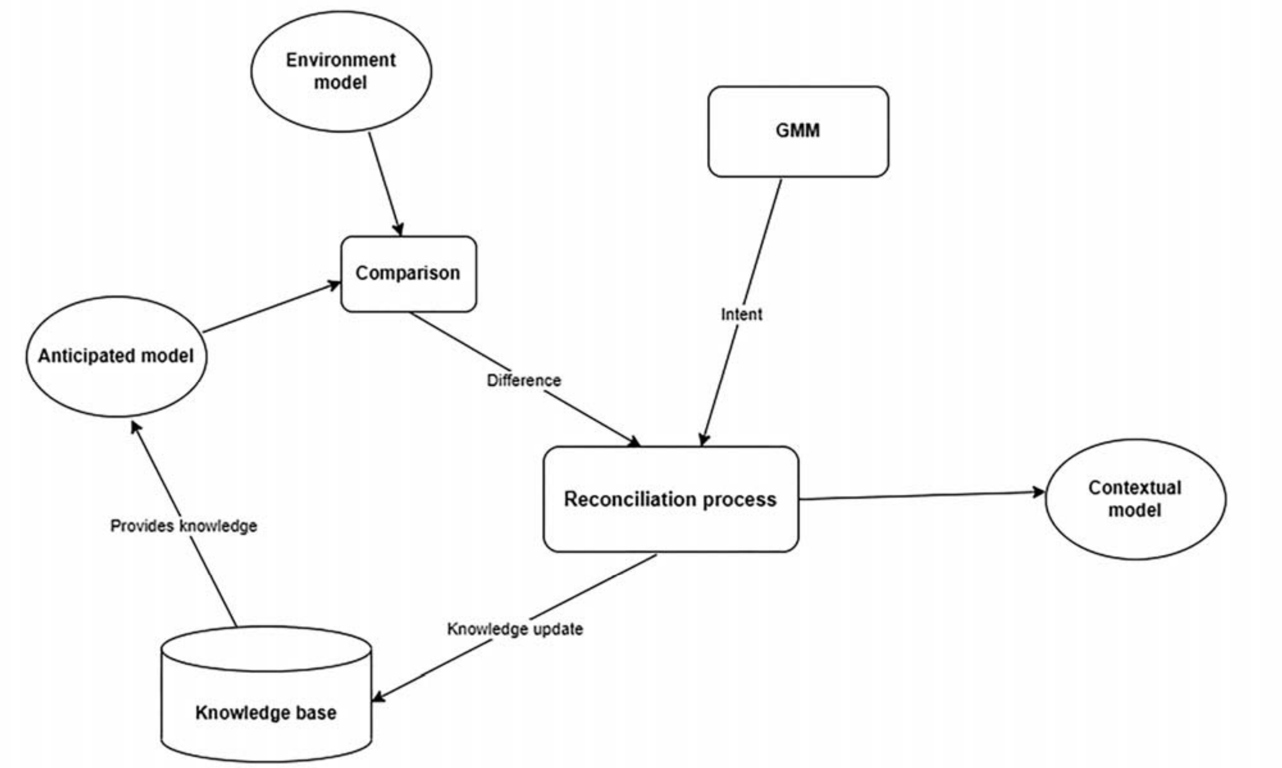

Figure 5 – Updating model with feedback from real-world data

The result of actions is tested observing the changes in Environment model. Errors and deviations from the expected results are noted and corresponding corrective actions are planned, changing the future situation projections.

The differences between the built projections and the real-world data are evaluated and, in case if they cannot be compensated by simple change of parameters of patterns used for anticipation, the patterns are updated, or new pattern is created in knowledge base for the current context. Thus, the intelligent system constantly reconciliates its knowledge base patterns with the real-world feedback and updates its knowledge (Fig. 5).

Let's consider an example of real-world efficiency evaluation for the application of proposed framework for the reasoning about security in larger residential community. The environment is monitored using a variety of sensors, embedded in surveillance cameras, movement detectors, temperature sensors. System should detect and generate the sequence of actions for intruder detection, device malfunction or fire.

Let current context $Cm_{con,tc}$ in time moment t_c, obtained from the sensor supplied data be:

– Movement sensors: detected movement in parking area;

– Survellance cameras: unrecognized person detected;

– Temperature sensors: data are within the normal range.

Knowledge base Knb contains previously detected situations:

– Sit_1 – usual activity (community members are in the parking);

– Sit_2 – anomaly (intruder detected in the parking);

– Sit_3 – fire (detected by abnormal rise of temperature);

– Sit_4 – sensor malfunction.

Similarity function F_{sim} compares the current context to the situations in the knowledge base. Prior to using this function current context specification $Cm_{con,tc}$ should be transformed into vector form (using numerical encoding of parameters). Next, F_{sim} is calculated using the selected similarity metric (such as cosine similarity (6) or Euclidean distance).

$$F_{sim} = \frac{\sum_{i=1}^{n} Cm_i \; Sit_i}{\sqrt{\sum_{i=1}^{n} Cm_i^2} \; \sqrt{\sum_{i=1}^{n} Sit_i^2}}. \qquad (6)$$

The results of similarity function calculations are:

– $F_{sim}\left(Cm_{con,tc},\; Sit_1\right) = 0.45$ (low similarity);

– $F_{sim}\left(Cm_{con,tc},\; Sit_2\right) = 0.85$ (high similarity);

– $F_{sim}\left(Cm_{con,tc},\; Sit_3\right) = 0.25$;

– $F_{sim}\left(Cm_{con,tc},\; Sit_4\right) = 0.30$.

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Selecting the situation with the highest similarity function value, the system concludes that intruder is detected. As a result, system activates the security protocol for situation Sit_2, consisting of such actions as security personnel alerting, focusing additional cameras on the intruder and tracking his movement, switching on additional movement sensors.

The system anticipates several possible developments of the situation. For example, if security staff arrives current context reverts to usual activity (Sit_1). After the end of incident situoid, the system stores the data about the incident in knowledge base and updates the parameters of similarity function for better detection in the future.

For the evaluation of efficiency of research problem solutions following metrics are used:

1. The accuracy of situation detection is calculated by comparing the number of correctly identified situations TP to all possible situations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \quad (7)$$

For example, if $TP = 85, FP = 5, FN = 10$, the accuracy is 0.85.

2. Response time. Average time for detecting the situation and implementing a corresponding security protocol.

$$T_{responce} = T_{analysis} + T_{action}. \quad (8)$$

For example, if $T_{analysis}$ is 0.5 s and T_{action} is 2.5s. $T_{responce} = 3s$.

Similarity of contexts measure is calculated using formula (6). For example, if current context $Cm_{con,tc}$ is represented by vector [0.8, 0.6,0.9], and Sit_2 – by vector [0.7,0.6,1.0], then using (6) we obtain $F_{sim}\left(Cm_{con,tc}, Sit_2\right) = 0.91$ which reflects a high similarity level.

3. Precision – the probability of making correct actions after the situation detection.

$$P_{recision} = \frac{TP}{TP + FP}. \quad (9)$$

For example, if $TP = 85$ and $FP = 5$, then $P_{recision} = 0.944$. With those quantitative metrics the user can reveal the strengths and weaknesses of proposed framework implementation and specify areas for improvement.

6 DISCUSSION

The ability to anticipate the future based on previous experience is one of the main features of intelligence. Humans are proficient in building multiple models of future events, comparing and analyzing them to select the best course of action. In the process of such modeling the results are compared to real-world data, experiential models and patterns are updated and learning occurs.

Intelligent agents should also implement the ability of anticipation and planning to become fully autonomous and capable of rational decision-making in real-world situations. For example, intelligent security systems can use predictions and experiential knowledge analysis to detect unusual behavior patterns of visitors, responding in real time to threats and learning new threats patterns.

The intended usage of the proposed framework is in combination with knowledge graph based reasoning and ontological modeling.

Compared to other methods and frameworks which can be used to build goal-driven intelligent agents the proposed framework offers several substantial advantages.

Classical STRIPS (Stanford Research Institute Problem Solver) [35] method is working in deterministic environments and does not implement learning. It also lacks an ontological foundation.

BDI (Beliefs, Desires, Intentions) framework [36], which is used to model goal-driven behavior of intelligent agents, is general, it does not focus on situational dynamics.

In recent years intelligent agents are increasingly using a variety of neuronal networks methods to acquire and process knowledge. The proposed network offers the explainability advantage when compared to them.

Situational calculus [37] is modeling the situations and transitions between them. However, it lacks modeling support for temporal, configurational and spatial data and ontological foundation. The usage of topoid, chronoid, configuroid constructs in proposed framework enhances the expressivity of the developed model.

The proposed framework operates with situations as basic units of analysis and predictions tracking and anticipating changes between situations. Situations are represented as knowledge graphs with elements relevant to current context. This context is defined by the current state of environment and intention of intelligent agent. Situations are anticipated using experiential knowledge about changes in similar context in the past, stored in the form of patterns in knowledge base. Knowledge patterns are updated in the process of reconciliation with real-world data, collected from sensors and external knowledge providers.

Situations are described using GFO which is a rich 4d ontology providing the ability to model the temporal, spatial and configurational evolutions of situations. Situoid element from GFO was chosen to represent the bounded situation evolution corresponding to the process of accomplishment of a task or a goal or just modeling the natural course of events. Situoid represents the unit of comprehension and is considered as a whole. The basic anticipation is represented by two consecutive situations and the specification of event/actions leading to change from one situation to another. The framework allows to track and analyze the change trajectories for specific ob-

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jects, situations or situoids over time or contingent to specific conditions.

The proposed framework has the following advantages:

– It is based on the GFO ontology, which provides a logically coherent set of concepts and allows modeling spatial, temporal, and structural data.

– Supports predictions with different levels of specificity. They range from a very detailed specification of the implementation of an intention leading to the next situation to a high-level description of the future situation with a small set of conditions. This allows us to work with incomplete information in an unstable environment, when the exact path leading to the expected situation is not yet known. For example, in the security domain, a situation can be defined in general terms as an unauthorized access of a person to a restricted area, without specifying how exactly this is done.

– Prediction and modeling of change trajectories allows the system to build and compare the impact of several courses of action, which forms the basis for making a decision on the desired course of action. In addition, typical trajectories can become templates stored in a knowledge base, and the system will be able to justify these templates at a higher level of abstraction.

– The system uses knowledge from experience, which can be obtained and improved by studying real data. In the learning process, the system finds typical configurations – templates and their dependencies, abstracting from a lot of irrelevant details and finding the most important properties of situations. For example, the system can find typical behavior of end users in intelligent communities. In addition, it can identify dangerous behavior and take timely measures.

Among the drawbacks of proposed framework, we can cite the high level of generality and abstraction, which on one hand can lead to difficulties of building real-world systems based on it, but on the other makes it applicable to the large set of intelligent systems. Moreover, the representation and management of experiential, contextual knowledge requires further research and is a separate complex problem. Also, knowledge reconciliation with real-world data process is described only conceptually and requires development in future research.

Nevertheless, the authors hope that proposed framework will be useful in modeling anticipation functionality in intelligent environment and can form the basis for future research, leading to the implementation of intelligent environments capable of situation anticipation and analysis using experiential knowledge.

CONCLUSIONS

Representing and modeling the situation dynamics and anticipating the changes is an important feature of autonomous intelligent agent and a challenging task to implement.

The scientific novelty of obtained results is in the development of framework allowing to represent, model and reason about situation dynamics in the intelligent environment, such as intelligent residential community. The proposed framework is based on GFO ontology, which provides a coherent set of conceptual constructs and logical tools to reason about them. Framework allows to model different trajectories of situation development, compare and reason about them. It is also suitable for representing situations with different levels of specificity.

The practical significance of obtained results is that the proposed framework can be applied in intelligent environments, such as intelligent homes, communities, surveillance systems, built using autonomous intelligent agents to represent, anticipate and model the situation dynamics, select the preferred course of actions.

Prospects for further research include the elaboration of contextual knowledge storing and processing, reconciliation and learning procedures based on real-world feedback and the application of proposed framework in the real-world system, such as intelligent security systems.

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ФРЕЙМВОРК ДЛЯ ПЕРЕДБАЧЕННЯ СИТУАЦІЙ ТА ПЛАНУВАННЯ В ІНТЕЛЕКТУАЛЬНИХ СЕРЕДОВИЩАХ

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АНОТАЦІЯ

Актуальність. Передбачення, прогнозування та планування ситуації відіграють важливу роль у інтелектуальних середовищах, дозволяючи вивчати та прогнозувати поведінку своїх користувачів, передбачати потреби в обслуговуванні та забезпеченні ресурсами. Об'єктом дослідження є процес моделювання ситуації, передбачення і планування в ситуаційно-обізнаних системах.

Мета роботи. Метою роботи є розробка та аналіз онтологічного фреймворку для моделювання та прогнозування динаміки змін ситуації для інтелектуальних агентів, що дозволяє реалізувати проактивну поведінку агентів.

Метод. У цій статті запропонована основа для передбачення та планування на основі онтології GFO. Кожна задача або задача розглядається як ситуоїд, що має ряд проміжних ситуацій. Фреймворк орієнтований на аналіз змін між ситуаціями, спричинених передбаченими діями або подіями. Контекстуально організована база знань використовується для отримання інформації про можливі сценарії розвитку подій і використовується для планування та оцінки. Фреймворк дозволяє будувати і порівнювати траєкторії зміни конфігурацій для конкретних об'єктів, ситуацій або сітуоїдів. Процес планування і передбачення працює в умовах неповної інформації і непередбачуваних зовнішніх подій, тому що прогнози постійно оновлюються за допомогою зворотного зв'язку від даних сенсорів і звірки цієї інформації з прогнозованою моделлю.

Результати. Фреймворк для міркування та планування ситуацій на основі онтології GFO, що дозволяє моделювати просторові, часові та структурні залежності даних.

Висновки. Фреймворк передбачення ситуації дозволяє подавати, моделювати та обґрунтовувати динаміку ситуації в інтелектуальному середовищі, наприклад, у розумному житловому будинку. Перспективи подальших досліджень включають розробку процедур зберігання та опрацювання контекстних знань, узгодження та навчання на основі зворотного зв'язку в реальних умовах та застосування запропонованого фреймворку реальних системах, таких як інтелектуальні системи безпеки.

КЛЮЧОВІ СЛОВА: GFO, ситуаційна обізнаність, передбачення, ситуаційний аналіз, сітуоїд.

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