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Adaptive BDI Architecture for Multi-Agent Systems

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Abstract- The increasing demand for systems that exhibits human like behavior and deals with real world problems at runtime, is drawing attention to the development of adaptive systems. The objective of our work is to define an adaptive architecture for multi-agent systems, that considers BDI (Belief-Desire-Intention) agents based on the organization theory. We define the scope of adaptation in multi-agent systems to clarify needs for the adaptation and to define an adaptive architecture to be able to perform the dynamic autonomous behavior at runtime. In this paper, we emphasize that using adaptive BDI agents for the development of complex adaptive systems are necessary to provide expected functionalities, such as adaptation to changes in the systems' environment and self-organization to ensure their continuity. Therefore, this approach makes developing realistic complex adaptive systems feasible and flexible.

Keywords Complex adaptive systems, intelligent agents, BDI architecture, organization theory.

1. Introduction

With the rise of the technology, expectations from information systems are increasing. The main expectations from the information systems are to exhibit human like behavior and to deal with real world problems at runtime. The term complex adaptive system (CAS) is often used to describe these systems. A CAS is similar to the live organisms. They change and grow continuously. Because, they need to adapt according to the changes that occur in and around their environment, to adapt or to organize their own to ensure their continuity. A CAS is expected to be able to deal with emerging problems and to organize autonomously in dynamic and changing environments. Due to these characteristics, the challenging requirements for information systems target the complex adaptive systems. By taking into account the aforementioned requirements, multi-agent systems (MAS) are ideal candidates to create the most appropriate solutions for CASs [1]. Because, one of the important goals of MAS is to create systems that can exhibit autonomous behavior, can make flexible decisions, and can cooperate with other systems. Multi-agent systems that are constructed for developing CASs are named as Adaptive MAS (A-MAS). A-MAS consists of agents that are autonomously acting and adapting themselves in changing and evolving environments according to their internal knowledge. Thus, agents are peeled off their isolated form in traditional artificial intelligence and they make it possible to develop CAS applications by operating a deliberation cycle similar to humans. Adaptation allows to increase the system's performance or to change the behaviors of agents in order to respond to changing systems' requirements, or to demonstrate autonomous behaviors.

Aforementioned characteristics of CAS can be mimicked by integrating MAS and agent organizations. This paradigm is considered as a solution to problems such as management, coordination, control/change of agent behaviors and evolution. Using organization-based MAS (O-MAS) provides a high level of abstraction to define and to realize the ability of adaptation and evolution. In addition, MAS that are developed using organizational theory to represent real world structures shows a high level of similarity to real organizations. Thus, defining the dynamic conditions and expected dynamic behaviors will be easier to express. As a result, MAS that are able to adapt and to evaluate probabilities of conditions, and to perform appropriate behaviors according to the environment conditions can be easily implemented.

A-MAS do not only consider individual agents' adaptation, but also organization and/or system adaptation are also being considered. The most prominent feature of CAS is emergent behavior that appears at the system level.

Organization level adaptation consists of chain of individual adaptations based on individual interactions corresponding to the changes in the environment.

In this paper, we defined an adaptive Belief-Desire-Intention [2] (BDI) architecture that provides the adaptation requirement for agents in order to create a CAS. By the way, an adaptation mechanism inside the deliberation cycle of the agents based on BDI model is also defined. Adaptive BDI (A-BDI) architecture provides reacting to the changes in the environment or changes in the behaviors of other agents in the organization at runtime. After detection of the environment, agents make local assessments and adjust their own behaviors according to their knowledgebase. To ensure these capabilities, we defined an agent architecture based on organization theory.

This paper structured as follows. In Section 2, adaptation in MAS and the scope of adaptation is presented. Section 3 presents the adaptive BDI architecture. The related work and the comparision summarized in Section 4. Lastly, Section 5 concludes the paper.

2. Adaptation in Multi-Agent Systems

Adaptive multi-agent systems (A-MAS) consist of agents that adapt themselves according to the domain's knowledge and self-knowledge responding to the changes in the environment. A-MAS detect changes in the environment where it acts and applies adaptation to its own behavior according to the local observations. Adaptation is generally performed to increase system performance or to change the behaviors of the agents in order to respond to the changing systems requirements and to demonstrate autonomous behaviors.

In this paper, organization-based MASs (O-MAS) [3] are considered. Dynamic agent organizations optimize their behaviors according to the local observations. These organizations are dynamic and evolvable over time. In an open and dynamic world, social factors that provide adaptation to allow organizations to reach a particular outcome should be defined. In order to achieve adaptation, it is necessary to describe a mechanism of adaptation to manage updates, changes, and growth of the system.

*2.1. Adaptation Persp*ectives

Many studies [4-16] tackle adaptation from different perspectives. Therefore, the scope and the meaning of the adaptation should be clarified.

Adaptation is an actual requirement for an autonomous agent acts in dynamic environments. Adaptation is dynamically changing the behavior of an agent to optimize their rewards according to the local observations. Furthermore, the adaptation can be emerged as a result of the behaviors of other agents in the environment. Agents detect the environment, evaluate the local assessments by taking into account the global state of the system and adjust their behavior accordingly.

Adaptation is tackled with four different perspectives. These perspectives also define the essential requirements of the adaptation mechanism.

- **Reaction:** Adaptive agents should react to changes in the environment. The reaction perspective defines the basic characteristic of the adaptation. The following perspectives define the scope of the agent reactions.

- **Reasoning:** Adaptation is an essential requirement for rational agents. When an agent detects the change in the environment, the second step is deciding what to do next accordingly. The decision is made as a result of reasoning called deliberation cycle for BDI agents [17]. As a result of the deliberation cycle, the agent chooses the most appropriate behavior, according to local observations by taking into account the global state of the environment and its own goals.

- **Learning:** Learning is accepted as an optional property agents. However, considering adaptation requirements it's the key feature to perform and to enable adaptation properly. A ripple in the environment can cause the adaptation. Adaptation performed by an agent can not only be based on local observations. It should also consider the history of adaptations performed by the agent. As a result, more suitable decisions can be made.

- **Evolution:** Up to now, adaptation is only handled in the scope of a single agent. Considering the MAS and CAS characteristics, the key is the interaction of the entities. Its inevitable that, the interactions (agent-agent, agent-environment) can cause adaptation. Consequenly, the scope of the adaptation is not only focuses on the changes of the agent behaviors. It also contains the changes in the agent organization or in the environment. The changes in agents' behaviors and interactions between agents cause organizational adaptation. In this circumstance, indirect changes in the environment can also cause local adaptation chains. This also be considered as the emergent behavior in CASs.

3. Adaptive BDI Architecture

An adaptive agent is a rational agent that chooses the most appropriate behavior, according to its knowledge and observations. In addition, it is aware of the environment and makes correct decisions. BDI agents have facts about the world they live in, and they perform the most appropriate and profitable behaviors. They behave according to the observation, and knowledge and they consider optimizing their expected performance [17]. Due to these features, BDI agents have the most appropriate architecture in order to implement A-MAS. As a result, we choose the BDI architecture for the adaptive agents.

In this paper, we define an adaptive BDI architecture (A-BDI) based on organization based MAS. The aim of our architecture is to form features like changing the behaviors of the agents according to the changes/events in the environment and behaviors of other agents in the organization at runtime. With this architecture, the agents arrange their behaviors after detection of the changes/events and make local assessments to optimize their performance. A-BDI architecture depends on role, goal and organization theories [18]. In this architecture, first class entities that bring adaptation capabilities are role, goal, and belief.

Role theory [18] is an analysis method based on social action and classification. It focuses on grouping similar types of behaviors to distinguish between different types of behavior in accordance with the principles of social classification. Applying role theory to the MAS brings an organizational perspective to the development of MAS, provides a flexible design as well as the creation of an open and dynamic MAS. Goals have been used to capture requirements for traditional systems as well as MAS as goals tend to capture "*what*" the system is supposed to do instead of "*how*" the system is supposed to behave. Goals [19] are a more natural way to model system requirements, as they tend to change less often that the functions of the software. In our model, goals express mental activities of the agents. Agent tries to achieve their goals or role goals corresponding to the state of the environment, its own state, and own knowledgebase. Complementary features of role and goal theory with essential features of BDI model make A-BDI architecture an important candidate to meet with the expectation of CASs.

We propose to represent a CAS with adaptive organizations. So, individuals of CAS are interpreted both agent and organization perspectives. Each different individual of a CAS is represented with a role in the organization. The different type of this role (different instantiation like being selfish or cooperative) can be expressed by defining different agent characteristics; agent self. The agent self, consists of individual level goals, rules, knowledge and capabilities. From the organization perspective, interactions in the CAS, organization rules, states, state transitions also are defined using organization models.

Adaptation starts with the initialization of the organization. After an agent takes its role in the organization, a role instance is created according to its self. Every role instance of a specific role in the organization is differently played from others. During the playing of the roles, each agent adopts its role, according to their self and plays the role originally. So, each deliberation cycle of the same goal will be different. The same situation also encountered at the point of the role playing in the organization. Thus, agents that play the same role within the same instance of the organization will perform different behaviors from each other. General characteristics of the CAS are expressed with adaptive organization models and individual levels' requirements like user preferences.

Adaptive organizations need models that provide the necessary definitions to perform adaptation capabilities. In these models, organization structure, roles, environment entities, events, and relations should be defined. The main objectives of the organization, top-level objectives, should be defined as the model relates to the environment model. In addition, a set of states in the organization with weighted transitions between states belonging to the objectives should be defined. Also, the relationship between goal pre-conditions, post-conditions, constraint definitions, and priorities are defined in the organization models. Thus, the goals of the organizations and roles can be performed properly by the agents; agents have adaptive roles playing and behaving capability. In this case, role definitions differently interpreted by the agents and integrated with the self-knowledge of the agent. Therefore, each instance of the role is constantly updated and differentiated according to the player agent. Differentiation is a result of changes in the environment, any observed event or any feedback on the agent behaviors. The composition of these features defines the motivation of the goal specialized for the corresponding role instance. In addition, the BDI architecture provides producing beliefs by defining partial achievement and motivation for the goals by taking into account local observations in agent's active knowledgebase.

4.1 Adaptive Organization Model

The adaptive organization model is based on three essential entities of the organization-based MAS: goal (G), role (R) and agent (A). Adaptation is defined corresponding to the capability (C), assignment (Φ), policy (P) and environment model (Σ) entities. Capabilities are used to decide which role to be played by agents. Also policies expresses the constraints for the role assignments of in the organizations. Environment models also define essential structures in the organizations and provide common knowledge for the organization.

$$O = < G, R, A, C, \Phi, P, \Sigma, oaf, achieves, capable, require, possesses, potential > \quad (1)$$

In the model, an organization consists of organization goals (G), roles (R), agents (A), capability set (C), assignments (Φ, G×R×A assignments of goal and role over agents, policies (P, over assignments), environment model (Φ, entities in the environment, states, output sets…etc.), organization assignment function (oaf) $P(G\times R\times A)\rightarrow[0..\infty]$ computes the quality of assignments, achieves function $G\times R\rightarrow[0..1]$ computes the achievement of the goals, capable function $A\times R\rightarrow[0..1]$ computes the role playing ratio of the agents, requires function $R\rightarrow P(C)$ considers the capabilities of the agents, possesses function $A\times C\rightarrow [0..1]$ measure the capabilities of the agents, and potential function $A\times R\times G\rightarrow[0..1]$ measures the goal achievement of the role.

Adaptive agents work on behalf of their users by taking into account rewards. Also, adaptive agents perform correct behaviors according to the environment's situation. Thus, role definitions should be enriched with reward functions. The reward function defines the performance criteria for the agent and the agent tries to maximize this criteria. A Role definition (R) contains reward functions (RF), interactions (S, **Ω**, O) and role goals (RG).

$$R_i = < S, RG_i, T_i, \mathbf{\Omega}_i, O_i, RF_i> \quad (2)$$

Equation (2) depicts the role definition. S indicates the state set related to the role. RG_i, represents the goals of the role and T_i represents the target output set of the role goals. The transition function T_i: S x RG_i x S $\rightarrow[0,1]$ computes the transition possiblities between states related to the goal achievements. $\mathbf{\Omega}_i$ is the sets of observations of the role. The output function (O_i) computes the outputs of the role according to the states and exhibits behavior corresponding to the observations (O_i: S x RG_ix$\mathbf{\Omega}_i\rightarrow[0,1]$). RF_i is the reward function of the role. By defining rewards, preferences are represented in the organization as RF_i: S x RG_i $\rightarrow$ Rp.

Behaviors of the agents in some situations are repeated or similar. Therefore, the reward functions should be evaluated by taking into account not only observations but also the history of previous actions and results. Thus, the adaptive agent can exhibit the most appropriate behavior. Beliefs (B) of the agents are represented by defined probability values over the state set (S). Initially, b_0 indicates the belief of an agent without any observation. Solely, after time t, t+1 observation and t actions are built in. In this situation, we assume that agent exhibit behavior and observes the environment at each time. ht_i, indicates the history of the agent observations, $ht_i = \{o_i^0, o_i^1, \ldots o_i^{t-1}, o_i^t\}$. While agent playing a role (r_i), belief of the agent at t time (b_t) is updated according to the local observations and results of the previous behaviors. So, the belief state of the agent can be defined as the sum of the local observations and the history of the observations. The local observations also contain the feedback of the agent behaviors. As a result of these actions, the states of the environment and agent self-state is updated. Equation 3 depicts the update function of the agent belief and state. In the equation, b_i^{t-1} is the belief before behavior, o_i observation at t, rg_i^{t-1} goal that is achieved at t-1. As a result of this update, new belief b_i^t and new state s_t of the agent is calculated.

$$b_i^t(s^t) = \beta O_i(s_i, o_i, rg_i^{t-1}) \sum_{s^t \in S} b_i^{t-1}(s^{t-1}) T_i(s^t, rg_i^{t-1}, s^{t-1}) \qquad (3)$$

4.2 Adaptive BDI Algorithm

The BDI architecture defines the reasoning process of an agent as deliberation cycle based on human practical reasoning [17]. Adaptive BDI (A-BDI) algorithm shown in Fig. 1 enriches the BDI deliberation cycle by taking into account the adaptive organization models and A-MAS. The adaptive BDI algorithm is the core of the A-BDI architecture.

The human practical reasoning consists of two complementary steps: deliberation and means-end reasoning. In the first step, deliberation, the goal is determined according to the current state. In the second step, means-end reasoning, the action/behavior that provides achieving the goal is selected. The adaptive BDI algorithm is designed to perform both of the two steps of the practical reasoning by focusing on the A-BDI model execution. A-BDI agent works according to the situation of the environment and its state to maximize its active role instance reward function.

The A-BDI algorithm represents the deliberation cycle of the adaptive agent. The algorithm starts with the initialization of the agent and is executed persistently during the life cycle of the agent. At the state, agent's initial state, initial beliefs and initial intentions (lines 1, 2, and 3) are starting points for the algorithm. Agent senses its environment and gets the observations (line 5). The local observation (o) can be result of its own behavior or a local perception. The local observation triggers loading the role instance/s (line 6) to the active knowledgebase of the agent. Because of an event from the environment can change the active role instance, or can activate two or more role instances at the same time. This step is the key step of the algorithm, that forms organization based execution of the adaptation for A-BDI agents. Thus, the deliberation cycle of the BDI agent is executed over the active knowledgebase that integrates active role instances knowledge and agent self-knowledge. In pursuit of, the agent decides what to achieve according to the observations and the target state that is determined to the current state. The agent determines the most appropriate state (line 8) based on its active beliefs.

```
1. s = S0
2. B= B0
3. I = I0
4. while (true)
5.  o   = observe_environment()
6.  kb  = active_knowledge (o)
7.  B   = belief_revision_function (kb, B, o)
8.  s   = state_revision_function (kb, s, o)
9.  D  = options (B, kb, s)
10.  I  = filter (B, D, I, s)
11.  π  = plan(B, I)
12.  while ( not( empty(π) or succeeded (B, I)
13.        or impossible (B, I)))
14.      α  = head(π)
15.      execute (α)
16.      α = tail(π)
17.      o = observe environment
18.      kb = active_knowledge(o)
19.      B = belief_revision_function (kb, o, B)
20.      s = state_revision_function(kb, s, o)
21.      if (reconsider(B, I, s) then
22.        D = options (B, kb, I)
23.        I = filter (B, D, I, s)
24.      end if
25.      if not sound(π, B, I) then
26.        π  =  plan(B, I)
27.      end-if
28.   end while
29. end while
```

Fig. 1 The Adaptive BDI algorithm

After determining the target state, the agent evaluates the alternatives (line 9), chooses the most appropriate goal considering the target state and state transition probabilities of its own. As a result, it decides what to achieve at that time and chooses the active goal (line 10) according to its reward function. After deciding on a goal to achieve, the second step of the practical reasoning is started (line 11). At this step, the agent tries to determine how to achieve the active goal considering active knowledge (do not conflict with belief set).

While selecting the correct behavior to perform; the agent state, the environment state, active goals and the history of previous decisions are also taken into consideration. As a result of this evaluation, an appropriate behavior that is suitable with the preferences is selected (line 11). Selecting a specific behavior does not terminate the reasoning cycle of the algorithm. After execution of the steps of the behavior, the state of the agent, the state of the environment and the active knowledge is updated continuously. Thus, the first step of the behavior is selected for execution (line 14) and executed (line 15).

The state of the environment and the agent are controlled after the execution (line 16) and the deliberation cycle is repeated. But unlike other agents decide that the current goal is still the target goal of its own and its active knowledge still supports its actions (line 21). As a result of a local observation or an update in the knowledgebase, agent can decide to interrupt the current behavior execution or decide to exhibit different behavior. At this point, determining a new goal (lines 22, and 23) and selecting a new behavior (line 26) steps are repeated. Occasionally, the change of the active goal does not require the change of the active behavior. So, the soundness control is required (line 25) before selecting a new behavior for the active goal.

Execution of the adaptive BDI algorithm is a continuous process for the adaptive BDI agents. Thus, the agent continuously senses its environment, loads appropriate role instances and determines the appropriate goals which maximizes its rewards. Observing the environment in each step of the execution provides soundness check at each time and enriches its adaptation capability. However, we assume that updates in the environment are not frequent as the execution frequency of the each step of the agent behaviors.

4. Related Work & Comparison

Based on their motivation and adaptation focus, related works can be divided into three categories; software engineering, the general architecture and learning-based approaches.

There are many suggestions in terms of software engineering [5-9]. All of the suggestions propose to define the adaptation in terms of agent model requirements. Weyns et al. [5], propose to use abstract protocol definitions to define adaptation. Thus, agent interactions in the MAS can be constructed by different agents corresponding to the environment situations. This approach points the correct directions for adaptation in the MAS, however it’s not clear how the adaptation occurs during agent interactions. Thus, the effect of local observations and behaviors are missing. Moridani et al. [6] define the development process and provide a framework to develop self-adaptive systems based on goal models. Reducing the scope of the adaptation to the goals makes the suggestion scope too narrow. Besides, changing of the BDI model elements like belief, desire, intention and also knowledge require changes in the deliberation cycle. DeLoach et al. [7], define an organization model for adaptive agents. This model provides agents to ensure adaptation capabilities corresponding to the changes in the environment. Changes in the environment is one of the reasons of the adaptation. Thus, in an organization based model, the primary elements (role, goal and belief) should derive adaptation. Besides the design of the adaptation on the model level deviates the agent autonomy which is the distinctive feature of agents. Polacek and Verma [8] consider adaptation in terms of requirement engineering. They aim to define a general requirement engineering solution for CAS considering uncertainty. This approach is similar to the previous study of DeLoach et al. [7]. Modeling the adaptation on higher levels deviates the definition of adaptation. Adaptation is not one of the primary elements of an agent. It’s a result of the agent deliberation cycle with primary elements. Besides, modeling adaptation forces agents to behave similarly. Therefore, agent autonomy cannot be followed in this approach. Rodriguez et al. [9], defines a framework based on virtual organizations and open MAS. They define adaptation requirements and propose using an open MAS infrastructure cross-platform. This study uses virtual organizations as classification elements of MAS. Therefore, they are not taking into account concept of role in the organization. Except researches focus on the narrowing the adaptation on the agent groups called virtual organizations.

Another category of the related works is defining a general architecture for the adaptation [6, 10-13]. The common approach of these works is the adaptation is considered as a part of the agent life cycle. Morandini et al. [6] define an architecture based on the previous work [4]. The architecture is goal-based and targets BDI agents. During the execution of goal models, agents evaluate the environment and try to achieve their goals. This approach fail to notice the role concept. Focusing the adaptation based on the goal limits the adaptation capability of agents. Guessom et al. [10] define an architecture to monitor the organization and agent level adaptation using graphs. They propose to monitor unexpected behaviors of the agents to correct their errors or to determine critical agents in the systems. This research take s into account adaptation as a deviation of agent behaviors. Adaptation is an essential requirement for building CASs. Capera et al. [11] propose a general monitoring architecture to determine agent composing and decomposing. This architecture provides the load balancing capability of the MAS. This approach is similar to the reach of Guessom et al. [10]. The assumption of monitoring agent behaviors in a MAS deviates the agent autonomy. Besides, creating a primary element for a MAS for the adaptation forces a centralized architecture. Razavi [12] defines a meta-model for adaptive agents and define a general architecture to execute the models. This study contains similar approaches to software engineering category researches [5-9]. The definition of adaptation on the model level limits the adaptation capability of the agents. Thus, the adaptation should not be predictable. Memon and Treur [13], present a generic adaptive architecture that integrates the interaction between cognitive and affective aspects of the mental functioning. The body loops are used to construct adaptive functioning to mimic the empathy. This approach has similarities to human practical reasoning. On the other hand, predefinition of adaptation functions on agent level makes the proposal too weak.

The last category is defining the adaptation in terms of agent learning [14, 15]. Sansores and Pavon [14], define an architecture based on learning in INGENIAS framework. They define the motivation property of agent goals that is integrated with the feedback mechanism. This study assumes the adaptation as the motivation value of the agent to achieve a goal or not. This assumption makes the scope of the adaptation too narrow and simple. Another learning-based approach is defined by Maes [15]. She proposes to use reinforcement learning based on adaptation models. The mechanism provides an adaptive behavior selection. This approach contains the essentials of the adaptation. On the other hand, it requires enrichment with BDI architecture in order to make it applicable for O-MASs. Therefore, learning is not the only reason of adaptation.

The aforementioned approaches handle the adaptation from different perspectives. The main reason of the categorization is to emphasize the scope of the adaptation on the studies. As discussed individually per study, modeling the adaptation on models, definition of adaptation on goals weaken the importance of adaptation on MASs. This prevents applying these approaches to MAS in order to create CASs. In order to use MAS for CASs, we have taken into account individual and system level; goals and observations. Each individual of the CAS (agents) has organizational and individual goals. During their individual deliberation cycle, the decision of each individual is isolated. On the other hand, each individual senses the state of the organization and perform desired behaviors.

5. Conclusion

In recent years, studies stand out based on organization theory to develop MAS are increasing. Because the design phase of the actual system is expressed with the realization of the system provides the most appropriate way to reality. This paper has introduced A-BDI architecture in order to develop realistic CASs. An A-BDI architecture based on O-MAS is an important lack in the literature. In this paper, we have emphasized that using A-BDI agents for the development of CASs are required to provide expected functionalities. Therefore, this approach makes developing realistic CASs feasible.

However, for the future work we intend to integrate the A-BDI architecture with an existing O-MAS framework. Moreover, implementing a case study on the framework to show the applicability of the architecture and its advantages. Our main motivation is developing a simulation framework that enables the development of CASs based on O-MAS and A-BDI approach which is another important gap in the literature. Thus, we aim to contribute solving real world problems.

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