vGOAL: a GOAL-based Specification Language for Safe Autonomous Decision-Making

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Abstract. Formal verification is a reliable approach to addressing safety concerns in autonomous applications. We have designed *vGOAL* based on the internal logic of the GOAL agent programming language, which serves as the formal specification language of our innovative formal approach to safe autonomous decision-making. A detailed description of *vGOAL* is necessary to present and justify our approach to safe autonomous decision-making, yet it is currently missing. Therefore, this paper aims to provide a comprehensive description of *vGOAL*, including its formal syntax, its operational semantics, a real-world robotic application, and a comparison with several comparable agent programming languages, namely, GOAL, Gwendolen, and AgentSpeak (Jason).

Keywords: Formal Specification · Autonomous Decision-Making · Safety Assurance · *vGOAL*

1 Introduction

The applications of autonomous systems have seen a remarkable increase in recent years. These systems are capable of operating without human intervention to achieve complex goals. As autonomous applications become increasingly common in industries like manufacturing and transportation, it is crucial to ensure their safety.

Safe autonomous decision-making is one of the key challenges in developing autonomous robotic applications. Agent programming languages (APLs), including AgentSpeak [2], Jason [3], Gwendolen [8], and GOAL [10], have been extensively researched for programming autonomous agents for decades, indicating two facts: (1) A multi-agent system can properly model agent-based autonomous systems; (2) APLs are well-suited for tackling the challenge of the decision-making of agent-based autonomous systems. Despite the potential benefits of APLs in the development of autonomous robotic applications, their research has not been widely used in the field. Integration with the Robot Operating System (ROS) may expand their applications to robotics, as ROS has become the de facto standard for developing robotic applications. If an APL has built-in support for ROS, it would be advantageous to integrate it with ROS-based robotic applications.

The Belief-Desire-Intention (BDI) model is a popular reasoning mechanism utilized in various APLs including Jason and Gwendolen [4]. GOAL shares many features with BDI APLs, such as beliefs and goals, but it is primarily a rule-based APL that differs in its approach to action selection [4]. Specifically, while BDI APLs select actions from a plan library, GOAL derives actions based on its rules to fulfill goals, making it highly suitable for specifying autonomous decision-making.

To facilitate safe decision-making of agent-based autonomous systems, we have developed *vGOAL*, which is a GOAL-based specification language that focuses exclusively on the internal logic reasoning mechanism of GOAL, motivated by three primary considerations. First, the decision-making mechanism of GOAL is highly suitable for autonomous decision-making, but many of its specifications are irrelevant to this domain, such as environment specifications. Second, the intrinsic logic-based nature of GOAL makes it highly suitable for formal verification, which is ideal for providing safety assurance for autonomous decision-making. Third, GOAL cannot directly access ROS, which limits its applicability in robotic applications. Therefore, *vGOAL* can be highly valuable for safe autonomous decision-making used in robotic applications, as it can leverage the strengths of GOAL, ROS, and formal verification.

On the basis of *vGOAL*, we have developed a three-stage formal approach to safe autonomous decision-making: formal specification using *vGOAL*, safe decision generation using the *vGOAL* interpreter, and the verification of *vGOAL* using an automated translator for *vGOAL* and a PCTL model checker (Storm [6] or PRISM [15]). Additionally, we have integrated the *vGOAL* interpreter into ROS via rosbridge to facilitate implementation and execution. We validated our approach in a real-world autonomous logistic system consisting of three autonomous mobile robots. There are three demonstration videos accessible for viewing at [18].

In [19], we established the preliminary groundwork for the formal specification and verification of *vGOAL* by outlining how to verify a GOAL program with specific restrictions, including a stratified program, a single agent, and a single goal. Building on this initial work, we described the rationale and implementation of the three-stage formal approach in [20]. [17] presents a high-level overview of the three-stage formal approach. However, a detailed description of *vGOAL* is crucial to thoroughly describing our approach to safe autonomous decision-making, similar to the descriptions of Gwendolen in [7] and in [8], and of GOAL in [10]. Therefore, the purpose of this paper is to provide a detailed explanation of *vGOAL*.

The paper is structured as follows. In Section 2, we present the formal syntax of *vGOAL*. In Section 3, we present the operational semantics of *vGOAL*. In Section 4, we demonstrate how to use *vGOAL* with a validated real-world autonomous logistic system. In Section 5, we will discuss the essential features of *vGOAL* and provide a comparative analysis with other APLs, namely GOAL, Gwendolen, and AgentSpeak (Jason). In Section 6, we draw conclusions on *vGOAL*.

2 Formal Syntax

This section introduces the formal syntax of vGOAL, which offers a rigorous and structured formalism for describing the safe decision-making of agent-based autonomous systems. Additionally, we employ a multi-agent system within vGOAL to model the decision-making process of an agent-based autonomous system.

$$
\begin{aligned}
id &::= string \\
b &::= ground\_atom \\
g &::= ground\_atom \\
B_{sensor} &::= B_{sensor} \cup \{b\} | \emptyset \\
B_{prior} &::= B_{prior} \cup \{b\} | \emptyset \\
B &::= B_{sensor} \cup B_{prior} \\
G &::= G \cup \{g\} | \emptyset \\
goals &::= G : goals | [\,] \\
p &::= predicate \\
neg\_p &::= \neg p \\
R &::= all | allother | id \\
msg_s &::= send{:}(R,p) | send!(R,p) | send?(R,p) \\
msg_r &::= sent{:}(R,p) | sent!(R,p) | sent?(R,p) \\
M_S &::= M_S \cup \{msg_s\} | \emptyset \\
M_R &::= M_R \cup \{msg_r\} | \emptyset \\
Agent &::= (id, B, goals, M_S, M_R) \\
MAS &::= MAS \cup \{Agent\} | \emptyset
\end{aligned}
$$

A multi-agent system consists of multiple agents in a modular manner. To specify a multi-agent system, the users only need to identify the agents that form the system and the corresponding agent specifications at first. An agent specification consists of five essential components: a unique identifier: id, beliefs: B, goals: $goals$, sent messages: M_S, and received messages: M_R.

The unique identifier of the agent is represented by a string, denoted by id. B_{sensor}, B_{prior}, B, and G are collections of ground atoms, representing a collection of real-time beliefs, a collection of prior beliefs, a belief base, and a goal base, respectively. The set B_{sensor} denotes the real-time beliefs obtained from sensors. The set B_{prior} denotes the prior beliefs that are essential for agents but cannot be received from sensors. The set B denotes the complete belief base of an agent. An agent can have multiple goals, denoted by $goals$, which is a list of G.

R represents a group of agents, with its domain consisting of three distinct elements: all, $allother$, and id. Specifically, all denotes all agents within the multi-agent system; $allother$ represents all agents within the multi-agent system excluding the individual responsible for transmitting messages; and id designates

a particular agent. A sent message is denoted by msg_s with the domain containing three different elements: $send!(R,p)$, $send!(R,p)$, and $send?(R,p)$, whereas a received message is denoted by msg_r with the domain containing three different elements: $sent!(R,p)$, $sent!(R,p)$, and $sent?(R,p)$. Notably, the communication messages involve six predefined functions: $send!$, $send!$, $send?$, $sent!$, $sent!$, and $sent?$. The specification of messages distinguishes between three types: indicative messages, identified by the functions $send!(R,p)$ and $sent!(R,p)$; declarative messages, specified by $send!(R,p)$ and $sent!(R,p)$; and interrogative messages, described by $send?(R,p)$ and $sent?(R,p)$. Furthermore, R denotes the receivers of a message in a msg_s, while it denotes the sender in a msg_r. The sets of sent and received messages are denoted by M_S and M_R, respectively.

$$
\begin{aligned}
D &::= D \cup \{constant\} | \emptyset \\
hs &::= hs \wedge p | hs \wedge neg\_p | True \\
rule_1 &::= hs \rightarrow p \\
qrule_1 &::= \forall x.qrule_1 | \forall x \in D.qrule_1 | \exists x.qrule_1 | rule_1 \\
K &::= K \cup \{qrule_1\} | K \cup \{ground\_atom\} | \emptyset \\
lh &::= a\text{-}goal(p) \wedge hs \\
rule_2 &::= lh \rightarrow p \\
qrule_2 &::= \forall x.qrule_2 | \forall x \in D.qrule_2 | \exists x.qrule_2 | rule_2 \\
C &::= C \cup \{qrule_2\} | \emptyset \\
A &::= A \cup \{qrule_1\} | \emptyset \\
rule_3 &::= hs \rightarrow hs \\
qrule_3 &::= \forall x.qrule_3 | \forall x \in D.qrule_3 | \exists x.qrule_3 | rule_3 \\
E &::= E \cup \{qrule_3\} | \emptyset \\
rule_4 &::= hs \rightarrow msg_s \\
qrule_4 &::= \forall x.qrule_4 | \forall x \in D.qrule_4 | \exists x.qrule_4 | rule_4 \\
S &::= S \cup \{qrule_4\} | \emptyset \\
update &::= insert(b) | delete(b) | adopt(g) | drop(g) \\
response &::= msg_s | update \\
rule_5 &::= msg_r \wedge hs \rightarrow response \\
qrule_5 &::= \forall x.qrule_5 | \forall x \in D.qrule_5 | \exists x.qrule_5 | rule_5 \\
rule_6 &::= lh \rightarrow response \\
qrule_6 &::= \forall x.qrule_6 | \forall x \in D.qrule_6 | \exists x.qrule_6 | rule_6 \\
rule_7 &::= hs \rightarrow response \\
qrule_7 &::= \forall x.qrule_7 | \forall x \in D.qrule_7 | \exists x.qrule_7 | rule_7 \\
P &::= P \cup \{qrule_5\} | P \cup \{qrule_6\} | P \cup \{qrule_7\} | \emptyset
\end{aligned}
$$

The specification of a multi-agent system involves six rule sets, each with a unique designation: K represents the knowledge base, C denotes enabled con-

straints, A refers to action generation, E describes action effects, S pertains to sent message generation, and P concerns event processing. Moreover, *a-goal* is a predefined function to evaluate if its argument is included in the focused goal base.

The operational semantics of *vGOAL* involves the syntax and semantics of first-order logic. Consequently, the syntax of *vGOAL* incorporates the domain of variables. The core implementation of the *vGOAL* interpreter is the automated logical derivation and minimal model generation over first-order theories constraint by the *vGOAL* syntax. It is noteworthy that the rule sets K, C, A, S, and P have been defined with no negative recursion, a finite domain for each variable, and quantification of each variable, thereby ensuring the existence of the minimal model of these rule sets. Additionally, users are only required to specify the domain of universally quantified variables that appear on one side of a rule, due to the implementation of the interpreter.

In a multi-agent system, each agent generates its decisions in a modular manner. The agent takes the first goal in sequence as the focused goal and accomplishes all goals sequentially in this manner. Each decision-making reasoning cycle involves six steps. First, the agent derives its current beliefs and desired beliefs from the belief base and the focused goal, respectively, using the knowledge base. Second, the agent derives enabled constraints using C and its current and desired beliefs. Third, the agent derives enabled actions based on enabled constraints and A. Fourth, the agent derives enabled sent messages based on enabled constraints and S if no enabled action is generated. Fifth, the agent processes events, specifically, reacting to received messages, generating subgoals towards its desired goal, and revising its current beliefs. Finally, all agents will send their enabled sent messages to receivers, and the sent messages queue of each agent will be emptied. Furthermore, the state of the multi-agent system responds to changes in either the current beliefs or the focused goals.

Remark: Belief Base and Goal Base

In *vGOAL*, the belief base and the goal base both contain information that cannot be inferred by logical deduction. More specifically, an agent's current beliefs are obtained by combining its belief base with its knowledge base, while its desired beliefs are obtained by combining its goal base with its knowledge base. As a result, the belief base represents a subset of an agent's current beliefs, and the goal base represents a subset of an agent's desired beliefs.

3 Operational Semantics

This section presents the operational semantics of *vGOAL*. The reasoning cycle is a fundamental concept that underlies the definition of the language's operational semantics, involving both logical derivation and minimal model generation of first-order theories constrained by the syntax of *vGOAL*.

In *vGOAL*, a state is the collective state of all agents in the multi-agent system, with each agent's state serving as a substate of the entire system. During a reasoning cycle, agents are capable of modifying their specifications, which include beliefs, and goals, as well as sent and received messages. Such information is indispensable for the decision-making process of an agent. Therefore, we use sub_info to denote the necessary information about the substate, which consists of its identity, its belief base, its goal base, its sent messages, and its received messages. Moreover, we define the substate as consisting of its unique identifier, its belief base, and its goals, as any change of the substate will reinitialize the sent and received messages in our setting. Consequently, we formally define the state and the corresponding state information of *vGOAL* as follows:

$$\begin{aligned} substate &::= id : (B, goals), \\ sub\_info &::= id : (B, goals, M_S, M_R), \\ state &::= state \cup \{substate\}|\emptyset, \\ state\_info &::= state\_info \cup \{sub\_info\}|\emptyset, \end{aligned}$$

3.1 Stage 1: Substate Property Generation

For one agent, each substate can only differ from either its belief base, its goal base, or both. Consequently, we define the substate property as the combination of the current beliefs and the desired beliefs.

The current beliefs and the desired beliefs are defined as follows:

$$\begin{aligned} G_1 &= goals[0], \\ CB &::= B \cup K, \\ DB &::= G_1 \cup K. \end{aligned}$$

Each agent aims to achieve its first goal base, denoted as G_1. CB is a first-order theory to derive current beliefs, consisting of its current belief base, denoted as B, and its knowledge base, denoted as K; DB is a first-order theory to derive desired beliefs, consisting of its focused goal base and its knowledge base. The semantics of CB and DB is determined by the minimal model of each theory, which is formally defined as follows:

$$\begin{aligned} model_C &::= \{\rho(A)|CB \models \rho(p)\}, \\ model_G &::= \{\rho(A)|DB \models \rho(p)\}, \end{aligned}$$

where ρ is a ground substitution.

Accordingly, we define the properties of a substate as follows:

$$substate\_properties ::= (model_C, model_G).$$

3.2 Stage 2: Enabled Constraint Generation

The constraints that constrain an agent to generate feasible actions or sent messages are referred to as enabled constraints. Constrained by the current and desired beliefs, an agent generates decisions.

While the semantics of most predicates occurring in the specifications are determined by $model_C$, the semantics of *a-goal* predicates is determined by $model_C$ and $model_G$, which is defined as follows:

$$\textit{a-goal } p = \begin{cases} True & if\ model_C \models \neg p \wedge model_G \models p, \\ False & \text{otherwise.} \end{cases}$$

The predefined *a-goal* offers the advantage of enabling the decision-making module to exclusively generate decisions that transform the current state toward the desired state, thereby avoiding pointless decisions.

The enabled constraints are defined as follows:

$$EC ::= \{model_C, model_G, C\}.$$

EC is a first-order theory expressing enabled constraints. The generated constraints, GC, is defined as follows:

$$GC ::= \{\rho(p) | EC \models \rho(E) \wedge model_C \not\models \rho(p)\},$$

where ρ is a ground substitution.

3.3 Stage 3: Enabled Action Generation

An action can be triggered only when a related enabled constraint and its preconditions are satisfied by the current beliefs. The enabled actions are defined as follows:

$$EA ::= model_C \cup GC \cup A.$$

EA is a first-order theory expressing enabled actions. The generated actions, GA, which are defined as follows:

$$GA ::= \{\rho(p) | EA \models \rho(Act) \wedge model_C \cup CG \not\models \rho(p)\},$$

where ρ is a ground substitution.

An agent changes its current belief base based on the rules of action effects and the enabled actions. The action effects will change the state of the agent, subsequently changing the state of the multi-agent system. The effects of an action are defined as follows:

$$EE ::= model_C \cup GA \cup E.$$

EE is a first-order theory describing enabled action effects. According to the syntax, each rule in E is defined in the form of $rule_3$. Its semantics is defined as follows:

$$GE ::= \{\rho(hs) | model_C \cup GA \models \rho(hs)\},$$

where ρ is a ground substitution.

It is noteworthy that $\rho(hs)$ may comprise both positive and negative ground atoms, which correspond to belief insertion and deletion, respectively.

3.4 Stage 4: Enabled Sent Message Generation

During a reasoning cycle, if the decision-making module fails to generate a feasible action, it will attempt to generate enabled sent messages for exchanging information with other agents. A message can be sent only when the related enabled constraint is satisfied. The enabled sent messages are defined as follows:

$$ES ::= model_C \cup GC \cup S.$$

ES is a first-order theory expressing enabled sent messages and the corresponding belief change of the agent. The generated sent messages, GS, are formally defined as follows:

$$GS ::= \{\rho(msg_s) | ES \models \rho(msg_s) \wedge model_C \cup GC \not\models \rho(msg_s)\},$$

where ρ is a ground substitution.

sub_info of the agent will be changed if GS is not an empty set. M_S will be assigned with GS, which is defined as follows:

$$M_S ::= GS$$

3.5 Stage 5: Event Processing

In each reasoning cycle, each agent processes events including adopting subgoals to achieve the desired state, revising current beliefs, and responding to the received messages from the last reasoning cycle. The state of the multi-agent system may change as a result of the event processing altering the state of an agent. In the reasoning cycle, the received messages of an agent are denoted with M_R. The enabled event processing is defined as follows:

$$EP ::= model_C \cup M_R \cup P.$$

EP is a first-order theory expressing the results of event processing. The results of event processing, PR, are formally defined as follows:

$$PR ::= \{\rho(response) | EP \models \rho(response) \wedge model_C \cup P \not\models \rho(response)\},$$

where ρ is a ground substitution.

If M_R is not an empty set, the sub_info of the agent will be altered. This modification occurs because M_R undergoes reinitialization, resetting it to an empty set after event processing, which is formally defined as follows:

$$M_R ::= \{\}$$

3.6 Stage 6: Communication

During each reasoning cycle, agents exchange information on the basis of the information of sub_info. To define the effects of communication of the sub_info of each agent, we utilize the following functions.

We utilize three functions to convert sent messages into their corresponding received messages. First, $inst(S, msg_s)$ instantiates the receivers of a sent message. Secondly, $Inst(S, M_S)$ instantiates all messages sent by an agent, using $inst(S, msg_s)$ as the basis. Third, $MP(S, msg_s)$ converts a sent message to its corresponding received message.

$$inst(S, msg_s) ::= \begin{cases} \bigcup^{r} send(r, B), \text{ if } R = all, \text{ and } r \in \bigcup id \\ \bigcup^{r} send(r, B), \text{ if } R = allother \text{ and } r \in \bigcup id \setminus S, \\ \bigcup^{r} send(r, B), \text{ if } R = id, \text{ and } r \in \{id\}, \end{cases}$$

$$Inst(S, M_S) ::= \begin{cases} \{\}, \text{ if } M_S = \{\}, \\ inst(S, msg_s) \bigcup Inst(S, M_S \setminus msg_s), \text{ otherwise} \end{cases}$$

$$MP(S, msg_s) ::= \begin{cases} sent(S, B), \text{ if } msg_s = send(r, B), \\ sent!(S, B), \text{ if } msg_s = send!(r, B), \\ sent?(S, B), \text{ if } msg_s = send?(r, B), \end{cases}$$

Next, we use three functions to update the subinfo of one agent. First, $P_1(sub\_info, S, msg_s)$ defines how an agent updates its sub_info for a single sent message. Second, $P_2(sub\_info, S, M)$ defines how an agent updates its sub_info for a set of sent messages, using $P_1(sub\_info, S, msg_s)$ as the basis. Third, $P_3(sub\_info)$ describes the initialization of M_S of an agent.

$$P_1(sub\_info, S, msg_s) ::= \begin{cases} r : (B, goals, M_S, M_R \bigcup MP(S, msg_s)), \text{ if id=r} \\ sub\_info, \text{ otherwise,} \end{cases}$$

$$P_2(sub\_info, S, M_S) ::= \begin{cases} sub\_info, \text{ if } M_S = \{\} \text{ or } id \neq r \\ P_2(P_1(sub\_info, S, msg_s), S, M_S \setminus msg_s), \text{ otherwise,} \end{cases}$$

$$P3(sub\_info) ::= id : (B, goals, \{\}, M_R).$$

We define the $state\_info$ as a collective set of the sub_info of each agent within the multi-agent system, denoting as $(sub\_info)_{\times n}$. After the reasoning cycle of each agent, the update of $state\_info$ is formally defined as follows:

$$(sub\_info)_{\times n} \xrightarrow{(id:M_S)_{\times n}} (P_3((P_2(sub\_info, id, M_S))_{\times n}))_{\times n}.$$

3.7 State Update

For a multi-agent system, agents participate in a modular reasoning cycle and communicate with other agents during the final stage of the cycle. The state of the multi-agent system is updated once all agents have completed their current reasoning cycle.

The substate of a multi-agent system, i.e., the state of an agent, can only be modified by the effects of an action, GE, and the processed results of the event processing, PR. In each reasoning cycle, the agent can only generate either an enabled action or a sent message, but it can handle all received messages. We define a function T to update *substate* based on action effects during each reasoning cycle, and T will not modify the substate if there is no enabled action effect.

A generated effect only changes the current belief base, and a generated effect of GE is an instance of hs, which is in the form:

$$\rho(hs) ::= \rho(\bigwedge_m B_m \wedge \bigwedge_n \neg B_n),$$

where ρ is a ground substitution.

For the generated action effect, the substate is updated as follows:

$$\begin{aligned} update(B) :: &= B \cup \bigcup^{m} \rho(\{B_m\}) \setminus \bigcup^{n} \rho(\{B_n)\}, \\ T(substate, GE) :: &= \begin{cases} id : (update(B), goals), & \text{if } GE = \{\rho(hs)\}, \\ id : (B, goals), & \text{if } GE = \emptyset, \end{cases} \\ substate :: &= T(substate, GE). \end{aligned}$$

A processed result of event processing can modify beliefs, goals, or both. Additionally, an instance of a *response* can take the form of either msg_s or *update*. It is worth noting that only an instance of *update* will modify the substate, which includes $insert(B, b)$, $delete(B, b)$, $adopt(goals, g)$, and $drop(goals, g)$.

For a processed result, the substate is updated as follows:

$$\begin{aligned} insert(B, b) :: &= B \cup b, \\ delete(B, b) :: &= B \setminus b, \\ adopt(goals, g) :: &= \{goals[0] \cup g\} \cup goals[1:], \\ drop(goals, g) :: &= \{goals[0] \setminus g\} \cup goals[1:], \\ H(S, r) :: &= \begin{cases} id : (insert(B, b), goals) & \text{if } r = insert(b), \\ id : (delete(B, b), goals) & \text{if } r = delete(b), \\ id : (B, adopt(goals, g)) & \text{if } r = adopt(g), \\ id : (B, drop(goals, g)) & \text{if } r = drop(g), \\ id : (B, G) & \text{, otherwise.} \end{cases} \end{aligned}$$

For the processed results of the event processing, PR, we define the function F to update the substate as follows:

$$F(S, PR) = \begin{cases} F((H(S, r), PR \setminus r) & \text{if } PR \setminus r \neq \{\}, \\ S & otherwise. \end{cases}$$

Assuming a multi-agent system containing n agents ($n \geq 1$), the state is represented as $(substate)_{\times n}$. In each reasoning cycle, the substate can only be changed by the effects of enabled actions and the processed results of event processing. We use the $(id : (GE, PR))_{\times n}$ to represent a transition that may change the substate, subsequently changing the state. The operational semantics of a *vGOAL* specification is defined as follows:

$$(substate)_{\times n} \xrightarrow{(id:(GE,PR))_{\times n}} (F(T(substate, E), PR)_{\times n},$$

where GE represents the generated effects of an action, and PR denotes the processed results of the event processing. Although GE and PR can both be empty for an agent, if any agent has a goal, at least one agent will have non-empty GE or PR. In our setting, if an agent fails to generate any decisions based on its current beliefs, it should send messages to other agents to obtain more information to accomplish its goal.

Moreover, if any *substate* is updated, each sub_info within the multi-agent system will be automatically adjusted, namely, the belief base and goal base will be modified to align with the *substate*. Furthermore, the sent and received messages of each agent will be reinitialized to an empty set.

4 Case Study

Using a real-world autonomous logistic system, we have validated our formal approach to safe autonomous decision-making. Accordingly, we use the system to explain how to use *vGOAL*.

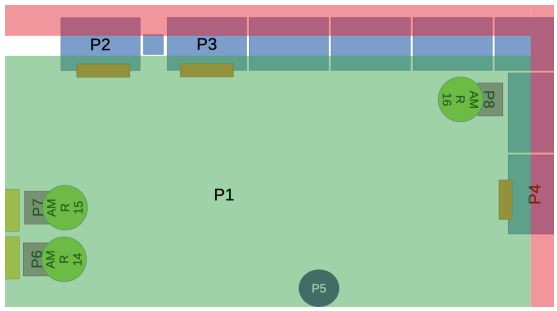

Fig. 1. Layout of the Robot Environment

The autonomous system is composed of three autonomous mobile robots, situated in the environment depicted in Figure 1. The case study aims to perform a collaborative transportation task. Non-red areas are considered safe places, denoting from P_1 to P_8, while red areas are considered unsafe, denoting by P_9. P_2 is the destination of the delivery task; P_3 and P_4 are the pick-up station; P_5 is

a waiting point for the charging station; P_6, P_7, and P_8 are the charging stations; and P_1 is the other places except the aforementioned areas. The nine areas can be classified into four categories. Category I only contains P_1. The location of Category I is a safe place, but agents do not need permission to access it, and it has no dock. Category II includes P_2, P_3, P_4, P_6, P_7, and P_8. The locations of Category II are safe places, and agents need permission to access them. There is a dock for each location. Category III includes P_5. The location of Category III is a safe place, and agents need permission to access it, but it has no dock. Category IV only includes P_9. The location of Category IV is an unsafe place, and agents need to avoid moving there.

We demonstrate each key aspect of the *vGOAL* specifications using a subset of the specifications that specify the case study. For a comprehensive version of the formal specification for the case study, we refer readers to [18].

First of all, we have to determine how to specify agents within the multi-agent system. We need to define four agents in the case study: three for the real-world agents, designated as A1, A2, and A3, and one for a dummy agent, denoted as C. In our approach, we utilize a dummy agent to manage competing requests for critical resources, such as permissions for locations. The specification of the multi-agent system is specified as follows:

```
Agents = [A1,A2,A3,C],
```

where A1, A2, A3, and C are an instance of the agent class defined in the *vGOAL* interpreter.

To facilitate real-time autonomous decision-making, an agent will take both the real-time beliefs abstracted from sensor information and the prior beliefs as the complete belief base to make decisions. As it is common that not all required information can be sensed in practical scenarios, we need prior beliefs to specify the necessary but unperceived information, and it is shared by all agents within the system. The belief base of A3 and the prior beliefs of the system are specified as follows:

```
belief_base3 =[],
prior_beliefs=["on(1,3)","on(2,4)","on(3,3)","on(4,3)"].
```

Furthermore, the *vGOAL* interpreter receives real-time beliefs abstracted from sensor information on location, docking, and battery level. The initial complete belief base of A3 consists of the prior beliefs and the initial real-time beliefs, which is listed as follows:

```
belief_base3 =["on(1,3)","on(2,4)","on(3,3)","on(4,3)",
"at(8)", "battery(2)","docked(8)","assigned(8)"].
```

An agent can have no goals, one goal, or multiple goals. Agent A3 has two goals, which are specified as follows:

```
goal_base3 = ['delivered(2,3)'],
goal_base4 = ["delivered(2,4)"],
goals3 = [goal_base3,goal_base4].
```

Dummy agents are used to manage critical resources. Their specifications are similar to those of real-world agents, including belief bases and goals. However, while real-world agents rely on sensor information to update their belief bases, dummy agents' belief bases are not affected by sensor information. Furthermore, dummy agents have no goals to pursue. The case study only requires one dummy agent, denoted as C, whose belief base and goals are listed as follows:

```
dummy_agents=["C"]
belief_base4 = ["idle(2)", "idle(3)", "idle(4)","idle(5)",
      "reserved(A1,6)", "reserved(A2,7)", "reserved(A3,8)"]
goals4 = []
```

The *vGOAL* interpreter provides a class for agents, whose attributes involve a unique identifier, a belief base, goals, sent messages, and received messages. The sent messages and received messages are empty by default. Therefore, users only need to specify an agent with the other three values. The specifications of Agent A3 and the dummy agent are specified as follows:

```
A3 = Agent("A3", belief_base3 , goals3)
C = Agent("C", belief_base4 , goals4)
```

A knowledge base is a collection of facts and rules that the decision-making module uses to reason about the world. In *vGOAL*, a knowledge base can contain either a first-order implication without negative recursion or a ground atom. Two representative rules in the knowledge base are specified as follows:

```
"forall w. on(w,4) implies available(w)",
"equal(charging,charging)".
```

vGOAL utilizes a set of rules, referred to as the constraints of action generation, to ensure that the generated decisions are moving towards a goal. These constraints are either related to the generation of actions or the generation of messages to acquire more information about the environment. Two representative constraints are specified as follows:

```
"forall w,y in D2 . a-goal holding(w) and docked(p) and not
holding(y) and docked(4) and available(w) implies A(w)",
"forall p,w in D2 . a-goal at(p) and not holding(w) and
                        not equal(p,2) implies S(p)".
```

The first constraint pertains to the action generation, and the second constraint pertains to the generation of sent messages. As mentioned in Section 2, users only need to specify the domain of variables that only occur on the left side of the implication due to the implementation of the interpreter.

In *vGOAL*, feasible actions are derived using a set of rules called the enabledness of actions, which requires including a generated constraint and may impose restrictions on the current belief base. Two of the enabledness of action generation are specified as follows:

```
"forall w. A(w) implies pickup(w)"
```

```
"forall p. exists y. C(p) and at(y) and equal(y,1) and
                    not equal(p,5) implies move1(y,p)".
```

The first rule only involves a generated constraint, whereas the second rule involves both a generated constraint and current beliefs.

In *vGOAL*, sent messages are derived using a set of rules, which only includes a generated constraint and may impose restrictions on the current belief base. One rule for the generation of sent messages is specified as follows:

```
"forall p. S(p) implies send!(C) idle(p)".
```

vGOAL includes rules related to event processing, which encompasses responding to received messages and adopting subgoals of the focused goal on the basis of current beliefs. Five rules for event processing are specified as follows:

```
"fatal implies drop all",
"forall z. exists x,y. sent!(x) at(y) and reserved(x,z)
              and not equal(z,y) implies insert idle(z)",
"forall x. exists y. sent!(x) idle(y) and reserved(x,y)
                          implies send:(x) assigned(y)",
"exists x,y. sent!(x) idle(y) and reserved(z,y) and
                     equal(x,z) implies delete idle(y)",
"exists x,w,p. a-goal on(w,2) and on(w,p) and at(x)
                                    implies adopt at(p)".
```

The first rule states that all goals should be dropped if a fatal error occurs. The next three rules illustrate three distinct approaches to responding to a received message, including belief insertion, message sending, and belief deletion. The last rule specified how to adopt a subgoal toward the desired goal.

vGOAL employs action effects to determine how to modify the current belief base. These effects can either involve belief insertion or deletion. As a result, the associated rule may involve negative recursion, a property not shared by rules in other components. An example rule for the generation of action effects is provided below:

```
"pickup": "forall w,p,y in D2 . pickup(w) and not holding(y)
              and on(w,p) implies holding(w) and not on(w,p)"
```

Moreover, the real-time information can include error messages, necessitating error handling. We emphasize that our framework can conveniently handle errors. In another word, users can simply specify how to handle errors in the specifications without changing any implementation of the framework. In the case study, we identify four types of errors: E_1, *dock* errors; E_2, *pick up* errors; E_3, *drop off* errors; and E_4, *charge* errors. In our setting, the non-fatal errors are E_1, E_2, and E_3, and the fatal errors are E_4, which is specified in the knowledge base as follows:

```
"E1 implies nonfatal",
"E2 implies nonfatal",
"E3 implies nonfatal",
```

```
"E4 implies fatal",
```

If an agent encounters a fatal error, it should send a message to the dummy agent to report its current location. If an agent encounters a nonfatal error, we need a dummy rule to avoid any meaningful constraints. Therefore, two constraints on error handling are specified as follows:

```
"forall p. at(p) and fatal implies M(p)",
"nonfatal implies Dummy",
```

If an agent encounters a fatal error, the agent will be considered broken and will drop all goals and beliefs. If an agent encounters a non-fatal error, it will drop all focused goals and adopt new goals. After inserting new goals, it will delete corresponding nonfatal errors to enter the next reasoning cycle. The rules on error handling are specified in the event processing as follows:

```
"fatal implies drop all",
"fatal implies delete all",
"nonfatal and not goal_change implies drop all",
"nonfatal and not goal_change implies adopt located(charging)",
"nonfatal and not goal_change implies adopt at(5)",
"nonfatal and not goal_change implies insert goal_change",
"nonfatal and E1 implies delete E1",
"nonfatal and E2 implies delete E2",
"nonfatal and E3 implies delete E3",
```

5 Discussion

The motivation of *vGOAL* is the generation of verifiably safe decision-making for autonomous systems. Consequently, it is pertinent to conduct a comparison with the APLs capable of generating verified decisions. In this section, we discuss the key aspects of *vGOAL*, along with a comparison with GOAL, Gwendolen, and AgentSpeak (Jason).

vGOAL stands out from GOAL, Gwendolen, and AgentSpeak (Jason) in generating safe decisions without the need for additional computation. As discussed in Section 3.1, the first stage of each reasoning cycle involves generating the substate property, which links each state to a state property. Hence, we can prove that a state satisfies its safety properties by showing that all safety properties are contained within the state properties without additional computation. However, GOAL and AgentSpeak necessitate formal specifications of the original programming language and verification tools [1] [13], while Gwendolen relies on the Agent Java PathFinder (AJPF) for model checking, thereby encountering efficiency problems [9].

Durative action modeling and error handling are crucial and challenging issues in autonomous decision-making. Notably, we address the challenge of error detection in a different way than GOAL, Gwendolen, and Jason. Specifically,

vGOAL logically handles errors by separating error detection from the decision-making module and allowing users to specify how to handle errors in the specifications without modifying the implementation of the framework. In contrast, error handling is hard-coded into the implementation of Gwendolen and Jason, requiring users to modify the implementation to specify how to handle action failures [2] [16]. While GOAL does not have a specific error-handling mechanism, it can recognize action failure by comparing received perceptions with desired effects. In practice, the method involves comparing the received perceptions with the desired effects [12] [14], which can be laborious to identify all potential situations of action failure.

Despite being based on speech-act theory, the communications of all four languages have different performatives. *vGOAL* and GOAL employ the least performatives, namely indicative, declarative, and interrogative, which do not directly alter current goals [11]. In contrast, Gwendolen utilizes performatives such as *tell*, *perform*, and *achieve*, which directly affect intentions [7]. Jason employs more performatives, compared with *vGOAL*, GOAL, and Gwendolen [2]. In summary, *vGOAL* and GOAL use a simpler communication mechanism than Gwendolen and Jason, employing mailbox semantics without direct modification of goals. Notably, in *vGOAL*, the communication component is encoded in a first-order logical manner to allow automated logical derivation and minimal model generation.

The implementation of the interpreter for *vGOAL* is in Python, which differs from the implementation of the interpreters for GOAL, Gwendolen, and AgentSpeak in Java. *vGOAL* has the advantage that only it can be readily encoded in a decision-making node in ROS, compared with GOAL, Gwendolen, and AgentSpeak. *vGOAL* has already been integrated with ROS using rosbridge, as well as Gwendolen and AgentSpeak [5]. Additionally, there is currently no known research that connects GOAL with ROS.

6 Conclusion

To achieve verifiably safe autonomous decision-making, we have developed an innovative formal approach based on *vGOAL*. In this paper, we aim to give a comprehensive introduction to *vGOAL*, as it is pivotal in presenting and justifying our formal approach to safe autonomous decision-making. Initially, we presented its formal syntax and operational semantics, providing a solid foundation for formal verification. To demonstrate the applicability of the language, we described a real-world autonomous logistic system that has been validated using *vGOAL* and its interpreter. Finally, we compared the key aspects of *vGOAL* with comparable APLs to demonstrate its advantages. In the future, we aim to enrich the case studies of *vGOAL* with numerous complicated real-world autonomous systems. Moreover, we intend to conduct an empirical analysis to compare *vGOAL* with GOAL, Gwendolen, and AgentSpeak (Jason). We believe *vGOAL* can be highly valuable for developing safe autonomous robotic applications.

Acknowledgements

This research is partially funded by the Research Fund KU Leuven. We thank Jens Vankeirsbilck for providing Fig.1.

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