Knowledge-based Framework for Human-Robots Collaborative Context Awareness in USAR Missions

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***Abstract*— Urban search and rescue (USAR) missions can benefit a great deal from teams of mobile robots endowed with advanced perception capabilities. To effectively collaborate with humans, these robots should have situation awareness about their robotic and human teammates, for intuitive decision making. Moreover, robots should be able to contextually share information so that humans can benefit from augmented situation awareness provided by robots, and at the same time, actions taken by the robots be transparent to humans.**

In this paper, a knowledge-based framework for human-robots collaborative context awareness in USAR missions is proposed. The main contributions are: an ontological representation of contexts at mission, agent, scenario, and team levels of the mission; a knowledge base integrating different tools required for such scenario; and an efficient and robust knowledge sharing strategy. The framework is efficient in terms of communication delay, capable to cope with communication failures and different event frequencies, and scalable in terms of team size.

I. Introduction

Mobile robots can help humans in urban search and rescue (USAR) missions with their perception, actuation, and communication capabilities. Mobile robots can, for example, help firefighters in finding victims and fire sources, floor-mapping, and providing tele-presence in an urban fire scenario. In addition to these capabilities, they are redundant and stress-proof [1]. However, unstructured and unpredictable environments present a new set of challenges for mobility, perception and communication [2], [3], therefore humans are are also required in the loop, in addition to robots autonomy.

Previous collaboration efforts between robots and humans in USAR scenarios demonstrated the need for representing robot's perception in a human comprehensible format and developing intuitive reasoning methods, so that robots actions should seem plausible to a human operator [4]. Moreover, the robot teams should also compensate for the absence of a reliable communication infrastructure, as communication has a significant effect on the performance of multi-robot systems in search and rescue missions [5].

In this paper, we report research that has been done in order to address this problem of human-robot collaboration by devising: a knowledge representation framework, homogeneous to all the robots, and capable of reasoning based on rules provided by humans; and an efficient and robust knowledge sharing strategy that can aid robots in sharing their knowledge for better decision making. The knowledge concepts are based on those contextual information that can influence the decision making at individual and team levels.

The rest of the paper is organized as follows. In section II, we discuss related work and background. Section III presents the collaborative context awareness framework. Section IV presents and discusses experimental results obtained both in simulations and with real robots in a firefighting simulated scenario. In section V, conclusions are summarized.

II. Related work

The use of robots in USAR scenarios has gained importance for the last decade with their participation in important disasters and crisis management [2], [6]. Moreover, robot teams have proven to be faster in search and rescue missions in an indoor scenario as compared to a single robot [7]. The pioneering deployments of robots in USAR scenarios used teleoperation, wherein human operators were easily stressed and fatigued due to the lack of situation awareness [2], [6]. This has led to the rise in demand for autonomous robots. Hence, a lot of work has been done to improve mobility, mapping, localization, deployment and connectivity [1], and has also been applied to control robot teams in USAR missions [8]. However, the increase in robots' autonomy creates the need for trust and transparency, leading to the requirement of contextual information and feedback [9].

These past experiences emphasized the need for intuitive human-robot collaboration in USAR missions, in order to decrease the cognitive workload on humans. In [10], three functions were identified for effective collaboration with robots: collaborative control, effective communication, and adaptive attitude. The authors stressed the importance of context awareness to implement these functions and stated that robot should have situation awareness for effective collaboration, not only about its own situation but also about the user's situation. There has been a recent shift from teleoperation and situation-based human intervention, to higher level knowledge abstraction and knowledge-based human-robot collaboration [11].

Collaborative context awareness and its definition in ontological form can help in seamless interaction between robots and humans, and also for adapting robot behavior as the situation evolves, because situation awareness is intimately related with the notions of context, context awareness and collaborative context awareness [12] from ubiquitous systems [13]. In [14], collaborative context is defined as

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the "summary of the situation of the other devices in the local range corrected by the local context". A collaborative context-aware system is defined in [12] as one that comprises a group of entities capable of sensing, inferring and actuating, which share information through communication to achieve a common goal.

The fundamental requirement for context awareness is a formal context model that is needed to represent the notion of context in a way computers can interpret it. Context modeling deals with how contexts are collected, organized, represented, stored and presented. In [15], an ontological knowledge representation is proposed for capturing relevant information about robots and their capabilities in search and rescue missions, which we have adapted for developing and representing an ontology, narrowed down to the use case described in Fig. 1, and enhanced with a reasoning module.

III. Collaborative Context-Aware System

In order to implement a collaborative context-aware system, we studied the requirements of USAR missions in basement fire scenarios and the expectations of firefighting teams from assistive robot teams. A simplified use case was developed, which includes some probable situations and desired behavior from the robot team under those circumstances. This use case is presented in Fig. 1. For decision making and information sharing, the robot team should be able to comprehend and take firefighters' context into account, in addition to the context of individual robots and environment. Many of these features require the fusion of knowledge from distributed robots, therefore representing the collective understanding of the team is also required.

An incident had been reported to the Fire Fighting Command Center (CC) about a fire outbreak in the basement of a residential apartment. The Firefighters (FFs) team arrived near the incident and has started planning its response. For the reconnaissance phase, some FFs aided by a team of mobile robots entered in the apartment with the task of finding events, such as victims, fire outbreaks and other hazards, such as structural collapse, or inflammable materials near fire. The team was divided into smaller groups, where a FF led a team of robots and exchanged information using an handheld Android device. This device served as wireless router for the team, and it also provided information about FF location and mobility status to the robot team and the robot team sent a map to the FF with events location. The robot team started exploring the area and each robot could find victims using face detection and sound source localization features [16], and could detect fire using classification methods [17]. These events were automatically propagated to other connected teammates (robots and humans), along with their representation on a complete map, built by fusing its local map with the maps obtained from other robots [18], [19]. All the robots maintained a list of active teammates and in case any teammate was lost or out of range (out of network coverage), then this information was reflected in the reduction in size of active teammates and the same was also conveyed to the FF. When robots joined back, all the robots shared their complete list of unattended events.

Fig. 1: Use case – fire outbreak in a basement garage.

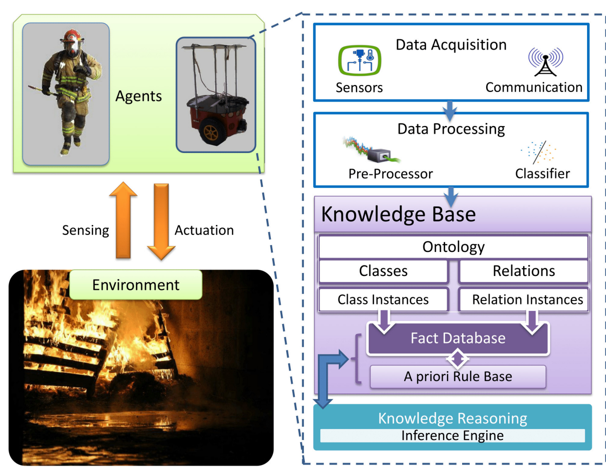

Fig. 2: Collaborative context-aware system architecture.

A. Architecture

As discussed in section II, the main requirements for implementing context-aware collaboration with humans are: (i) a framework for the collection of all the concepts related to the mission; (ii) a knowledge acquisition and sharing module that acquires information from the environment and other agents, updates the states of concepts as required, and shares them among teammates; (iii) a collection of rules required for efficient registration of new information and reasoning on the existing one; and (iv) an event management strategy to share events and related information among robots and humans, such as time of detection, location, *etc*. The architecture of the proposed system, along with the aforementioned modules, is presented in Fig. 2 and Fig. 5. Each one of these modules is detailed below.

1) Ontology: It is a knowledge representation method to represent key concepts, their properties and constraints, and relation between these concepts. Based on previous studies related to the study of USAR missions [15], and our discussions with firefighters/crisis management teams, we summed up the contextual concepts and divided them into four top-level classes, as depicted in Fig. 3.

Team_Based_Context class is incorporated to include information that can help us take advantage from multi-robot cooperation. Some examples of these advantages are: representing teammates' poses on a global map, known and shared by all teammates; selecting the best candidate to perform tele-presence; compensating for a teammate's immobility, *etc.* These top-level classes were further classified in an hierarchical form and the ontology hence developed is depicted in Fig. 3. The *Thing* class in the figure is the root class of our ontology and it represents the set of instances from all the classes. This ontology will serve as the entry point to the *knowledge base* of robots. Along with the classes shown in the figure, this ontology also covers object properties (relations between instances of the classes), and data-type

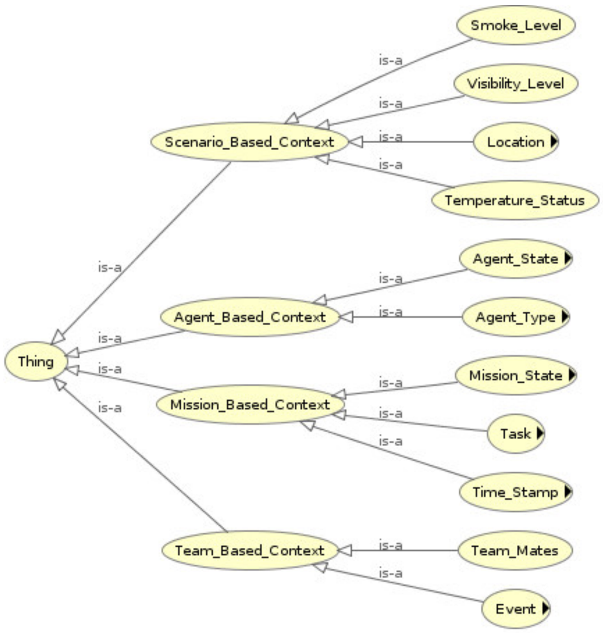

Fig. 3: USAR ontology.

```
a.
create_event_FireDetection_instance(Inst_Fire_Detected) :-
rdf_instance_from_class(chopin_owl:'Fire_Detected', Inst_Fire_Detected).

b.
link_to_time(Instance_General, Inst_Timestamp, Value_timeStamp) :-
create_TimeStamp_instance(Inst_Timestamp, Value_timeStamp),
rdf_assert( Instance_General, chopin_owl:'atTime', Inst_Timestamp).

c.
get_shared_eventInstance(EventInstance):-
rdf_has(A, rdf:type, chopin_owl:'Shared'),
rdf_has(EventInstance, chopin_owl:'hasSharingStatus', A).
```

Fig. 4: Rule base.

properties (relations between instances and data values). The proposed ontology comprises *323 triplets*, wherein a *triplet* is composed of a *subject*, a *predicate*, and an *object* [20]. A *triplet* on a 64-bit system takes 144 bytes of memory.

2) Rule base: It is a collection of *facts* and *rules*. The rules are provided as conditional statements to assert facts and derive new facts from the existing ones. Facts are stored in the *fact base* as a declarative predicate expressions (relation between concepts), whereas rules are stored in the form of predicates with logical implications to describe relations between facts. The rule base together with ontology is stored in the *knowledge base*.

In our implementation, the rules are divided into three categories based on their complexity: basic, class-relation, and convenience rules. *Basic rules* are used to assert basic facts, such as instantiation or initialization with data-type properties initialization. *Class-relation rules* are used to assert relation between classes. *Convenience rules* are more complex rules built upon the previous two categories, and are used for advanced assertions and reasoning, such as instantiating an event with all the background information, or checking duplications in the knowledge base, *etc.* A snippet of the three types of rules definition is given in Fig. 4. The size of the fact database, in terms of *triplets*, can be found by calculating the number of new instances and relations. For example, creating an instance of *Fire_Detected* uses one *triplet*, whereas creating a relation between two classes requires 3 *triplets*, one for each instance of their corresponding class and one for the relation between instances.

B. Knowledge acquisition and sharing

Since a USAR scenario is highly dynamic, a software framework is needed to perceive these changes and reflect them in the knowledge base. The knowledge acquisition and sharing strategy with respect to a given robot is depicted in Fig. 5. The robot obtains information about the environment using its own sensors, as well as from other agents (both humans and robots) and Command Center via wireless communication. After pre-processing, the information is classified and the following entities are derived: context classes defined in the ontology; relation between these classes; and the data-type properties of the classes. These information is then updated to the *knowledge base*. For instance, map meta-data obtained using a simultaneous localization and mapping (SLAM) technique has to be merged with other robots' maps to estimate agents' poses in a global reference frame. These poses are the instances of *Location* class given in Fig. 3, besides being spatial data-type properties of the agents. The same information is also used to obtain object relations (*e.g.,* vicinity) between different agents or between agents and landmarks. The information, as illustrated in Fig. 5, is exchanged in two ways: using a service for on-demand queries, and using advertisement/subscription for broadcasting periodic and special information (*e.g.* events).

Event management system: In addition to the knowledge acquisition and classification module, an event management

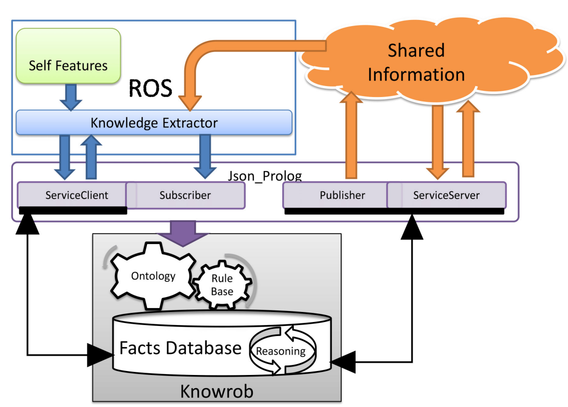

Fig. 5: Knowledge acquisition and sharing strategy.

system is required, which can not only store information but also propagate the same to other agents.

All the events that are detected by a robotic agent are shared with its teammates after storing the information in local *knowledge base*. The events are moved to a list of events that have not been attended yet (unattended events). In order to compensate for communication loss or teammates isolation from the network, when teammates join again, all robots share their list of unattended events with them.

IV. Results and Discussion

In this section, tests in simulations as well as with real robots in a firefighting simulated scenario are presented. The system was simulated in terms of communication delay, as efficient context sharing with variable team size is an important aspect of collaborative context awareness in scenarios without a reliable communication infrastructure. Then the system was validated with real robots in a representative firefighting scenario along with the underlying knowledge acquisition tools and reasoning capability.

A. Simulations

The proposed framework was tested for the delay in knowledge sharing for different frequencies of event occurrence and different team sizes.

1) Effect of frequency of event occurrence: We conducted experiments with 3 teammates for different frequencies ranging from 2 Hz to 10 Hz. Even though events are expected to be detected at much lower frequencies in a real scenario, the rationale for testing such high frequencies was that the same strategy of sharing events can be applied for sharing dense sensor data, which can be more useful for noise removal and statistical analysis. The team size chosen for frequency analysis was 3 as this is the least number of robots required for firefighter's handheld device localization using RSSI of Wi-Fi adapter and trilateration. Stochastic events were generated based on the cumulative Poisson distribution,

$$p_{\lambda}\left(r\right)=\frac{\lambda^{r}e^{-\lambda}}{r!}, \qquad \lambda=2,3,\ldots .10, \tag{1}$$

wherein λ indicates the average number of events per second. The delay Δ_j for a given event instance j was defined as

$$\Delta_j=\max_{1\leq q\leq n} {T_j}^{q}-{T_j}^{d}, \tag{2}$$

wherein ${T_j}^{d}$ is time of detection of event by agent d, n is the team size and ${T_j}^{q}$ is the time of event registration by another agent q receiving the event.

We simulated 100 events for each frequency and the results obtained are depicted in Fig. 6. The average delay, $\bar{\Delta}$, increases with the frequency of events generation, because more messages sent through the network leads to higher communication latency. However, even for the frequencies simulated, which are larger than usually found in a real scenario, the delay observed can be considered negligible for sharing events.

2) Effect of team size: The performance in terms of information sharing delay ($\bar{\Delta}$) was also assessed through simulations for different team sizes varying from 2 to 5 and a fixed average frequency of event occurrence equal to 10 Hz. It can be observed from the results depicted in Fig. 7 that there is a steady increase in $\bar{\Delta}$ with team size. As all the teammates generate events at a frequency of 10 Hz, sharing and instantiating these events leads naturally to an increase of the system delay. Nevertheless, these results show that the system is able to share knowledge with a negligible delay for frequencies of event occurrence commonly found in a real scenario, *e.g.,* 10 or 100 times lower than the ones simulated, and with an acceptable delay for higher frequencies and larger teams.

B. Real robots

In order to implement the use case (see Fig. 1), we integrated other sub-modules developed by our research team with the *knowledge extractor*, as depicted in Fig. 8. The *MRSLAM* node [18], [19] is built on top of *GMapping* SLAM algorithm [21] and provides relative transformations between different robots' frames. It is used to obtain a complete map and also to represent various features of the mission on a common map shared by all the robots. Fire, temperature, visibility and smoke detection nodes are based on the multi-sensor fusion and classification technique described in [17], while the victim detection node is based on the work described in [16]. *Protégé* [20] was used to define the ontology for our system. *KnowRob* [22] was employed for knowledge processing, *i.e.* for rule base implementation, interaction with ontology, and query processing.

For mapping and event detection, each of the Pioneer® P3-DX robots used in the experiments was equipped with a Hokuyo® laser range finder, and two of the robots either had a thermopile array (TPA81) or a Microsoft Kinect®. The firefighter (FF) was assumed to wear an Android smartphone as a simulated handheld device. This device was used to interact with the system and estimate the FF's motion status (*standing*, *walking*, and *running*) by processing data from the embedded inertial sensors. It was also used as a mobile hotspot to connect all the teammates. A RSSI-based localization module was implemented for estimating the FF's pose in the robots' map using trilateration.

1) System integration results: The framework was verified by simulating a fire and victim scenario in a 5x5 m^2 test area, as depicted in Fig. 9. The arena, even though small compared to a real scenario, was targeted to demonstrate all the features of the system. Two fire events were simulated using tungsten halogen bulbs and a mannequin was used to represent a victim. The event *agent_down* was identified if the FF stayed in status *standing* for more that 30 secs. Any of these events, when recognized by a given robot, were successfully propagated to other teammates after storing the information in its knowledge base.

Three robots were deployed to autonomously navigate in the scenario and each one of the robots was responsible for identifying one of the three kinds of events considered in the

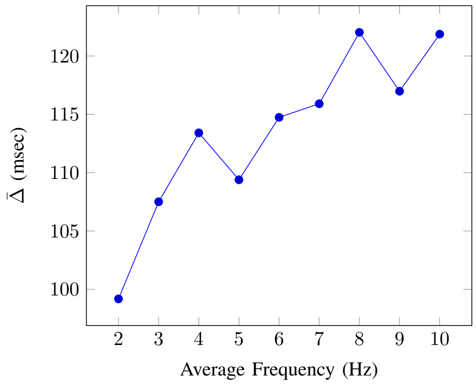

Fig. 6: Delay for different frequencies of occurrence.

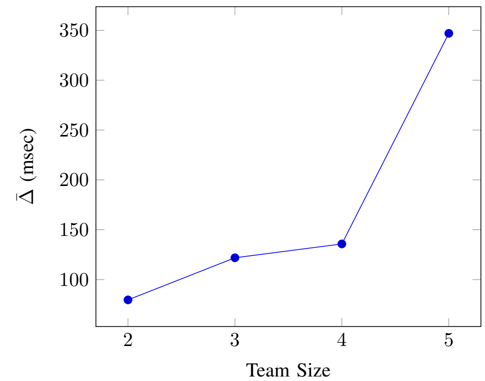

Fig. 7: Delay for different team sizes.

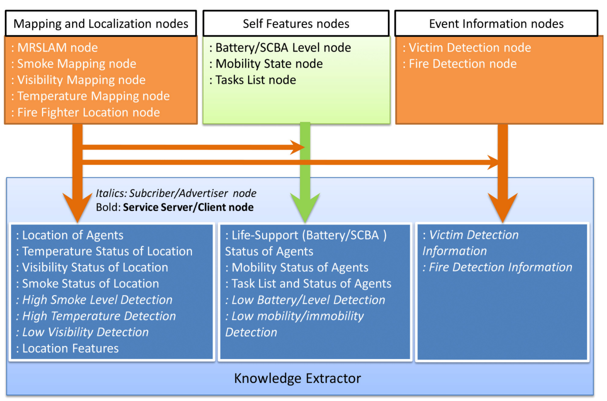

Fig. 8: Knowledge extraction for reasoning and efficient communication.

Fig. 9: Firefighting simulated scenario and event sites: fire outbreaks are indicated by red ellipses, the handheld device by the blue ellipse, and the victim with the green ellipse.

Event	No. of events	No. of detections	Final Count
fire	2	28	1
agent_down	1	10	1
victim	1	4	1

TABLE I: Comparison of actual number of events present in scenario, number of events detected, and number of events left after removing duplicates.

experiments (see Table I). The information gathered by the 3 robots were merged for a global representation using data from the *MRSLAM* module. Their individual detections as well as the global representation are depicted in Fig. 10.

Even though the real events were limited to two for *fire*, one for *victim* and one for *agent_down*, the experiments demonstrated that the actual sensing resulted in multiple detection instances of the same events, and which were spatially dispersed, because of the robots' movement during sensing. The comparison of the count of the actual events in the scenario and the detected events in given in Table I. These results are further discussed in the next subsection.[1]

2) Reasoning and resiliency against communication failures: The system herein proposed was designed to detect the inclusion of new teammates, or reduction and re-addition of teammates. This is important because, for instance, a robot might become temporarily out of range and join again the team later. In these situations, all the events stored in the local knowledge base are re-propagated within the team, so as to synchronize the knowledge of all the teammates. In order to cope with the problem of overloading the network with redundant information, the reasoning aspect of the system is employed.

A decentralised duplication removal routine was designed, which goes through all the stored events, self-detected and shared by the teammates, before sharing the knowledge with a new teammate. Events located within a distance of 4 m were assumed to be the same. The result after the use of the duplication removal module for one of the robots is shown in the last column of Table I. The 28 instances of fire present in the scenario were reduced to a single event after removing duplicates.

[1] A video presenting the system and one of the experiments can be downloaded from: `https://goo.gl/JKVZf4`.

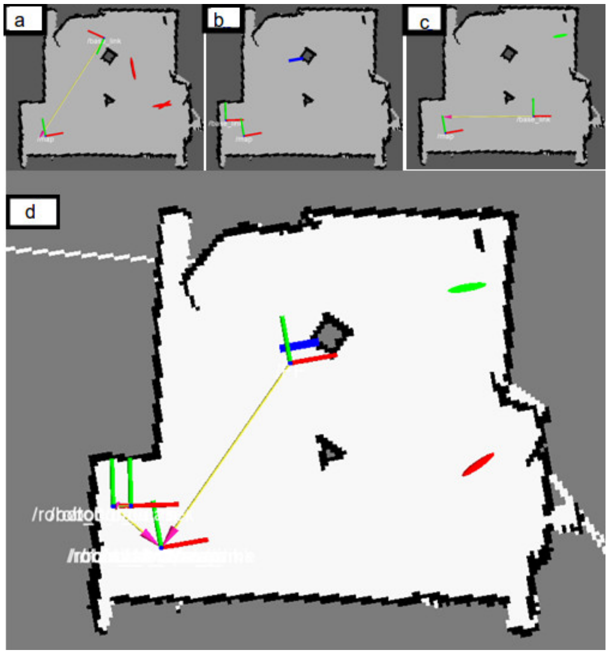

Fig. 10: Local event detections: *fire* (a), *agent_down* (b), and *victim* (c). In the global representation (d), these events are also represented: *fire* (red ellipse), *agent_down* (blue ellipse), and *victim* (green ellipse).

V. Conclusion

The knowledge-based system for collaborative context awareness was proposed along with the development of an ontology that covers high-level aspects of USAR missions. By taking a firefighting scenario as example, the framework was integrated with knowledge acquisition tools for fire, firefighter-in-danger and victim detection events. A decentralized map-merging tool was used to represent these events and teammates' pose on a global map.

The framework was found to be advantageous for efficient knowledge sharing and for incorporating user-defined rules. The use of an ontology helped in representing and correlating different concepts of the mission, which otherwise would have been a daunting task. The results presented in this paper for a simulated scenario allowed to successfully validate the system's main features, which are context sharing and context-based reasoning.

The applicability of the framework can be enhanced by providing human rescuers with an intuitive representation of the scenario and events on a semantically annotated global map, *e.g.* providing humans with the list of events in their vicinity through the firefighters' handheld device. The real power of the proposed knowledge-based system can be tapped by incorporating rules for robots' decision making that take into account the prevailing situation, thus invoking context-sensitive behaviours.

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