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A methodology for sustainable monitoring of micro locations at remote, hard-to-access and unsafe places

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Abstract. Smart structures and intelligent systems play pivotal roles in numerous areas of applied sciences ranging from civil engineering to computer and communications systems engineering. Although such structures and systems have been intensively deployed in these areas, they have been, interestingly, very rarely deployed in the field of cultural heritage preservation.This paper presents one of thefirst such attempts. A new methodology is describedthat deploys smart structures andlinks them with artificial intelligence methods.These solutions are referred toas advanced hybrid engineering artefacts. By their use,important environmental factors can be monitoredin hard to access, remote or unsafe locationsby minimizing the need for human involvement. In addition toproviding safety the methodologyalso reduces costs and, most importantly,providesa new way to modelany particular micro-environment in a much more efficient way than this is possible with traditional ways. Last but not least, although themethodology has been developed for cultural heritage preservation, its application areas are much broader and it is expected that it will find its applicationin other domains like civil engineering and ecology.

Keywords: sustainablemonitoring; measurement and modeling;smart structures; intelligent systems; sensors; preservation of artworks; multidisciplinary research

1. Introduction

In numerous areas of applied sciences and engineering there is a perennial need for measuring and monitoring various kinds of factors in environments that are hard to access, located in remote or unpopulated areas, or may be health or life threatening. Such measurements or estimates of physical quantities need to be as accurate as possible. Often, an additional requirement is that this is carried outin an economically efficient way and with the minimal direct involvement of humans.

Thanks mainly to recent advances in computer and electrical sciences and engineering, new possibilities are emerging that profoundly advance possibilities for meeting the above

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requirements. In particular, these advances include newly developed sensors of various kinds and (wireless) communication technologies, together with advanced modelling, simulations, and artificial intelligence techniques. We present a new methodological and technical solution that enables the measurement and decision making support necessary when monitoring and managing objects that are located in remote, hard to access or unsafe locations. So although the problem that has been solved with the new approach belongs to cultural heritage domain, the solution is applicable to many other domains that range from civil engineering to mechanical engineering (after all, many cultural heritage objects like castles, churches, cloisters and alike are plain civil engineering artifacts and their preservation does require involvement civil engineers). The solution deploys as its basis, smart structures (smart objects) and links them to neural networks to obtain tailored, or customized, models that enable prediction of key environmental factors needed to monitor accurately objects at otherwise hard to access locations.

The paper is structured as follows. In the second section there is an overview of the field with emphasis on smart structures, smart objectsand intelligent systems. In the third section there is a brief description of the background of the projectthat has stimulated the development of the research work. This isfollowed by a description of the newly developed solution. In the fourth section the solution is discussed, with conclusions in the fifth section, followed by acknowledgements and references.

2. A brief overview of related fields

Recent advancements in sensor and actuator technologies have enabled their application in various sensitive and demanding areas, ranging from e-health, for example in monitoring physiological data (Trcek 2013), to civil engineering, such as in structural health monitoring of advanced engineered artifacts (Zonta 2010, Jo 2103). Equally important has been the parallel development of (mostly wireless) communications systems and the further miniaturization of integrated circuits. In addition, sensors and actuators are becoming extensively backed by microcontrollers (collectively referred to as motes) and autonomous.

In order to enable extensive autonomy, i.e., long term independent operability and an extended range of application, energy consumption has to be addressed accordingly. Two basic approaches can be taken: one is low-energy footprint hardware and software implementations like, for example, lightweight protocols (Trcek 2013), while the other is that of enabling sensor motes by harvesting energy from their environments (Casciati 2012). Another important issue related to autonomy is the addition of more and more advanced pieces of code to these artifacts. Some years ago, artificial intelligence methods like fuzzy logic became implemented on wirelessly linked controllers in the area of smart structures, (Casciati 2004). These were soon followed by the possibility of running full-blown intelligent agents on wireless sensor platforms (Georgoulas 2008),while towards the end of the last decade smart objects (and Internet of Things) emerged.

2.1 Objects, structures, systems – from smartness to intelligence

To clarify terms and concepts that are central to this paper, they will be elaborated here in more detail to ensure proper understanding:

- Smart structures (Spillman 1996) are non-biological physical structures that have a definite purpose, together with the means and imperative to achieve this purpose, but with a biologicalpattern of functioning. The purpose is designed into the structure by integrating the functionalities of sensing, actuation, communication, and data processing, together with control algorithm(s).
- Smart objects are autonomous physical and/or digital objects augmented with sensing, processing, and network capabilities (Kortuem 2012). Together with Radio Frequency Identification Tags, RFIDs, they comprise a so-called Internet of Things, IoT. But in contrast to RFID tags, smart objects carry chunks of application logic that enable them to interpret what is occurring within themselves and the world. Further, they act on their own, communicate with one another, and exchange information with humans. They can be classified along three dimensions: the first is awareness, the ability to understand events and human activities occurring in the physical world. The second is representation, which refers to the objects' application and programming model(s), and the third is interaction, which denotes the object's ability to converse with the user, where inputs and outputs are subject to control and feedback.
- Intelligent systems are systems that accomplish feats that, when carried out by humans, require a substantial amount of intelligence (Truemper 2004). A special kind of intelligent systemcomprisesintelligent agents that perceive their environment by sensors and which use that information to act upon this environment using actuators, while directing its activity towards achieving goals (Russel 2003).

It can be seen that there is notable overlapping of these three definitions. The first two are about almost the same concept, while the third definition, in its basic form, is broader, although its reduction to intelligent agents leads to overlap with the second definition. In thinking about implementing the above functionalities, termed collectively as smartness and intelligence, typical methods from the artificial intelligence domain, such as evolutionary computation, logic and neural networks, are used, so they have a common denominator. Moreover, the terms "smart" and "intelligent" are (almost) synonyms. Knowing further that terms "system" and "structure" are also (almost) synonyms, their distinction is basically domain based – smart structures denote civil engineering artifacts, while intelligent systems denote computer engineering artifacts.

The solution, newly developed in this paper, is based on one side on smart structures (smart objects), which are linked to intelligent systems. And to properly convey this fact by implying its constituent parts, the solution will be referred to, throughout this paper, as an Advanced Hybrid Engineering Artifact, AHEA.

2.2 Fine arts preservation basics

In addition to clear concepts and terms, some basics about fine artwork preservation should also be given in order to properly communicate the main contribution of this paper.

Of the numerous environmental factors that strongly influence fine arts preservation, the key ones are temperature, humidity and light. These factors play a pivotal role in the degenerative processes of artworks, so their monitoring and control is at the top of the agenda for preservation. Of the three, when considering deterioration of cultural heritage placed indoors, temperature and moisture have to be the first to be considered (Camuffo 2010). Temperature causes changes in physically based phenomena like tensions in materials due to extension, contraction, torsion. It also influences the rate of deterioration of many chemical reactions. Similarly, moisture is also the basis for many physical phenomena, like tension and condensation, and chemical phenomena, like corrosion and hydrolysis. The third key variable is light, which also has many consequences for the deterioration of artworks, ranging from physically based ones like absorption (and hence varying local temperature, etc.) to photochemical effects (like photo-reduction, photo-oxidation and photo-fragmentation) (Baci 2010).

Of these three main environmental factors, relative humidity is generally considered to be the most detrimental. The main reason is that artworks are multilayered systems (in oil paintings these layers are canvas and on-layered pigments with adhesives). Such structures respond differently to relative humidity, which leads to stresses of and between the layers, resulting in deformations like cracks and detachment. Another fact is that, in many environments, relative humidity takes place in cycles with varying frequency and amplitude–and the greater the frequency and/or amplitude of these oscillations, the greater the damage.[*]Many of these detrimental changes are first visible only on a microscopic scale and can be hard to measure.[†]

To summarize, relative humidity has to be kept stable and at the right level as much as possible. Next come similar requirements for temperature, where its stability is more important than its absolute value. As to light, “keep it low and avoid direct illumination” is the maxim. But the bottom line for any activity is – get the relevant data first.

3. From problem to solution

This section first gives the background of the problem and continues with its solution to solve the above discussed problems. Obtaining relevant data is the starting point, so measurements have to be done first. But in many cases extensive measurements are costly, impractical, dangerous or even impossible. So one has to find appropriate alternatives to obtain data indirectly, which in our case will be AHEA supported simulations.

3.1 The research problem: its background, evolution and statement

In 2011 we started a project with the basic goal of obtaining an insight *in situ* into micro-climate conditions for a sample of twenty-four artworks of the Slovene baroque painter Bergant. The initial intention had been to produce a comparative analysis of temperature and humidity conditions for a representative sample of artworks kept in historical buildings at various locations. The analysis was aimed at better planning and ensuring more adequate conditions for artworks in the historical buildings where they are kept. This basic and apparently simple goal turned out to be all but simple, despite that fact that the appropriate sensor technology is widely available for remote monitoring - see, e.g., Botterman (2009).

At the beginning of the project twenty five locations were identified (churches, cloisters, museums and galleries) at which a selected group of the above noted artworks were kept. These artworks were restored at the same time a few decades ago and transferred back to their domestic locations, where they were exposed to very different conditions. Some of them remained in the National gallery under the best possible, well controlled conditions and these served as a reference for determining deterioration of the other works in uncontrolled environments. A comparative

[*] This basic principle can be used in a laboratory to simulate an accelerated aging process on samples of artworks or their imitations, to predict the deterioration of artworks in their domestic environments.
[†] A method that can be deployed is digital speckle pattern interferometry.

analysis of the two groups could then be performed, enabling new insights into the dynamics of artwork deterioration to be obtained.

Although the procedure was straight forward and the necessary technological means in principle existed, it turned out that in reality there were so many obstacles that completing the project was close to infeasible. First, placing sensors in more than twenty selected locations required many days of extensive travelling. Secondly, many of these places were unattended, which required getting in touch with persons in charge of buildings at remote locations a few weeks in advance. Thirdly, electricity outlets were almost nowhere available at the places where they would be needed– so we had to rely on batteries to operate sensors. Thus remote monitoring was impossible, because the radio part for mobile (wireless) communications required significant power for operation (not to mention that some places might not be covered well by mobile operators networks). Moreover, during the second round one year later, some batteries were so drained due to severe winter conditions that six sensors were out of operation (although only tested and high quality batteries had been used). This is not to mention the physical damage caused by environmental factors, including fauna. Clearly, managing even such a small set of sensors for many years under such conditions was close to impossible.

The problem we had to solve can be stated as follows: ”How can *insitu* dynamics data of environmental factors at remote and hard to access locations be monitored with smart objects by minimizing the need for human involvement?” What is important with this problem is to note that it is of a broad nature and that an appropriate solution to it would lead to a wide range of applications in other domains.

3.2 The solution with AHEA – AHEA monitoring procedure

In order to solve the above described problem, we relied on our expertise with sensors and neural networks (see, e.g., Trcek 2012 and Trcek 2013) to design and deploy an AHEA solution as presented in Fig. 1. The key idea of the whole solution was to deploy sensors to measure key factors indoors and outdoors for one year at a selected location. Indoor measurements were made by placing appropriate sensors *in situ*, while outdoor measurements were made by sensors from a nearby meteorological station. These data were later used to train a neural network. Next, only data from the nearby station were used as input to the neural network, in order to obtain the simulated output for indoor dynamics of the observed factors. These dynamics could be tailored to any particular point within the observed object.

A concrete example with humidity and temperature dynamics is given in Fig. 2. for one selected location (the original *in situ* data are presented on the left hand side and the data from the closest meteorological station on the right).

Once the neural network had been trained with these data, a data set was chosen for outdoor conditions during the following year (these data are given in Fig. 3 on the left). Feeding the neural network with these data enabled the micro-climate (indoor) dynamics at the observed location during the same period to be obtained (see Fig. 3 on the right).

Next, we performed an analysis of how well the proposed methodology performs compared to real, *insitu* data. For this purpose we obtained data for an overlapping period from a year away – in our case these were data in the winter period, for December 2011 and December 2012. Fig. 5 shows on the left hand side the absolute error in observed temperature, and, on its right hand side, in observed relative humidity.

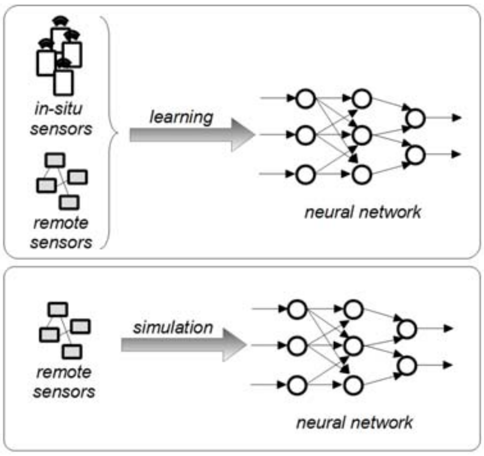

Fig. 1 AHEA suited for cultural heritage preservation management

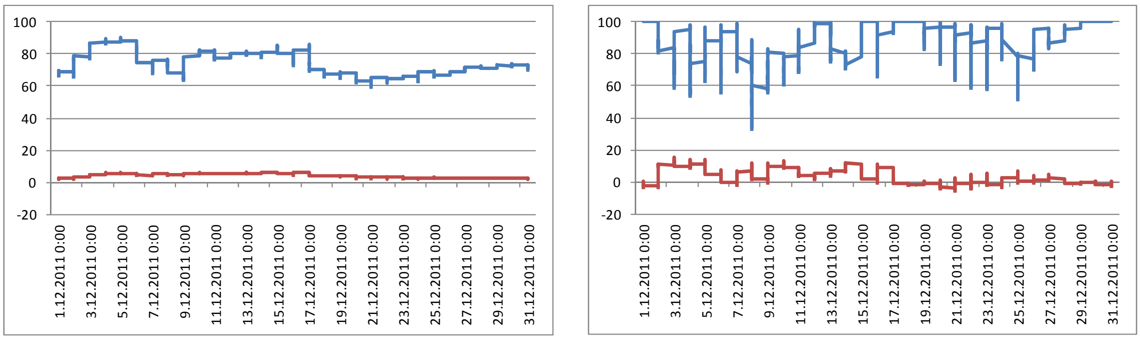

Fig. 2 Insitu real data and data from the closest meteorological station (blue line denotes humidity, while red line denotes temperature)

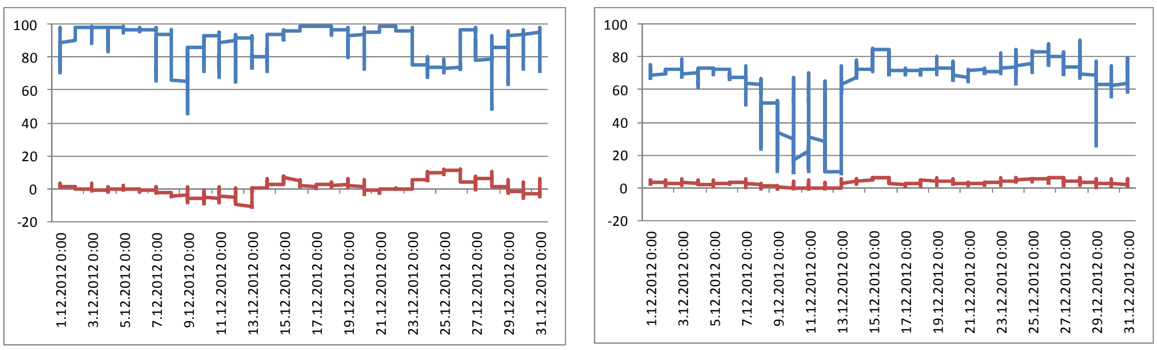

Fig. 3 Data from the meteorological station and the in situ data from a neural network (blue line denotes humidity and red line temperature)

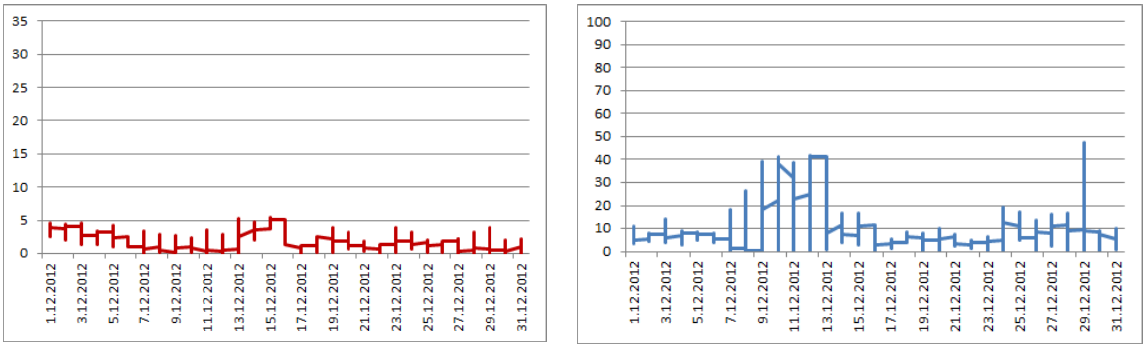

Fig. 4 Absolute error between measured and simulated values (left for temperature, right for relative humidity)

It is interesting to note that the obtained temperature (taking into account the area of application) is of a sufficient quality for practical deployment. Similar holds true for approx. 80% of the observed controlled period for relative humidity, but for the rest of the observed period, some relative humidity deviation can be noted. The reason is that 92 data points out of 272 data points were beyond the data space used for the neural network training therefore the errors made by the model are higher as elsewhere. Neural network modeling is not well suited for data extrapolation, i.e., to provide data outside the range where it was trained. In such cases additional neural network training is required to extend the model's usability range.

As to details of neural network - we have used the Chesire Neuralyst software. Based on the nature of the problem, the architecture deployed was multi-layered, feed-forward architecture and it was trained with an error back propagation algorithm. Further, the gathered data contained information that implied a highly non-linear model, thus the neural network consisted of four layers: the input layer with 2 neurons, the first hidden layer with 10 neurons, the second hidden layer with 15 neurons, and the output layer with 2 neurons.

Before any training of the neural network could take place, the data had to be prepared accordingly. For comparably similar temperature and relative humidity values the corresponding indoor values varied significantly. This was a very inconvenient situation since network training process cannot handle ambiguous data effectively. Therefore data had to be pre-processed to provide an unambiguous training dataset. The gathered data was first reorganized into several sub-sets. The criterion for a data point to be a member of a particular sub-set was the equality of the temperatures detected in the outside space. The complete sub-set was then represented by one data point constructed from the centroids of the inside and outside data respectively.

Finally, the training process took place that consisted of 520.000 iterations to achieve a 5% tolerance (in neural networks domain, the basis for a tolerance presents the difference between the maximal value and the minimal value in the dataset). As detailed elaboration of neural network issues is outside the scope of this paper, the reader is referred to, e.g., Hertz (1991) for more details about their architectures, training algorithms, etc.

4. Discussion

The most straightforward approach to modeling indoor micro-climate conditions by knowing outdoor conditions would be to produce a model of an object where the observed artworks are stored. To produce such a model, all the relevant construction details have to be included, such as the materials that the walls and the roof are made of, their dimensions, the isolation material used, the (average) thermal conductance of all these materials, absorbed radiation due to colors of the walls, etc. But even with all these details the model is still likely to be too simplified, because micro-climate conditions within such object may vary due to interior, its placement, the sunlight dynamics depending on the time of a year, and so on. On top of this, such modeling has to be done for every object where the observed artworks are located.

Clearly, such modeling is very demanding in terms of time, knowledge required and man-power. It is very unlikely to be feasible even for a moderate number of monitored locations. In order to make it feasible, many assumptions and simplifications have to be made as is the case with the interesting approach described by Brasatz (Brasatz2012). The authors based their solution on outputs of the Hadley Model (HadCM3), which is a coupled atmosphere-ocean general circulation model (Gordon (2000), and on simple derived transfer functions that enable indoor temperatures to be predicted, together with relative humidity changes on the basis of outdoor climate changes. These changes are used to predict physical damage of the design layer on polychrome art works, caused by repeated variations quantified through the frequency and magnitude of corresponding cycles. More precisely, the authors have derived a risk index for the climate-induced damage to the design layer on wood, subjected to complex climatic variations, by decomposing them mathematically into simple relative humidity cycles of various sizes.

The above approach shares one principle with our approach and this is the prediction of indoor temperature by having access to relevant outdoor data. However, the rest of our approach is, to the best of our knowledge, novel and has some important advantages. First and most important, the above approach uses simple transfer functions to predict indoor (homogenous) temperature, while our approach enables modelling of any arbitrarily chosen point within a selected object. Neural networks based modeling takes (indirectly) into account all the subtleties of a building, its illumination by the sun, irregularities caused by, e.g., services performed in the building, varying temperature caused by seasonal changes of the sun's trajectory, and so on. Secondly, our approach uses more fine grained data obtained from the closest meteorological base station. Thirdly, our methodology is not limited to temperature and relative humidity, but can be applied to any other important environmental factor that is measured by nearby meteorological stations, e.g., sulphur-dioxide concentrations can be observed to predict damage caused by acid formed on artwork surfaces. Fourthly, our approach is suitable not just for fine arts, but for any kind of cultural heritage and for environments ranging from underwater shipwreck heritage as described in Gregory (2012) to underground »stones and bones« heritage as described in Becherini (2010). Last but not least, the method is suitable not only for cultural heritage, but can be used for other application areas like monitoring civil engineering arte facts.

5. Conclusions

Smart structures and intelligent systems are enabling sophisticated applications in numerous areas of applied sciences ranging from civil engineering to electrical engineering and mechanical engineering. The approach in this multidisciplinary paper presents a novel methodology that deploys smart structures linked to intelligent systems (that comprise so-called advanced hybrid engineering arte facts, AEHA), and consequently enables cost effective and fine grained modelling of conditions at remote, hard to access or dangerous locations.

The paper starts with a brief overview of smart structures and intelligent systems through their evolution, introduces appropriate definitions to clearly identify the above mentioned advanced hybrid engineering artifacts that are the basis for the whole methodology that this paper is about. Next, the paper focuses on the area of fine arts preservation to provide the background of research motives together with the research problem statement. Afterwards the complete methodological framework is presented in detail. By using data from sensors placed indoors and data from nearby meteorological stations, a neural network is trained to obtain a micro-conditions adapted model for observed phenomena (in our case humidity and temperature). Next, when these sensors are no longer operational (e.g., they have drained their energy resources, or are damaged by environmental factors) the data from the nearby meteorological stations is used to feed the neural network model and obtain the estimated dynamics of the observed factors at the selected micro locations.

It should be noted that, although the method has been developed and applied to monitoring fine arts materials located at distant and hard to access locations, its applicability is much broader. For example, in civil engineering it could be applied to structural health monitoring and maintenance (e.g., to properly manage consequences of corrosion, or material stress because of unpredictable environmental factors), while in ecology it could be used for monitoring environmental changes (e.g., to predict acid rain and its consequences in topologically non-homogenous and diverse environments, or to manage catastrophes where slowly spreading hazardous and polluting substances allow placements of sensors infrequently).

Future work will address the best fit between a concrete observed micro location and particular AHEA structure (e.g., to take into account drifting characteristics of sensors in a laboratory and model them with a neural network accordingly to ensure that this drift is compensated and the sensor values thus reported are still valid). Despite open issues like this one, the presented methodology is a promising candidate for deployment in numerous applications for direct and indirect supervision where, in the case of indirect supervision, the solution may act a redundant part of the whole monitoring system. This redundant part could serve not only as a back-up for direct measuring with sensors, or as its replacement, but also as an additional control structure to monitor the health of sensors themselves.

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