Multi-agent Systems for Estimating Missing Information in Smart Cities

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Abstract: Smart cities aim at improving the quality of life of citizens. To do this, numerous ad-hoc sensors need to be deployed in a smart city to monitor the environmental state. Even if nowadays sensors are becoming more and more cheap their installation and maintenance costs increase rapidly with their number. This paper makes an inventory of the dimensions required for designing an intelligent system to support smart city initiatives. Then we propose a multi-agent based solution that uses a limited number of sensors to estimate at runtime missing information in smart cities using a limited number of sensors.

1 INTRODUCTION

The concept of *Smart City* refers to a territorial context where the use of human and natural resources, properly managed through different Information and Communications Technologies (ICTs), allows the creation of an ecosystem that provides integrated and more intelligent systems (Roscia et al., 2013). The concept of smart city remains strongly ambiguous; it has been growing from empirical experiences and therefore a systemic theoretical study about this phenomenon still lacks (Dameri, 2013). A work commissioned by the European Union defines smart city initiatives as multi-stakeholder municipally based partnerships aimed at addressing problems of common interest with the aid of ICTs, which supports the smart classification (Manville et al., 2014). Dameri (Dameri, 2013) analyzed five areas of study concerning the smart city: (*i*) intelligent city, (*ii*) digital city, (*iii*) sustainable city, (*iv*) technocity and (*v*) well-being city. However, even if such distinction allows to define precisely what is a smart city, these concepts share some common aspects. Thus, they do not represent disjoint areas of analysis. In this paper we focus on intelligent, sustainable and well-being city. An *intelligent city* is able to produce knowledge and to translate it into unique and distinctive abilities; this city is smart because it is able to create intellectual capital and to ground development and well-being on this intellectual capital. A *sustainable* city uses the technology to reduce CO2 emissions, to produce efficient energy, to improve the buildings efficiency; it aims at becoming a green city. A *well-being city* aims at producing the best quality of life for citizens, but also to create regional attractiveness both for people and for business. The technology is only a part of the means used to reach these goals; also culture, climate, history and monuments are considered as important success factors (Dameri, 2013). Well-being is commonly related to the user's comfort. Thermal, visual, luminosity and noise are some of the main indicators used to define a comfortable environment (Frontczak and Wargocki, 2011). Thermal standards are required to help building designers to provide an indoor climate that occupants will perceive as thermally comfortable (Wong et al., 2014; Ghahramani et al., 2018; Herkel et al., 2008).

Because the smart city concept embraces multidisciplinary fields, it is important to provide a short description of Internet Of Things (IoT) and Ambient Intelligence concepts. IoT aims at providing a global infrastructure for the information society, enabling advanced services by interconnecting physical and virtual things based on existing and evolving interoperable information and communication technologies. The main challenge of the IoT is to achieve full interoperability of interconnected devices while guaranteeing the trust, privacy and security of communications (Piette et al., 2016). These interconnected devices become more unobtrusive and thanks to their embedded sensors they can perceive the physical environment in which they are situated. *Ambient Intelligence* provides to ambient systems the mechanisms necessary to carry out environmental reasoning using

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a representation of the environment perceived by IoT devices. Ambient systems are designed to provide adapted services that respond to an individual, collective, and social requirement. The term *environment* refers to a physical space enriched with sensors and computational entities that are seamlessly and invisibly interwoven (Pirttikangas et al., 2010). To be considered as smart or intelligent, an environment needs to be associated with a representative description that can be constructed from the perceptions of the *ambient components*. These includes the IoT devices that must be able to interact with other components that are not known *a priori* by humans/users. The interactions of ambient components enable a smart city to enhance its services such as transports, health, cultural events and so on. Nevertheless, avoiding the installation of new components in an ambient system to provide precise everywhere and anytime information on the environment is a difficult task.

After a presentation of some different application domains for the smart-city in section 2, we present the main dimensions in designing a system to support smart cities. Section 3 introduces our research context as well as our proposition to estimate missing environmental information in smart contexts. Our contribution, based on a cooperative multi-agent system, allows to avoid the installation of ad hoc sensors. In section 4 we evaluate the proposed solution using a real weather dataset. Section 5 briefly describes our research direction and perspectives.

2 SMART CITIES AND MULTI-AGENT SYSTEMS

As stated in the previous section, the definition of smart city embraces different area of analysis and finds application in different domains. Reviewing all the smart city applications goes beyond the purpose of this paper. For this reason we explore different applications in which the concept of smart city takes place in order to emphasize the relevance of multi-agent systems in this domain.

2.1 Multi-agent Systems Application Domains in Smart Cities

The growing power of sensors and connected devices makes the Smart Grid gain much attention. A smart grid can be defined as an autonomous electrical network able to adapt itself to client's needs in a secured, ecological and economical way. It enables bidirectional exchanges of electricity and information through lines. Perles et al. propose an approach based on multi-agent systems to estimate the voltage of each bus in an electric network without having sensors inside each bus (Perles et al., 2017). As the system is specifically devoted to the smart grid, information employed are not heterogeneous.

Roscia et al. propose a model of smart city that that employs multi-agent systems (Roscia et al., 2013). The proposed model is based on a system of systems that embraces different technologies to provide a basic infrastructure for the definition and the creation of a smart city. The composition of these systems will change as technology evolves, generating new businesses and new interactions. For each model domain of smart city, each individual device is associated to an software agent: its behavior is decided specifically according to the domain in which the agent takes place.

Smart Health provides artificial intelligence and cognitive computing in order to assist the doctors when they have to interpret medical data and to establish the right diagnosis for their patients. In the context of the 3Pegase project, whose main goal is to offer an efficient solution to follow-up old people at their home, an approach based on a multi-agent system has been proposed to detect at runtime behavioral anomalies by using feedbacks from the medical staff (Verstaevel et al., 2018). The system employs different sensors that track the activity of the users. This analysis lets the system rise alerts when a deviant behavior is detected. This solution is not suitable for large scale applications. As the system uses a limited number of sensors deployed in a home context, its deployment at large scale remains difficult. Moreover, the amount of data processed is limited with respect to the quantity of data produced by sensors at smart city scale.

Cook et al. propose the MavHome project whose goal is to create a smart home that acts as a rational agent, perceiving the state of the home by means of sensors (perception of light, humidity, temperature, smoke, gas, motion) and acting on the environment through effectors (in this case, device controllers) (Cook et al., 2006). An agent acts in order to maximize its goal, which is a function that maximizes comfort of the inhabitants and minimizes operational costs. This solution assumes that data from sensors are always available; thus unpredictable situations where information from sensors are unavailable are not taken into account.

Karnouskos et al. propose an agent-based solution for simulating the dynamic behavior of a smart city (Karnouskos and Nass de Holanda, 2009). Their proposition simulates discrete heterogeneous devices that consume and/or produce energy. The software agents, associated to real-world devices, are able to monitor efficiently the consumption of a high number of devices. agents are not cooperative and their behavior is decided *a priori*. However cooperation would enable agents to acquire more knowledge and experience from other agents in order to improve their own knowledge or act in a more appropriate way in the environment in which they are situated.

2.2 Challenges in Smart Cities

When dealing with systems to support smart cities, we have to consider five different challenges (Guastella and Valenti, 2018). (*i*) *Openness:* the system must be able to work with intermittent devices. For example, devices such as city users' smartphones are not always available; (*ii*) *Heterogeneity:* the observations that come from heterogeneous devices produce large volumes of data that have to be pruned and correlated in order to generate valuable knowledge; (*iii*) *Large-scale:* due to the amount of entities (physical and virtual) involved in smart cities and the huge amount of data to process, there is a need for efficient data storing and manipulation techniques. Also, the data must be always available to the final user; (*iv*) *Unpredictability:* systems to support smart city initiatives have to be able to continuously self-adapt to changes that may occur in a high dynamic environment; (*v*) *Privacy:* non-intrusiveness is a key point when collecting data from ad-hoc sensors in a smart city context.

Multi-Agent Systems are a promising way to address these challenges. Indeed, agents are autonomous, they are capable to reasoning and are proacting, thus enabling a system to be intelligent and able to make anticipations (Olaru et al., 2013). Moreover, each agent has its own local perceptions, knowledge and goals (Georgé et al., 2011). The conception of a system for addressing the described challenges requires an ever-increasing reliability that centralized systems could not provide due to their low performance in precise tasks. On the other hand multi-agent systems are able to get high performance thanks to their local, distributed intelligence and self-adaptation ability. The propositions presented in section 2.1 show how multi-agent ambient systems can be used to assist users in a smart city context. However, there is a need to design multi-agent systems that are able to operate in a highly dynamic environment with heterogeneous and intermittent sensors by using entry-level instrumentation. This means that the system must not require any specific type of device to operate.

Despite the advantages of the reviewed state-of-art propositions, to the best of our knowledge the problem of conceiving an efficient technique to estimate missing environmental information in smart contexts using mobile and intermittent devices is a field that remains unexplored. Therefore, our primary interest is to propose a solution to avoid the deployment of a high number of sensors in smart environments. In fact, even if nowadays the ambient sensors have a more and more affordable cost, the deployment of numerous high-quality sensors in a smart context can still be an expensive operation due to their installation and maintenance costs notably. Thus, the definition of intelligent systems to reduce the costs of both deployment and maintenance of sensors enables these technologies to be more attractive for smart cities initiatives. Furthermore, our goal is to design an open system being capable of performing environmental estimation by means of mobile and intermittent devices (Figure 1). The openness is crucial in developing a system that can be deployed at large scale, in the case of a university campus as well as a smart city.

3 MULTI-AGENT SYSTEM PROPOSITION

After a brief description of the neOCampus project devoted to the construction of the campus of the future, we present our multi-agent solution to estimate missing environmental information in smart contexts by limiting the number of sensors to deploy.

3.1 Context and Objectives

The neOCampus project, supported by the University of Toulouse III - Paul Sabatier, plays a major role in terms of technologies that could be employed in smart cities by doing experiments in a university campus context (Gleizes et al., 2018). Due to their size, to the number of users and their mixed activities, university campuses can be considered as districts or small cities. As a matter of fact, more and more researchers consider university campuses as great places to experiment innovative services and techniques for smart cities, building what is called a *smart campus*. With an area of more than 264 hectares, the campus of the University of Toulouse III - Paul Sabatier can be considered as a small city where several thousand data streams come from heterogeneous sensors placed inside and outside the buildings (CO_2, energy and fluid consumption, humidity, luminosity, ...). In such a context, it is important to collect and integrate information that come from a large number of ad-hoc sensors. Moreover, installing and maintaining a large

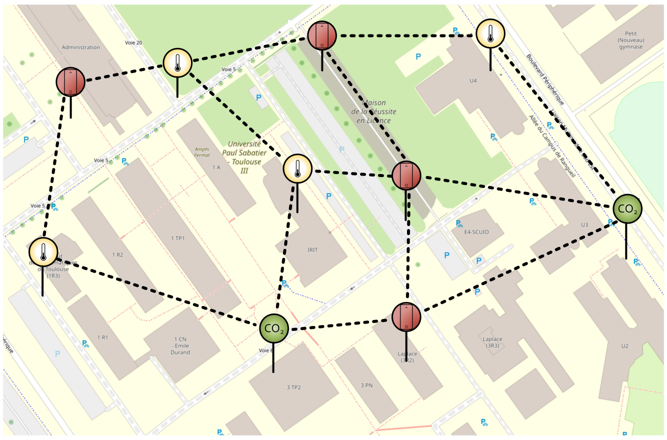

Figure 1: We aims at performing environmental estimation by means of mobile and intermittent devices in smart cities (obtained through OpenStreetMap (OpenStreetMap contributors, 2017)).

number of sensors to monitor environmental parameters of the campus can be expensive. The costs are mainly related to the installation, the maintenance and the infrastructures of sensors in existing buildings. For this reason, we propose a system able to provide environmental information everywhere and every time without having to install numerous sensors.

In our work, we consider that in the University of Toulouse III - Paul Sabatier the number of people per day on the campus is around 36 000 among which 80% own a smartphone, but only 30% are volunteer to share information from their smartphone. We can consider that these people stay on the campus on average 6 hours a day, their smartphones provide correct data about 10% of the time from 5 onboard sensors, about 40 times each hour. By multiplying these parameters, we acquire more than 500 000 data every day only using people' smartphones. Thus, the use of such a device represents a good solution for avoiding the installation of ad-hoc sensors, but this solution opens new challenges:

- Intermittent information: smartphones move along the campus together with their owners, so the required environmental information are not always available. The system has to take into account the unavailability of smartphones as well as their displacement within the campus. This enables the system to deal with both openness and unpredictability;
- Data privacy: personal users' information have to be secured in order to prevent malicious activity or users tracking;
- Data heterogeneity: smartphones are often equipped with different types of sensors. Because the aim of our proposition is to design a system able to provide the maximum number of environmental information, we must define an efficient solution to correlate and estimate missing information;
- Large scale: the system has to be able to collect and process data through an effective and distributed architecture in order to ensure a high quality service to users.

These requirements enable to address the challenges discussed in section 2.2. In neOCampus, we assume that users agree on installing third-party software to support our project: it is easier to find students, teachers and researchers motivated to experiment innovative services and techniques.

3.2 Multi-agent System Proposal

Our goal is to propose a multi-agent system to estimate missing information in smart environment by using a limited number of ad hoc devices. To do this we propose a system based on two different types of agents: (*i*) a *Real Sensor Agent* (RSA) which is any physical instrumentation that can provide accurate environmental information value (such as a temperature), and a (*ii*) *Virtual Sensor Agent* (VSA) which is responsible for the estimation, at a given point of the environment, an information that a real sensor would perceive if it was situated at the VSA's location. The goal of a VSA is to provide an accurate estimation and an approximated confidence zone, that represents an area of the physical environment where mobile devices provide, through their sensors, reliable values to be used by the VSA in order to estimate the environment state. The confidence zone is defined as a polygon centered in the position where the corresponding VSA is situated. The RSAs are autonomous and aware of the state of their local physical environment; they send their perceptions to VSAs. In this way, RSAs support VSAs in pursuing their goal. This is the basis of the cooperative process; it consists in the exchange of information perceived by RSAs with VSAs in order to allow the latter to estimate environmental information whereas real sensors are actually missing at the VSA location.

Algorithm 1 describes the behavior of a RSA. At line 2, the RSA perceives the physical environment through an *ad hoc* sensor. We assume that a VSA is associated to a RSA and a RSA are associated if the RSA is situated within the confidence zone of the VSA. At line 4 the RSA checks if a VSA sent an association request. At line 5 the RSA gets the list V of associated VSAs. At line 6 the RSA sends its last perception to the VSAs in V.

Algorithm 1: RealSensorAgent.

1: {—*perceive*—}
2: $p \leftarrow$ perceiveFromSensor()
3: {—*decide and act*—}
4: checkAssociations()
5: $V \leftarrow$ getAssociatedVSAs()
6: send(p, V)

Algorithm 2 describes the behavior of a VSA. Initially a VSA is associated to a predefined confidence zone that has an octagonal shape that further evolves. The algorithm starts by getting the list R of associated RSAs within the confidence zone (line 2). At line 3 the VSA sends an association request to the RSAs inside its confidence zone. Once associated, a RSA sends regularly its perception to a VSA. At line 4 the VSA receives the perceptions of the RSAs in its confidence zone. At line 6 the VSA evaluates the pairs of RSAs and returns the set D of data fields. The pairs of RSAs are chosen to be the most aligned with respect to the VSA. A *data field* between two sensors is a vector field in the Euclidean space. Each point is associated to a vector which is oriented towards the sensor which provides a higher data value; the magnitude is the value of the gradient between the data perceived by the sensors. Figure 2 shows an example of gradient between two sensors T_a and T_b.

Algorithm 2: VirtualSensorAgent.

1: {—*perceive*—}
2: $R \leftarrow$ getRSAsInConfidenceZone()
3: associateTo(R)
4: $P \leftarrow$ receivePerceptionsOfRSAs()
5: {—*decide and act*—}
6: $D \leftarrow$ evaluateRSAsPairs(R, O)
7: $e \leftarrow$ evaluateEstimation(D)
8: updateconfidenceZone(D)

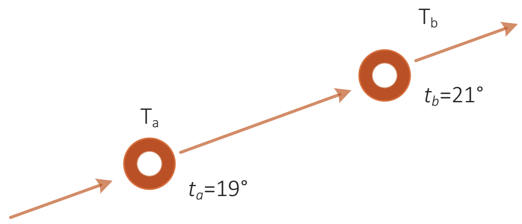

Figure 2: Example of a data field between T_a and T_b. The data field is oriented towards T_b since $t_b > t_a$.

At line 7 the environment state is estimated using the data fields in D. Finally, the confidence zone is enlarged or reduced according to the data fields in D (line 8). Standard techniques are used to determine the pairs of RSAs which provide data fields that are considered as outliers, so to be excluded from the confidence zone. Then the VSA cooperates with RSAs and modifies its confidence zone. However, the VSA does not have any knowledge about how to shape the confidence zone in an optimal way in order to keep only the best pairs of RSAs. Thus, the VSA reasons on the perceptions and the location of the RSAs in order to determine if they have to be excluded or not from the confidence zone of a VSA.

3.3 Case Study

In the scenario illustrated in Figure 3 there are two rooms including four temperature sensors whereas the corridor does not contain any real sensor available. In our proposed multi-agent system solution, RSAs correspond to *ad hoc* devices they are associated with (T_1, T_2, T_3, T_4, T_5, T_6), whereas T_7, T_8 T_9 are VSAs.

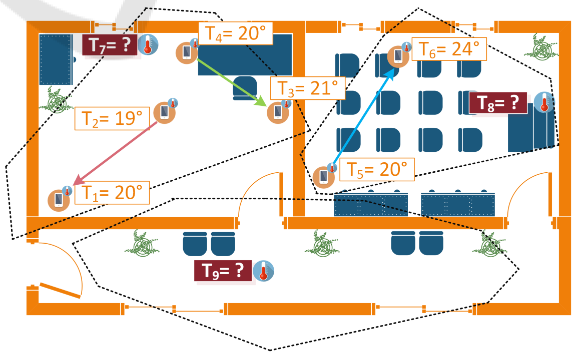

Figure 3: Case study illustration. The dashed zones represent the confidence zones of VSAs T_7, T_8 and T_9.

The solving process for estimating the temperature in T_7, T_8 and T_9 is roughly the following:

1. Each RSA perceives the physical environment through its sensor and spreads it into the virtual environment.

2. The RSAs situated inside a VSA's confidence zone (represented by a black dotted line in Figure 3) are associated to the corresponding VSA and the perceptions of the RSAs are sent regularly to this VSA. Thus T_1, T_2,T_3, T_4 send their perceptions to T_7, while T_5, T_6 send their perceptions to T_8.
3. The VSA determines pairs of RSAs within its confidence zone. It sorts the RSAs in its confidence zone according to their distance. Each RSA is coupled with the most aligned RSA with respect to the VSA. The pairs (T_3, T_4) and (T_1, T_2) are formed by T_7, the pair (T_5, T_6) by T_8.
4. Each VSA evaluates the data field provided by the pairs of RSAs.
5. The data fields are used to estimate the environmental state.
6. The VSA T_9 cannot estimate its current value because there is no real sensor in its confidence zone. Its confidence zone cannot be updated.

This is only a didactic example with homogeneous sensors but in a real world scenario, different situations have to be considered: (*i*) an information has to be estimated in an environment where there is no sensor capable of providing the same type of information; (*ii*) there is no sensor available in a certain room; (*iii*) sensors can be intermittent and imprecise: there is no certainty of obtaining precise and reliable informations at a given instant from sensors.

4 EXPERIMENTAL RESULTS

As the campus of the University of Toulouse III - Paul Sabatier is currently being instrumented and not operational, we evaluated our solution on a freely weather dataset using available temperatures in degree Celsius recorded by Arpae-SIMC, a weather service of the Emilia-Romagna region in Italy. This service provides weather warnings to the Italian Civil Protection Department (Bressan et al., 2017). We consider the average daily air temperatures at 2 meters of altitude collected over a period of time that goes from September 8 2017 to April 25 2018 (196 days) from 80 weather stations (Figure 4). We do not take into account the days where stations were not operational. The dataset consists in an array of 196×80 numerical values. For each station the dataset is provided with geographic coordinate (longitude and latitude) that were projected to the Cartesian plane through the Mercator projection (Monmonier, 2010).

4.1 Evaluation of the Multi-agent System Proposal

To evaluate our proposition we applied a leave-one-out cross validation: for each experiment a precise station has been replaced by a VSA in order to evaluate the estimation from the remaining stations. This evaluation has been done using the optimal confidence zone for each sensor. That is, for each sensor the method has been executed once for evaluating the best confidence zones and then for estimating the temperature using the confidence zone previously found. Each VSA contains initially all the weather stations within its confidence zone. Moreover, the formed pairs of RSAs have different weights according to the position between the VSA and the RSAs: this influences the estimation of the VSA. For this reason, the initial error of each station varies. Each station, replaced by a VSA to do the leave-one-out validation, tries to reduce its confidence zone to keep only the stations that are near the VSA and situated in a homogeneous environment. Figure 5 shows the average error and the standard deviation of each station during the considered 196 days together with a line plot that marks the error produced by the technique based on cluster analysis and normalized convolution presented in section 4.2. The average overall error is just 0.036 degree. Figure 6 shows the cumulative error: each bar indicates the amount of absolute average error for a certain percentage of samples. The difference between the absolute error of the proposed technique is comparable to a pipeline of state of art methods we present in section 4.2. Moreover, there is a small number of samples (10%) for which the proposed solution behaves better by evaluating a more reliable confidence zone and thus obtaining a more precise estimation.

Figures 7 shows the confidence zones of weather stations 3, 10, 80 and 29 respectively. Figures 7a–7c show confidence zones of VSAs that take into account weather stations placed in different, far environments because their data fields are not identified as outliers. As shown in the error bar plot in Figure 5 these stations have a relevant average error. Figure 7d shows an example of confidence zone where the involved weather stations are in a similar environment. The confidence zones in Figure 7a, 7b and 7c assume a star shape because in the corresponding directions there is not enough information to decide if they have to be modified. This is due to the fact that the sensors used in the experimentation are fixed. By using mobile devices as sensors, the VSAs will be able to estimate the confidence zone in a more precise manner.

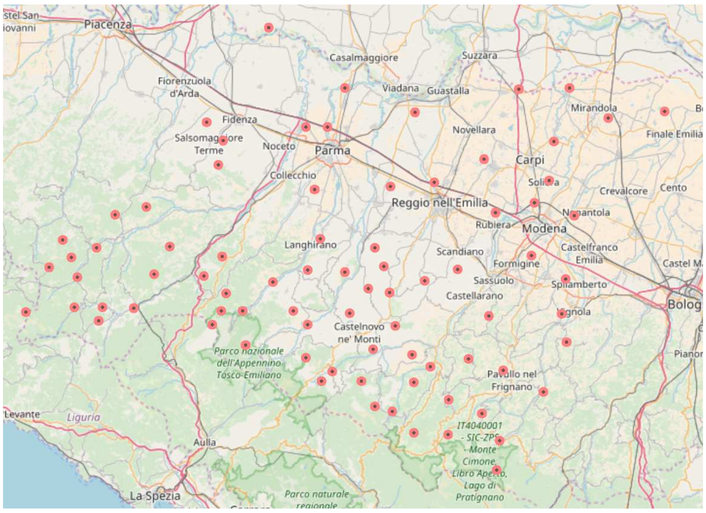

Figure 4: The map of Emilia-Romagna (obtained through OpenStreetMap (OpenStreetMap contributors, 2017)). The stations are indicated by the red dots.

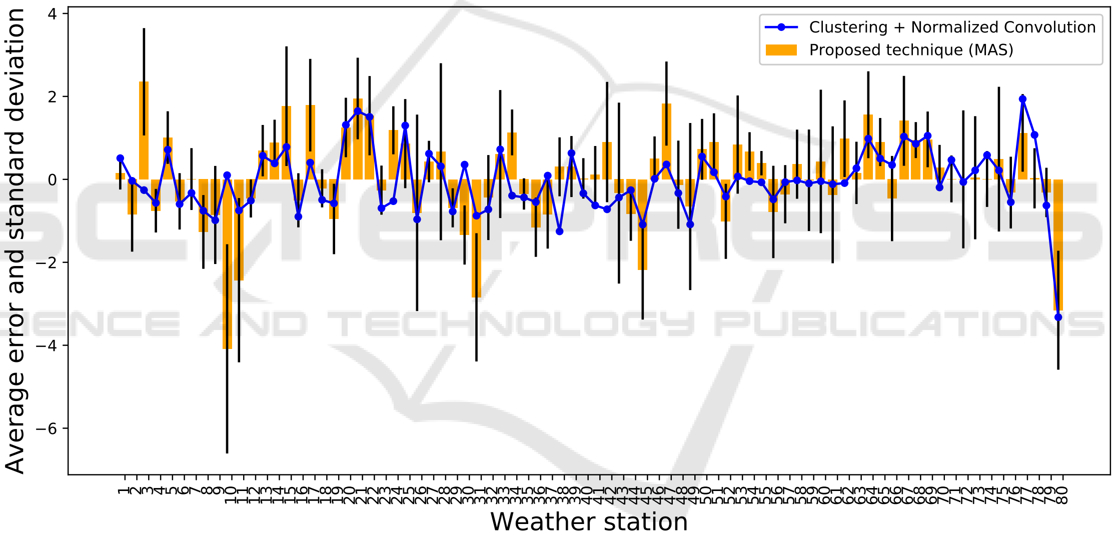

Figure 5: Error bar of estimated temperatures (degree Celsius) for each station.

Figure 8 shows the error plot for the weather stations 3, 10, 80 and 29. The error for station 3 increases while reducing its confidence zone: as shown in Figure 7a the confidence zone takes into account weather stations that are not situated in a homogeneous environment. The stations 10 and 29 maintain a low error rate. The error for station 80 is also reduced as the confidence zone of the weather station reduces.

The proposed solution was coded in Java language. For each station the algorithm takes about a second to execute the entire leave-one-out validation process for all the samples. The experiments were carried out on an entry-level machine equipped with i7-7820HQ, 32GB RAM and Windows 10.

4.2 Comparison to Standard Techniques

We compared the results of the proposed solution to a pipeline of standard techniques using the same dataset and leave-one-out validation (Guastella and Valenti, 2018). This pipeline, implemented as a preliminary study for the problem of estimating missing environmental information, includes Voronoi tessellation to determine the confidence areas of the stations (Okabe et al., 2000), hierarchical clustering to group together the stations that behave in a similar manner (Rafsanjani et al., 2012) and normalized convolution to estimate missing information (Knutsson

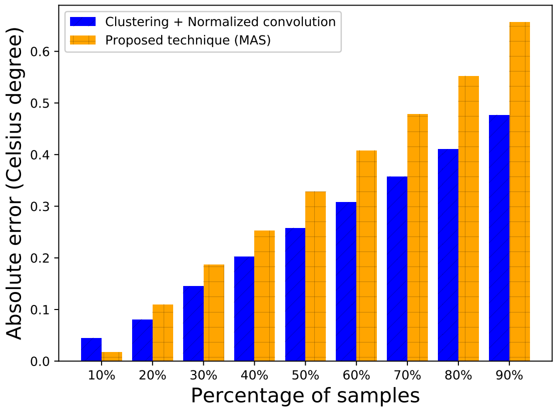

Figure 6: Cumulative error (degree Celsius).

and Westin, 1993). The areas of two or more stations are merged if their Voronoi areas are adjacent and they are grouped together by the clustering process. Finally, for a given point, a normalized convolution is used to estimate a missing environmental information using the stations in the corresponding relevance area. Normalized convolution is a standard method used to reconstruct incomplete or uncertain data from a spatio-temporal signal (Pham et al., 2006), widely used in geo-statistical applications (Higdon, 1998; Lemos and Sansó, 2006).

The pipeline based on Voronoi, clustering and normalized convolution shows better results with respect to the multi-agent proposal because the optimal subset of sensors is used to estimate missing information. This is due to the fact that the clustering and the Voronoi tessellation establish *a priori* the best groups of sensors to be used for the estimation by using all the available data. In this case the confidence zones are evaluated after the clustering process; thus any modification at a single real sensor implies a reconfiguration of the entire system. So this pipeline can be used in the case of weather stations, but cannot be used when considering mobile and intermittent devices.

With respect to the pipeline, the multi-agent proposal has the advantage of being able to enlarge or reduce the confidence zone of a VSA in a dynamic way according to the knowledge of the RSAs that are within the confidence zone at a given time. Moreover, we assume that a RSA is not fixed because it is related to a smartphone device: if one or more RSAs are being moved, classical approaches such as clustering need an entire reconfiguration of the system that could require a significant amount of time. Also, the multi-agent system has the advantage of being able to continuously learn using intermittent devices without reconfiguring the entire system at runtime.

5 CONCLUSION AND PERSPECTIVES

After a discussion of the state-of-art contributions that exploit multi-agent systems in the context of smart city, we presented the neOCampus project devoted to our work. Then, we introduced a multi-agent system to estimate missing information in smart environments. The goal of the proposed solution is to provide anytime and everywhere accurate information where *ad hoc* sensors are missing. The solution does not require any parameter and is able to provide an estimation of the environmental state at runtime.

Our work is a preliminary study to address the challenges discussed in section 2.2. The autonomous, adaptable and pro-acting behavior of agents allows the system to work with intermittent devices, thus addressing the openness problem. Moreover, distributing the intelligence among all the agents allows a deployment of the system at large scale. Unpredictability is addressed through the dynamics of the agents. In fact, a VSA is currently able to provide an estimation through the RSA that are situated within its confidence zone. Moreover, a VSA will be capable of providing an estimation even if different RSAs are excluded from the confidence zone or they move within it. This avoid the system to do an entire reconfiguration. Even if it has not been considered, privacy can benefit from multi-agent systems: agents have a local behavior, so a security problem involving an agent would be locally limited, so that the system is being able to easily identify and restore the entity concerned.

As soon as the campus of University of Toulouse III - Paul Sabatier is sufficiently instrumented we aim to conduct an *in vivo* experimentation using data coming from sensors within the campus and to compare the obtained results to state-of-art techniques to provide an innovative infrastructure for the smart campus. The proposed solution currently focuses on homogeneous information and provides promising results. Our future work will focus on processing heterogeneous and intermittent information.

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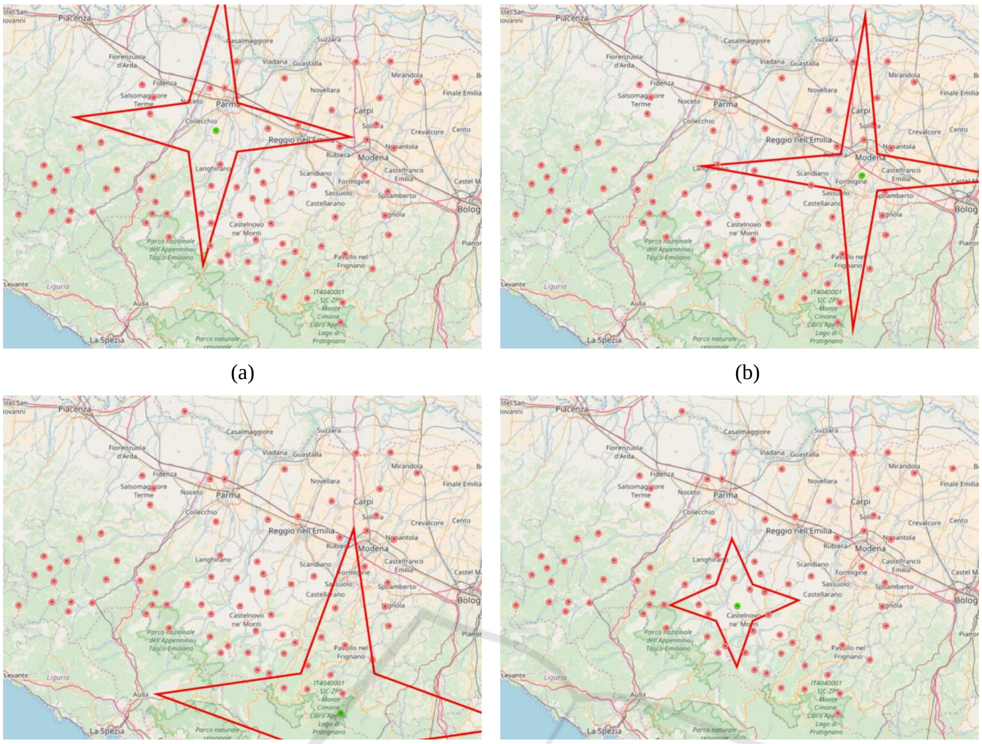

(a) (b) (c) (d)

Figure 7: Resulting confidence zones of sensors 3 (a), 10 (b), 80 (c), 29 (d).

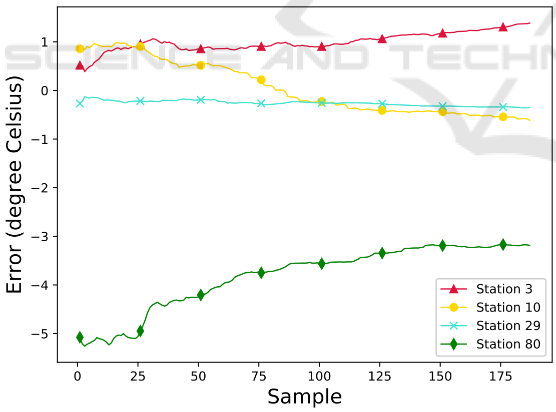

Figure 8: Error plot for stations 3, 10, 80 and 29.

REFERENCES

Bressan, L., Valentini, A., Paccagnella, T., Montani, A., Marsigli, C., and Tesini, M. (2017). Sensitivity of sea-level forecasting to the horizontal resolution and sea surface forcing for different configurations of an oceanographic model of the Adriatic Sea. *Advances in Science and Research (European Meteorological Society)*, 14:77–84.

Cook, D. J., Youngblood, M., and Das, S. K. (2006). A Multi-agent Approach to Controlling a Smart Environment. In Augusto, J. C. and Nugent, C. D., editors, *Designing Smart Homes: The Role of Artificial Intelligence*, pages 165–182. Springer.

Dameri, R. P. (2013). Searching for smart city definition: a comprehensive proposal. In *International Journal of Computers & Technology*, volume 11, pages 2544–2551. Council for Innovative Research.

Frontczak, M. and Wargocki, P. (2011). Literature survey on how different factors influence human comfort in indoor environments. *Building and Environment (Elsevier)*, 46(4):922 – 937.

Georgé, J.-P., Gleizes, M.-P., and Camps, V. (2011). Cooperation. In Di Marzo Serugendo, G., Gleizes, M.-P., and Karageorgos, A., editors, *Self-organising Software: From Natural to Artificial Adaptation*, pages 193–226. Springer.

Ghahramani, A., Castro, G., Karvigh, S. A., and Becerik-Gerber, B. (2018). Towards unsupervised learning of thermal comfort using infrared thermography. *Applied Energy (Elsevier)*, 211:41–49.

Gleizes, M.-P., Boes, J., Lartigue, B., and Thiébolt, F. (2018). neocampus: A demonstrator of connected, innovative, intelligent and sustainable campus. In De Pietro, G., Gallo, L., Howlett, R. J., and Jain, L. C., editors, *Intelligent Interactive Multimedia Systems and Services*, pages 482–491. Springer.

Guastella, D. A. and Valenti, C. (2018). Estimating missing information by cluster analysis and normalized convolution. In *2018 IEEE 4th International Forum on Research and Technology for Society and Industry (RTSI)*, Palermo, Italy.

Herkel, S., Knapp, U., and Pfafferott, J. (2008). Towards a model of user behaviour regarding the manual control of windows in office buildings. *Building and Environment (Elsevier)*, 43(4):588–600.

Higdon, D. (1998). A process-convolution approach to modelling temperatures in the North Atlantic Ocean. *Environmental and Ecological Statistics (Springer)*, 5(2):173–190.

Karnouskos, S. and Nass de Holanda, T. (2009). Simulation of a smart grid city with software agents. In *2009 Third UKSim European Symposium on Computer Modeling and Simulation*, pages 424–429, Athens, Greece.

Knutsson, H. and Westin, C.-F. (1993). Normalized and differential convolution. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pages 515–523. IEEE.

Lemos, R. T. and Sansó, B. (2006). Spatio-temporal variability of ocean temperature in the portugal current system. *J. Geophys. Res. (AGU)*, 111(C4):C04010.

Manville, C., Cochrane, G., Cave, J., Millard, J., Pederson, J. K., Thaarup, R. K., Liebe, A., Wissner, M., Massink, R., and Kotterink, B. (2014). Mapping Smart Cities in the EU. Technical report.

Monmonier, M. (2010). *Rhumb lines and map wars: a social history of the Mercator projection*. University of Chicago Press.

Okabe, A., Boots, B., Sugihara, K., and Chiu, S. N. (2000). *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*. Probability and Statistics. Wiley.

Olaru, A., Florea, A. M., and El Fallah Seghrouchni, A. (2013). A context-aware multi-agent system as a middleware for ambient intelligence. *Mobile Networks and Applications (Springer)*, 18(3):429–443.

OpenStreetMap contributors (2017). Planet dump retrieved from https://planet.osm.org. https://www.openstreetmap.org.

Perles, A., Camilleri, G., and Gleizes, M.-P. (2017). Self-adaptive distribution system state estimation. In Criado Pacheco, N., Carrascosa, C., Osman, N., and Julián Inglada, V., editors, *Multi-Agent Systems and Agreement Technologies*, pages 202–216. Springer.

Pham, T. Q., van Vliet, L. J., and Schutte, K. (2006). Robust fusion of irregularly sampled data using adaptive normalized convolution. *EURASIP Journal on Advances in Signal Processing (Springer)*, 2006(1):083268.

Piette, F., Caval, C., Dinont, C., Seghrouchni, A. E. F., and Tailliert, P. (2016). A multi-agent solution for the deployment of distributed applications in ambient systems. In Baldoni, M., Müller, J. P., Nunes, I., and Zalila-Wenkstern, R., editors, *Engineering Multi-Agent Systems*, pages 156–175. Springer, Singapore, Singapore.

Pirttikangas, S., Tobe, Y., and Thepvilojanapong, N. (2010). Smart environments for occupancy sensing and services. In Nakashima, H., Aghajan, H., and Augusto, J. C., editors, *Handbook of Ambient Intelligence and Smart Environments*, pages 825–849. Springer.

Rafsanjani, M. K., Varzaneh, Z. A., and Chukanlo, N. E. (2012). A survey of hierarchical clustering algorithms. *Journal of Mathematics and Computer Science (ISRP)*, 5(3):229–240.

Roscia, M., Longo, M., and Lazaroiu, G. C. (2013). Smart city by multi-agent systems. In *2013 International Conference on Renewable Energy Research and Applications (ICRERA)*, pages 371–376, Madrid, Spain. IEEE.

Verstaevel, N., Georgé, J.-P., Bernon, C., and Gleizes, M.-P. (2018). A self-organized learning model for anomalies detection: Application to elderly people. In *IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*, pages 70–79, Trento, Italy. IEEE.

Wong, L. T., Mui, K. W., and Cheung, C. T. (2014). Bayesian thermal comfort model. *Building and Environment (Elsevier)*, 82:171–179.