Active Situation Reporting: Definition and Analysis

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Abstract. In a lot of situations a human is incapable to observe their environment properly. This can be due to disabilities, extreme conditions or simply a complex and changing environment. In those cases, help from an artificial system can be beneficial. This system, equipped with appropriate sensors, would be capable of perceiving things that a human cannot and inform them about the current state of the situation. In this short position paper, we introduce the notion of Active Situation Reporting, in which an agent can inform another agent about the evolution of a situation. We define this notion, study the challenges such a system raises and identify the open research questions by reviewing the state of the art.

1 Introduction

Alice is blind and love to sing in a choir. She uses her autonomous car every Mondays to go to her singing lesson. She is very involved and would not like to miss or be late to a lesson without warning the teacher. This Monday, the route Alice's car usually uses is blocked by a wide load. The traffic information system in the car detects that taking an alternative route would take 15min more to travel while waiting for the wide load to leave takes an unknown amount of time (from 5 to 60 minutes). Alice notices that the car slows down and stops unusually and she is a bit stressed she might miss her lesson. She would like the car to be able to tell her what is happening and why it is acting unusually.

Barbara is a firefighter. Today she is entering a burning building with her teammates to try to find any victim. The team is accompanied by a robot that can perceive and navigate even in deep smoke. The robot can explore the environment and guide Barbara through the building, warning her if a roof collapses or if path is becoming too dangerous to take. Since the firefighters can hardly manipulate a tablet or other computer device in these extreme conditions, the robot is guiding them with voice.

Carl is living alone at home with an AI assistant to help him in his everyday life. The hospital just called him to tell him that his daughter had an accident and has been injured. Carl decides to go to the hospital right away but in his precipitation, he does not manage to find his car keys. His artificial assistant monitored that Carl took his keys in the bedroom the night before instead of putting them in the usual bowl in the entrance. It needs to inform Carl about it as soon as it detects that Carl is preparing to go out and is looking for something.

These three simple examples illustrate the advantages of having a system capable of helping a human understanding the environment they evolves in when this human cannot observe their environment properly. We refer this ability as *Active Situation Reporting*. In this paper, we study the problem of Active Situation Reporting and propose a definition in Section 2. Then, in Section 3, we highlight the different research challenges encountered while dealing with active situation reporting, study possible leads from the literature and identify open research questions. Finally, Section 4 identifies related research topics.

2 The Problem of Active Situation Reporting

Active Situation Reporting is not bound to an artificial system, and we define it as follows:

Definition 1. *Active Situation Reporting (ASR) is the process for an agent (called the reporter) to give* relevant *information about an* evolving *environment to another agent (called the user) without the user explicitly asking for this information. Automatic Active Situation Reporting is Active Situation Reporting performed by an artificial system.*

As we see, the reporter in an ASR system can as well be a human. Human journalists are in fact performing ASR for the newspaper or channel they work for by selecting information to deliver at a certain moment in time in order to give the reader or viewer an overview of a situation they cannot perceive directly. The nature of the information reported depends of what the journalist considers important and relevant. Automatic Active Situation Reporting works on the same principle: the reporter needs to select information that it considers relevant for its user at a certain moment in time and deliver it in the most appropriate way. We can already point out the main aspect (and challenge) of automatic ASR: how to automatically select the relevant information as it greatly depends on the user's preferences and knowledge as well as on the state of the situation at a certain time.

We can also note, as illustrated in the scenarios described in Section 1, that ASR can be the main goal of an artificial system (as for the firefighter case) or a mission to improve the user's comfort (as for the autonomous car). In the latter case, it is important that the situation reporting does not interfere with the main goal of the system.

Active Situation Reporting is at the crossroads of three different research areas which are Active Sensing, Semantic Perception and Human-Machine Interaction, as shown on Figure 1.

3 Research challenges and open questions

3.1 Active Sensing, Change detection and Relevance

Active Sensing is defined as the "problem of controlling strategies applied to the data acquisition process which will depend on the current state of the data interpretation and the goal or the task of the process" [2]. A system performing active sensing will therefore act in order to maximize the amount of information it can gather. This can be the sole purpose of the system, as in exploration or surveillance applications, but can

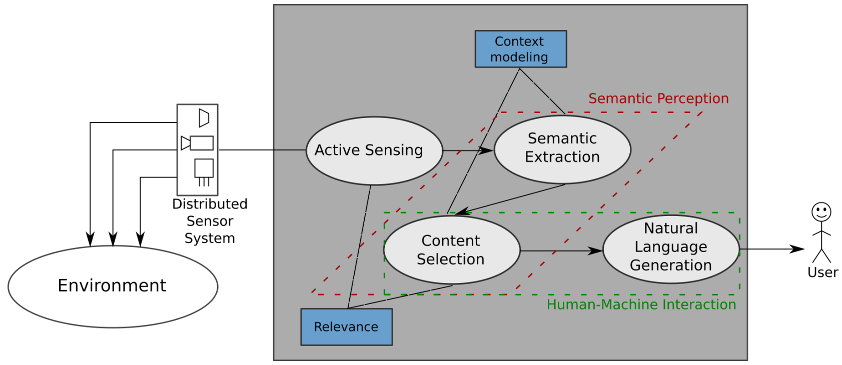

Fig. 1. Overview of an Active Situation Reporting system

also be combined with other type of mission performed by the agent such as in [31]. The reader can refer to Chapter 1 of [25] for a review about active sensing. As stated in Definition 1, an ASR system notifies the user about changes in their environment. Those changes can happen gradually (a staircase burning and finally being destroyed) or be encountered suddenly (the wide load on the road), which raise the question of their detection.

In Computer Vision, change detection algorithms aim at detecting significant changes occurring in a video by analyzing the frames of this video. State of the art algorithms use statistical methods such as Kalman filter [5] or Bayesian models [34], non-parametric methods [32] and machine learning [17]. In the domain of pervasive computing, multiple sources of information need to be combined in order detect changes. Small changes on single individual sensors might be considered insignificant but the fusion of signals coming from different sources may reveal important changes in the environment. Several algorithms have been proposed to detect changes in multivariate time series [11, 16] but they are computationally expensive and require a large amount of data for the model training. To overcome this issue, an information-theoretic change detection method for IoT systems has been recently proposed in [13]. One common aspect of all these methods is that they focus on anomaly detection, meaning detecting when the system changes from a *normal* state (often learned) to an *abnormal* state. However in the case of ASR, the changes are not related to anomaly detection but concern changes compared to previous states. In Data Mining and Machine Learning, the term *Concept Drift* refers to the possible change through time in the underlying model of a data stream and are usually tackled through adaptive learning algorithms [15]. One of the main challenges of concept drift detection algorithms is not to mistake noise with true drift. Many of existing algorithms assume sudden drifts [20], which is a big limitation compared to what can be observed in reality.

An ASR system cannot report all changes it detects in the environment but should select those that are *relevant* for the user at this moment. The concept of relevance is mostly studied in Information Science [29] and, technically, in Information Retrieval (IR) systems [10] and is usually called *system-based relevance*. In this topic, the goal of the system is to retrieve all the documents relevant to a request [27]. Here the relevance is objective and defined related to a subject. However, in intelligent autonomous systems, the relevance can be subjective and depends on the user's current state of beliefs and is referred to as *agent-based relevance*, *user-based relevance* or *epistemic relevance*. Agent-based relevance has received a lot of interest in knowledge theory and its different properties has been defined [14]. These properties have been used to derive a formal model of relevance within modal logic [28]. However, this model still assumes that the system knows with certainty the information need of the agent receiving the information, which is an unrealistic hypothesis when this agent is a human. In [26], Renoux et. al. suggested a model in which each agent uses approximations of other agent's beliefs in order to compute a degree of relevance. This system does not require an explicit request but depends on a lot of communication between the agents for the relevance computation to be efficient. In addition, the correspondence between the degree developed and what a human would consider relevant has not been directly demonstrated. Only indirect clues has been provided by experiments using this degree, as presented in [25].

With this study of the literature about active sensing, two important open research questions have already been identified:

1. How to detect gradual changes in an environment? As mentioned, all the methods we have encountered so far are hypothesizing (implicitly or not) sudden changes to detect. However, the environment will often change gradually and those changes are important for humans. Therefore a methods to detect such changes needs to be developed.
2. How to construct an efficient framework to quantify agent-based relevance? Such a framework would need to be able to compute the relevance of a piece of information for a human, based on a model of the human mind and knowledge. The degree proposed by Renoux et al. could be a interesting starting point but needs to be expanded with more advanced theories of mind such as the one suggested in [12].

3.2 Semantic perception

Sensor data as captured by artificial systems are not of much use for a human without their meaning. A human expert is capable, by analyzing the data, to extract meaning from them. An automatic ASR system needs to be able of the same in order to communicate meaningful information to its user.

Semantic perception is the systematic automation of observing/sensing the environment via sensors and the ability of extracting semantics from the data [23]. The Semantic Sensor Web proposes to annotate sensor data with semantic metadata in order to provide contextual information [30]. In this direction, the Semantic Sensor Network (SSN) ontology [7] provides a terminology to represent contextual knowledge and has been successfully used in various applications [18, 1]. In addition to being able to abstract sensors data to reason upon, artificial systems acting in the real wold need to make and maintain a connection between what concepts they reason upon and the actual real-world object these concepts represent or apply to, despite possible changes of the object in time (in position, shape, aspect...). This is the Physical Symbol Grounding Problem

[8]. This problem has been tackled from different angles and learning methods have been used [33] as well as spatio-temporal reasoning [22] and, more recently, ontologies [4].

Despite those recent advances in semantic perception and symbol grounding, some questions remain open and are being investigated by the research community, such as the problem of *shared symbol grounding*, or humans and machines using the same terms to denote the same entity [4] ; and perceptual anchoring, which is a subset of symbol grounding focused on maintaining a link between the object and the concept over time [9].

3.3 Human-Machine Interaction

The information perceived and abstracted needs to be reported in an adequate format to the user and therefore mapped to human-understandable language. Natural Language Generation (NLG) is concerned about ”building software systems that can produce meaningful texts in English or other human languages from some underlying nonlinguistic representation of information” [24]. NLG has been used in various applications to describe physiological data [3], to interact with the semantic web [6] or for spoken dialog. Despite recent advances in content selection and text generation, recent NLG systems are still rudimentary with regard to context-adaptation. They are capable of selecting a target language and adapt to a user's preferences but the modeling of the context remains rather simple. However, the semantic web and its modeling capabilities could be an excellent framework to model rich contexts and include them in a Natural Language Generation system [6].

4 Related work

In the previous sections, we studied ASR with regards to the fields of research needed to achieve it. In this section, we will give an overview of approaches that are similar or related to our problem and see where they differ from ASR.

First of all, one cannot fail to notice that Active Situation Reporting is some kind of monitoring. A lot of monitoring systems already exist and are doing very good job in verifying the state of an environment and its evolution. One could therefore rightfully wonder what Active Situation Reporting would do more or better. First of all, current monitoring systems are not *active*, in the sense that the user needs to request the information to be reported in order to get it. An ASR system is proactive by detecting that the user might need some piece of information and deciding to report it. In addition, classic monitoring systems do not select relevant information to report but report everything. They can highlight anomalies (usually based on thresholds) but offer a full access to all the information they are monitoring, which can be overwhelming for the user in large and complex environment such as the surrounding of a car. Finally, monitoring systems usually require the user to be trained at using them as the interface they offer is usually specialized for one type of operator. Active Situation Reporting aims at integrating flexibility, adaptability and user-friendliness in monitoring.

Two trendy topics currently in human-machine interaction are transparency [21] and explainable agency [19]. Autonomous agents are required to be able to explain their behavior, their beliefs, their intentions and their reasoning to a human user. Transparency and explainable agency are required to enable humans to trust artificial agents in critical situations where they are expected to collaborate. Similar challenges are encountered in those two topics and ASR, such as the human-machine communication, the extraction of semantics from data, etc. However, ASR aims at describing the environment around the agent more than the behavior of the agent itself, hence the importance of active sensing. Of course, agents describing their behavior and reasoning can be relevant for active situation reporting system, such as the autonomous car explaining that it decided to modify the planned route because of a closed road.

5 Conclusion

In this paper we described the problem of Active Situation Reporting, looked at the state of the art to determine what are the still open research questions in order to be able to build ASR systems and identified the following open questions:

1. how to detect gradual and incremental changes in the environment?
2. how to quantify the relevance of a piece of information for a human?
3. how to perform efficiently shared symbol grounding and perceptual anchoring?

In addition to those research questions, challenges arise in the combination of those fields that are Active Sensing, Semantic Perception and Human-Machine Interaction. Indeed, those three field use methods, assumptions and tools very different from one another and achieving interoperability between the components required by an ASR system is a great challenge. Finally, the complexity of the tasks considered by ASR involves a very complex modeling task. If ontologies seem to be a good tool to enable interoperability and rich context-modeling, connections between active sensing and semantic perception still need to be drawn in order to create an Active Situation Reporting system.

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