# Information Fusion for Context Awareness in Intelligent Environments

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**Abstract.** The development of intelligent environments requires handling of data perceived from users, received from environments and gathered from objects. Such data is often used to implement machine learning tasks in order to predict actions or to anticipate needs and wills, as well as to provide additional context in applications. Thus, it is often needed to perform operations upon collected data, such as pre-processing, information fusion of sensor data, and manage models from machine learning. These machine learning models may have impact on the performance of platforms and systems used to obtain intelligent environments. In this paper, it is addressed the issue of the development of middleware for intelligent systems, using techniques from information fusion and machine learning that provide context awareness and reduce the impact of information acquisition on both storage and energy efficiency. This discussion is presented in the context of PHESS, a project to ensure energetic sustainability, based on intelligent agents and multi-agent systems, where these techniques are applied.

**Keywords:** Information Fusion, Machine Learning, Intelligent Environments, Context Awareness.

## 1 Introduction

Ubiquitous spaces are a common research field nowadays, mostly due to the increase in sensors installed on environments and the technological opportunity it presents. This, coupled with the recent surge of ubiquitous devices and applications, has led to the opportunity to create budget-friendly intelligent environments with different objectives, ranging from energy efficiency, sustainability and user comfort [1], [2], acquiring user context, assisted living and automate tasks [3], [4]. Such environments are able to monitor users, objects and the environment itself, generating rich sets of data, upon which may be used to make decisions and perform optimizations.

In a wide range of practical applications, information is obtained not only from processing data acquired through sensors in a ubiquitous environment, but also from information and knowledge shared across environments, such as mathematical models, profiling and machine learning models. Contexts can be created by fusing data from sensors and other sources of information. Such concept is designated as information fusion and is used for tasks that involve gathering information from different

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sources, using it to improve its quality, accuracy or derive new information [5]. An example of this approach can be found in the Sensor 9K testbed [6] where data about humidity, temperature, air velocity, among others, is used to derive human thermal sensation. Such sets of data, information and knowledge can be used as context to help identify profile and optimize solutions and may be accessed directly through sensor data, middleware or context servers [7].

Considering a system designed to save energy, from a sustainable perspective [8], it entails a delicate equilibrium due to the fact that any effort made in order to gather knowledge incurs in energy expenditure and, thus, this expenditure needs to be significantly lower than the saving obtained with the information gathered. In terms of research methodology, this is usually called the observer dilemma, where the observation, by itself, introduces changes to the actual state of the system. In energetic terms, observing energy consumption and computing energy saving measures increases consumption, thus changing the problem in the process, creating an overhead that needs to be mitigated by the end solution.

Hybrid structures and planning are often means to reduce the impact of certain solution upon the global objective. One strategy to tackle this problem is to use shared data between different systems to their benefit. However, this solution needs to generalize assumptions about environments and thus reduce optimization opportunities in specialized environments. Some approaches use only user awareness by using monitoring sensors that transmit current data about consumption and aggregation systems. Other hybrid approaches use both generalizations with some contextual specializations in order to introduce some context to the solutions represented.

With information fusion, context awareness and machine learning models, it is proposed a set of strategies aiming to reduce energy and storage expenditure, reduce side effects from this workflow while maintaining accuracy and context-aware capabilities. Such strategies were used in the PHESS project, currently being developed with the aim to bring energy efficiency, comfort and sustainability to intelligent environments.

### 1.1 Information Fusion

Information fusion compromises the use of heterogeneous and homogenous data and information sources. There is some confusion with the terminology as some authors use the terms sensor fusion, data fusion and information fusion with the same meaning [8]. Nevertheless, it is commonly accepted that sensor fusion is a subdomain of information and data fusion as it only considers the use of data from sensors. With these theories it is possible to maintain and update information, enrich data creating new content, improving quality and providing more accurate contexts. Information fusion might also be used in order to enrich with additional contexts machine learning models describing environments, behaviors and actions inside intelligent systems. It offers basic steps for data pre-processing in machine learning activities, but they are also used to build data models and extract information [5]. Data by itself is limited in the type of knowledge and information that can be extracted from such environments. Analyzing data from different sources poses the opportunity to increase the quality of the measurements, although it may also increase some uncertainty as well [9].

Multi-sensor management and sensor fusion are terms applied when the source of data are sensors and it is defined by Xiong and Svensson [10] as a process that manages and coordinates the use of a number of sensors in a dynamic uncertain environment with the aim to improve data fusion. Sensor fusion tasks have to take in consideration a number of factors such as data imperfection and outliers, conflicting data, data modality, data correlation, data alignment, data association, processing framework, operational timing, static versus dynamic phenomena and data dimensionality [11]. In order to tackle data imperfection a number of filters and inferences were developed such as Bayesian inference, probabilistic grids, Kalman filters and Monte Carlo methods.

### 1.2 Machine Learning

Machine learning techniques allow the modeling and learning of preferences and habits in different contexts. These techniques also allow the learning of past and current trends and predict future results. Among the contexts where the use of machine learning provides an opportunity to enhance systems, there is the concept of sustainability. With information from one or several environments, machine learning theory can derive models of behavior and interaction based on specialized contexts.

Machine learning and data mining techniques can also be used to obtain information about user's habits in intelligent environments. In this aspect, there are re-search examples demonstrating several algorithms that perform this task from data gathered by sensors in the environment. These algorithms use theory from Sequence Discovery, Fuzzy Logic, Genetic Programming, Multi-Layer Perceptron and combinations of these techniques [12]. Other uses for machine learning is the discovery of rule sets to monitor and man-age the consumption of resources such as energy inside intelligent environments [13].

### 1.3 Context Awareness

Context-aware systems are a component of ubiquitous computing or pervasive computing environments. These systems consider information about location, environments, resources, users and relationships between each concept. It hopes to make informed and personalized decisions, based on contextual factors that might promote distinct decisions in similar situations with different contexts [14]. Universal models and information provide explanation about phenomena that may be accurate and useful. However, when there is a need to specialize to certain contexts, it may be needed to detail models making them more accurate according to a known context. On the other hand, their specialization often reduces their generalization which becomes a trade-off between increased accuracy and generalization. Nevertheless, methodologies employed may be repeatable among different environments even though they do not generate the same model for the same attribute. Context aware elements can be acquired by the use of information present in intelligent environments through direct sensor access, middleware infrastructure or, even, context servers, as detailed by Baldauf, Dustar and Rosenberg [7]. Sensors used in context aware systems may be classified in three groups: physical sensors, virtual sensors and logical sensors. Physical sensors refer to context gathered by physical devices sensing the environment. Virtual sensors are defined by the use of application and services as sources of contextual data. Logical sensors combine physical and virtual sensors to determine logical values for the attribute being sensed.

Elements of context are often gathered using all three types of sensor classification according to contextual nature inside intelligent environments. Strategies for the management of context models can be defined as Key-value models, Markup schemes, Graphical Models such as UML, Object Oriented models, Logic Based Models and Ontology based Models. Context in PHESS project is defined by sensor data models from the environment and status indicators in terms of sustainability indexes. Each of these factors provides important information saved in terms of context, towards the application of contextualized options in the PHESS project. Model development through machine learning is the methodology used to store information about sensors in the environment. So, with the help of sensor data, models, and user presence and sustainable indexes it is possible to assess the impact of users inside environments in a contextualized analysis.

### 1.4 Intelligent Environments

Intelligent Environments with applications towards user assisted living are already under study and object of discussion by the research community. Focus has been applied to the study of behaviors, routines, stress assessment, energy efficiency and task prediction. Ubiquitous environments present a significant opportunity for learning tasks and contextualized optimizations. The data and information shared between intelligent objects, environments and users entails a delicate balance that must be taken into consideration when assessing human comfort condition and planning interventions on the environment. Some implementations of intelligent environments are used to perform experiments on ambient intelligence theory. iDorm is an examples of such scenario, where sensors can gather data about temperature, occupancy, humidity, and light levels. The actuators can open and close doors, and adjust heaters and blinds. Other example is HomeLab [15] composed of a house filled with hidden cameras, microphones and a remote power control system able to operate switches and control lightning. This lab is used by researchers to assess social responses to different color schemes in lightning and monitor its users. Yet, another intelligent environment can be found in MavPad project, which uses a smart apartment created within the project [3]. This project consists of a living/dining room, a kitchen, a bathroom, and a bedroom, all fitted with different types of sensors to gather information from objects, users and contexts. Saves is a project that encompasses an intelligent environment designed to use building and user occupancy profiles to maintain and regulate temperature inside a building [1]. Sensor 9k acts as an intelligent environments middleware for creating and promoting intelligent environment applications [6].

The testbed I3A is composed by a sensor network displayed through a building sensing information about temperature, humidity, carbon, carbon dioxide, dust and electrical appliances [16]. This testbed is used to prototype solution for intelligent systems as each sensor node can be independently programmed in the wireless sensor network covering the building.

The approach taken for intelligent environments embedded in this work use concepts shared from the environments and platforms already mentioned such as sensor net-work, profiling and sensorization of users and environments. Nevertheless, focus has been made in creating and maintaining machine learned models reduce dependence on constant sensorization and ease the data storage effort while providing context-aware computing.

# 2 PHESS – People Help Energy Savings and Sustainability

The PHESS project (People Help Energy Savings and Sustainability) is an integrated system to monitor and reason about environments and users with the objective of helping users save energy and ensure sustainability as well as their own comfort [17]. This system makes use of sensor networks, spread both on environments and users, acquiring data about user actions, environment variables and environment status to deliver a contextualized analysis. The PHESS project uses a layered architecture in which are included layer for sensors, models, reason. Each of these layers is responsible for a segment on the system's operation.

## 2.1 Sensor Layer

Currently, the PHESS project is able to integrate results from different sensors, using a multi-agent architecture where agents publish sensor interfaces for the consumption of other sensors. Sensor fusion is obtained creating virtual sensors that, instead of relying in physical hardware to provide sensor data, rely on the consumption of sensors already present in the platform which are processes according to the sensor fusion strategy in place. Sensor fusion is then obtained from specific virtual agents launched in the platform. These algorithms will be used in order to mitigate some characteristics of the devices: sensor inaccuracy, false readings or conflicting data. These virtual agents are the responsible for data fusion, creating new variables, such as thermal sensation and user occupancy.

## 2.2 Model Layer

The main goal of the layer dedicated to models is to reduce both the energetic impact of the sensing platform and the traffic flow, and, at the same time, optimize the general system response. Models are able to characterize behavior, anticipate and predict values for the attribute being studied and do so efficiently if properly built. Leveraging these properties it is possible to use models locally instead of demanding complex operations on databases such as aggregations and large quantities of storage space to record historic activity.

This layer is used to create models about environment, environment variables and user habits and preferences. Models are defined by intelligent agents present on the PHESS project. According to the type of model, they may require information and data from other agents.

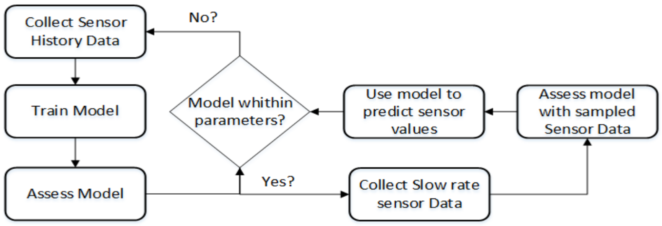


**Fig. 1.** Model Management

One type of models used encompasses mathematical models which use knowledge about attributes defined by mathematical and physic rules. Another type uses and combines data and information from other models on mature and accepted models that may also be described by mathematical rules. Lastly, from the data continuously gathered from the data layer, models that mimic the behavior of those attributes in order to provide description of their behavior and provide means to anticipate or predict the future state of the environment. These models require a constant validation in order to assess the validity of the models created in each environment. Also, due to possible high number of sensors and costs related to storage of records and historic data, these models may be used as historic descriptive models and as a sensor alternative in order to save in traffic messages as detailed in figure 1.

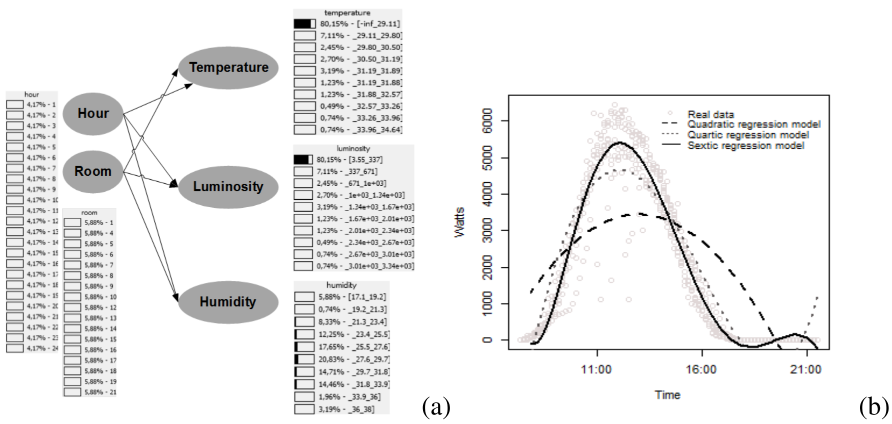


**Fig. 2.** Bayesian Network model describing an environment temperature, luminosity and humidity (a), Electrical Photovoltaic regression model (b)

Machine learning acts as a methodology to estimate sensor readings and, while doing so reduce the need to high sample rates in the sensor layer. With the combination of initial learning models and constant validation of its accuracy and significance in the system, refresh rates for sensor values can be dynamically managed. The usage of these schemes may also be relevant for sensor fusion tasks, since modeled sensors may be directly assessed in the server side of the platform, leaving the client side less demanding in terms of computational effort. As examples of agents in the model layer it can be considered electrical consumption, temperature, luminosity and solar exposure agents. Figure 2 (a) presents the representation of a Bayesian network model that stores a grid of conditional probabilities for the value of temperature, luminosity and humidity in an environment, according to the time of day and room. Figure 2 (b) details a regressive model to estimate photovoltaic electric energy production, according to weather (mostly cloudy in the case depicted) and time of day.

### 2.3 Reasoning Layer

The reasoning layer uses automated reasoning workflows, as well as on-demand simulation tasks taking the models created for the environment as reference and input variables. Examples of workflow methodology include automated case-based reasoning to find possible optimizations in terms of appliances, and behaviors through profile comparison. A first approach to reason about alternative solutions in the environment considers the use of case-based reasoning. In this approach, current models and environment specifications are compared to other known implementation and solutions in order to quickly assess optimized solutions for the environment. The static components in the environment, such as appliances or lightning bulbs, can be quickly assessed in order of efficiency in terms of energy consumption efficiency and whether changing them is beneficial to the overall process of energy optimization [18].

The final step of action of this agent is to use the newly calculated situations and use actuator agents to enforce the new plan or when such is not possible, send a report to the user so he can become aware of efficient changes in the environment without affecting its interaction with the environment.

## 3 Context Awareness in PHESS

The creation of context for intelligent agents on this platform is done as described in a survey on context-aware systems by Baldauf, Dustar and Rosenberg [7]. In detail, it is considered a context server, middleware and direct sensor access as a source of context. The context server is provided by an application server running PHESS modules in a multi-agent system which is responsible to keep information and profiles about environment, indicators defined and machine learning models updated with sensor information. The dependence on sensor data to create context was noticed and the impact of such workflow was present in terms of network messages between server and sensor nodes, energy efficiency due to active use of sensor nodes and storage size. With the aim to minimize such problem the concept of hybrid virtual sensors was adopted, where in the first stage an intensive use of sensors is performed to learn the behavior of the attributes being sensed through machine learning models and a second stage where these models substitute the sensor data keeping network messages, storage needs and active use of sensors down. Sensor are used at lower frequency rates to assure that the models created remain accurate within a defined error margin. The context server is used to push these models. For instance, one may consider solar exposure where the model takes both location and time to contextualize the number of hours with solar exposure. Such model may be maintained in a context server, not requiring an active agent. Other examples created within the PHESS project includes photovoltaic panels output according to atmospheric conditions and hour of day and exterior temperature from known weather API's in the internet. Although this approach is able to maintain context scenarios it may lack alert and fast response as the data from sensor is not actively being measured and so should not be used where short term context is relevant but rather historic context.

Middleware access is used to obtain answers to dynamic models maintained for specific environments, users or objects and for direct sensor access. These models developed inside the PHESS project are accessible from external sources through communication APIs developed in JAVA[1], ANDROID [2] and JADE[3] systems which enable the integration of the information created inside this platform available to other initiatives. The communication is made through an ontology written to provide information and data about the environment encapsulating the information displayed by in each API [19]. Such API is used for related projects such as stress assessment, emotional control and gamification purposes.

## 4 Model Assessment

Over a period of three days a simple application with the PHESS project was evaluated, where sensors for environment luminosity, humidity and temperature were used. It was assessed aspects related to storage space used and reliability of the model created using the theory described in sections 2 and 3. Initial results demonstrated that by adapting the learning rate on attributes monitored, there are gains in terms of storage needed as well as active use of sensors while keeping results with over 70% relative accuracy.

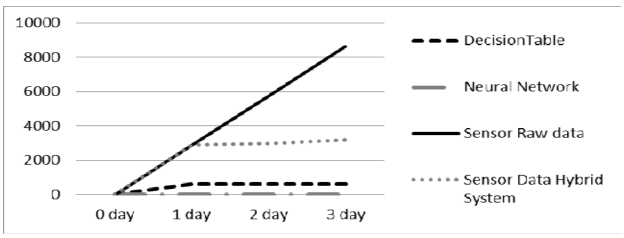


**Fig. 3.** Space required by each strategy

Figure 3, demonstrates potential savings with this approach, as less storage capacity is used to store sensor data and models being updated generally are fixed in size. The results presented refer to ambient luminosity which was modeled by a decision table algorithm and a multilayer perceptron using room location and time of day. Sensor values were assessed for the case of continuous monitoring (raw data at 1min

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1 Oracle Java. Source: `http://www.java.com/`

2 Android Project. Source: `http://www.android.com/`

3 Jade – Java Agent Development Framework. Source: `http://jade.tilab.com/`

intervals) and a hybrid approach with sensor values validating the model created after the learning phase at 30 min. The models created can be used in context server through the PHESS project to simulate context where such models are determinant easing the need to use middleware API to query sensors or databases of historic values.

Table 1, it presented accuracy values for the machine learning models for luminosity, humidity and temperature using a decision table algorithm. These results gather the error which the models are subjected and within which models are not re-trained. The correlation values are the correlation between predicted and real values which was also used to assess models initially.

**Table 1.** Continous Model Assessment

| Model Object | Mean Error | Relative Error | Correlation |
|---|---|---|---|
| Luminosity | 102.75 | 27.04 % | 0.88 |
| Temperature | 0.46 | 22.40 % | 0.97 |
| Humidity | 0.86 | 23.76 % | 0.96 |

The substitution of models instead of always requiring sensor data reduces message traffic between agents and increases system overall performance. Nevertheless, more precise studies are still necessary in order to maintain the stability of models found and their descriptive soundness. Overall, results are positive, with the approach demonstrated to be both feasible and adequate for the problems being targeted.

## 5 Conclusion

The work detailed in this paper describes how to take advantage of context awareness by using machine learning models in conjunction with concepts from information fusion inside intelligent systems. This approach, aims to reduce the impact of storage and sensor data problems while maintaining historic behavior description and preserving contextual information about the attribute. The results provided, show promise in maintaining storage levels contained and may be used as a proof-of-concept. The accuracy of models depends on their design, having detailed in this article some sample context models to be applied in these systems. Future development for the models created inside this system encompasses their use for multi-environments. The aim is to also reduce the learning cost of new environments with pre-trained models that are then contextualized in each environment with lifelong learning according to methods similar to ones presented in this paper.

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