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Learn to Sense vs. Sense to Learn: A System Self-Integration Approach

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***Abstract*—The diffusion of Internet of Things (IoT) devices has opened up new opportunities for decentralized data analytics. In this context, data transmission can be affected by both network issues and distance between devices and receivers. These factors can affect the ability to aggregate and analyze data from multiple IoT devices, resulting in noisy, partial, or incorrect information. To this end, self-healing techniques pursue corrective actions when information acquired from sensors is not reliable. In this paper, we propose a new self-integration approach to improve the performance of decentralized self-healing techniques.**

***Index Terms*—Self-Healing, Multi-Agent Systems, Cooperative Learning**

I. Introduction

Thanks to the diffusion of IoT devices, sensors-based applications are spreading in different fields such as bioprocess monitoring [4], aerospace [1], missing data imputation [2]. Such applications mainly aggregate data acquired from multiple IoT devices. Here we have two problems: (*i*) in an open, continuously evolving environment, devices can be faulty or no more available; (*ii*) the speed of change in the aggregation function can be faster than the speed of communication in a decentralized network, given resource constraints such as bandwidth. These problems result in inaccuracies as the communication network will be congested. Although sensor faults recovery techniques are available in the literature, most studies focus on validating sensors measurements rather than faults deriving from network issues; this is a challenging aspect, as measurements from sensors can be correct, but their aggregation can be delayed due to network issues, leading to inaccurate results. In this paper, we are interested in how to (self-)integrate collective measurements to improve the management of such complex systems and their cost-effectiveness. We sketch an approach based on a *Multi-Agent System* (MAS), bounding cooperative learning with a self-healing mechanism, to improve the accuracy of aggregation functions in decentralized systems.

II. Lifelong Cooperative Learning in Self-Healing Systems

Consider a remote monitoring process based on a heartbeat generator. Through a combination of hardware (the timer) and software (an heartbeat generator), "*I am alive*" signals are generated periodically to indicate all is well [7]. The absence of alive messages may indicate faults or problems that can be solved through corrective actions.

A corrective action is defined as a reverse computation, or simply a roll-back operation on an aggregation function [5]. Corrective actions are used to avoid using data acquired from unreliable IoT devices.

The use of corrective actions is at the basis of *Dynamic Intelligent Aggregation Service* (DIAS), an agent-based self-corrective model for orchestrating decentralized reverse computations in large-scale dynamic networks [5]. Nevertheless, DIAS does not offer a mechanism to predict the effect of corrective actions and assess their long-term cost-effectiveness. To overcome this limitation, aggregation agents can be endowed with learning capabilities: they can sense the physical environment and correlate different types of spatio-temporal information with latencies and continuously adapt the threshold value used to determine whether to pursue corrective action based on previous observations. This is the idea behind our self-integration approach: aggregating agents sense the environment to learn how to improve their goal (that is, determine whether to pursue corrective actions).

On-line heterogeneous multi-agent learning is still a timely computational challenge, mainly because of two problems: per-agent *curse of dimensionality*, where a large number of training samples or variables are available, making difficult to achieve online training , and the *multi-agent inverse problem*, where agents require feedback regarding their individual actions, which is complex in resource-constrained environments with a large number of agents [6]. In the former case, the high sparsity and volume of data makes difficult to obtain statistically reliable data in a short amount of time. The latter is a complex task because it is hard to attribute how an agent's individual action influences to a global aggregation result. Moreover, agents must be aware of unpredictable changes in the environment during the learning task as the evolving dynamics of the environment can affect the decision of agents of doing corrective actions. These challenges can be addressed by autonomous agents in a bottom-up way by a *cooperative resolution process*. For that, it is pertinent to attribute to agents a local behavior that ensures that the global functionality of the system (intended as the orchestration of the local activities of the agents) satisfies the goal of the system. To this end, agents cooperate by providing their knowledge to other agents that are unable to decide whether to perform or not a corrective action; this is a challenging aspect: agents do not have any prior knowledge about the information they perceive and their type, thus cannot be associated with metrics for assessing their performance due to the variability of the environment. For that, agents can learn relevant indicators from both human activity and other agents, enabling them to assess precise answers for the posed problem: this is called *implicit feedback*. Here another challenge opens up: agents use implicit feedback to improve their capacity to decide whether they should perform a corrective action; how to assess the validity of such feedback in a dynamic, continuously evolving environment? Implicit feedback disseminated in an epidemic fashion provides high cost-effectiveness and efficiency in decentralized collective measurements. At the same time, it opens up a "*pandora's box*" used by malicious agents to compromise the network by exploiting this efficiency.

III. Case Study: Local Measure of Traffic Density

In this section we discuss a planned case study to make collective measurements of traffic density locally (by each node in the network) in large-scale environments.

Similar to the pipeline proposed in [3], the system can be composed of agents bounded with connected vehicles, sending alive messages, and aggregating agents associated with Voronoi regions, used to determine the rough relevance area sensors according to geographical characteristics of the environment such as weather, altitude or human characteristics such as population distribution. Aggregating agents measure traffic density within Voronoi regions using alive messages from connected vehicles.

Let us consider a vehicle sending an alive message just before leaving a Voronoi region. In this case, the aggregation function calculates an inaccurate result, as it considers the alive message from a vehicle that is no longer into the corresponding Voronoi region. Therefore, the aggregator agent must do a rollback to avoid using an alive message from an unavailable device. To tackle this problem, the aggregating agent uses its knowledge to determine cooperatively whether to do corrective actions. Knowledge may include information such as vehicle direction, signal strength, latency. The aggregating agent cooperates with other agents to assess if corrective action should be taken when observing similar environmental dynamics. The cooperative process results in a new knowledge produced by the agent, associating an environmental context with a decision on corrective action.

IV. Proposal

We propose a self-integration approach for improving the performance of self-healing systems. Our approach allows agents to learn when to take corrective action by correlating heterogeneous information such as connectivity status, proximity, the density of antennas, and physical obstacles. Such information is perceived online by available agentified devices. Here we intend "*learning*" as improving agents' ability to decide whether to do corrective actions. Agents do online learning and adapt continuously to the unpredictable dynamics of the environment, affecting agents' decisions. We use the DIAS system as a working basis for the development of our proposal, to which we add a cooperative learning technique.

The proposed approach is based on a cooperative resolution process between agents. The inability of some agents to decide if doing a corrective action denotes a *Non-Cooperative Situation* (NCS) [2]. A NCS is triggered when agents did not observe similar environmental configuration priorly, thus are not able to determine when corrective actions are necessary. A NCS is solved through a cooperative resolution process: agents help the one that encountered a NCS by providing data windows containing latency, environmental characteristics, and a prediction on the effect of corrective action: the higher it is, the more corrective action is necessary. In this way, the agent uses implicit feedback (other agents' knowledge) to determine if doing a corrective action. The cooperative resolution process enables solving in a bottom-up way the problem of avoiding unnecessary corrective actions in a MAS-based self-healing system. Moreover, cooperation enables agents to learn based on implicit feedback of the system (from agents themselves).

V. Conclusion

Decentralized systems are often fragmented and information about the agents is partial, noisy, or even incorrect. To this end, self-healing techniques can recover the system from erroneous behaviors. We propose a new self-integration approach to improve the performance of decentralized self-healing techniques. Our proposal is based on a cooperative multi-agent approach where agents learn to improve their capacity to decide if doing corrective actions through a cooperative resolution approach. Agents cooperate by sharing their perceptions and provide implicit feedback. This allows addressing in a bottom-up way the goal of improving the performance of the system by determining when to do corrective actions.

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