Contextual Adaptative Interfaces for Industry 4.0

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Abstract. Information technologies are intrinsically connected to the manufacturing processes, with more data generated each second. To efficiently operate machines, users must sort out information that is relevant to them in specific moments and contexts. In this paper, we propose an architecture that combines context – e.g. location, type of order, available assets, previous actions – with information established through user stereotypes.

Keywords: Context-aware applications · Adaptative interfaces · Industry 4.0

1 Introduction

With the advent of the Industry 4.0, information technologies have become an inescapable part of the manufacturing processes, generating and facilitating data to all parties involved. As systems grow in complexity, more expertise and data are required to handle them; and more information is necessary to properly learn how to use them [1, 2]. Selecting which information is important and relevant for a specific user in a given context is, therefore, a relevant step.

While an Enterprise Resource Planning system may have information regarding all possible tasks, there is the possibility not all of them can be executed on a given place or moment; therefore, for a more precise and adequate information filtering process, context and user data are both required. Additionally, the expertise of the user also comes into play: frequently, more experienced users are autonomous, while the less experienced require more guidance [3, 4].

User Modelling (UM) is frequently used in contexts where the system needs to adapt its behaviour to how it perceives the user. Systems and applications have, over the years, applied different approaches to how user information is stored and how it is affected through user-system interaction [5, 6]. For the UM to be able to fulfil its role as an adaptative force for the system, it requires a degree of ground information, i.e., an initial formalization of the assumed characteristics and preferences of its users. This information can be in one of two categories: (1) Domain Dependent Data (DDD) or

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(2) Domain Independent Data (DID). DDD features degrees of knowledge the system assumes its users would have regarding its application domain. Complementarily, DID includes psychological information about the users and their generic user profile.

Context Awareness (CA) approaches can be incorporated into a system in order to enhance user experience in different ways, such as the adaptation to different scenarios, by applying different algorithms and for personalized suggestions [7–9]. Regarding the adaptation to different scenarios, one can consider that context awareness can be relevant so that the right information can be delivered, in the right format and to the right user. E.g., this can be done through an intelligent and adaptative interface, in scenarios where the user can change places, change of status during a production process, among others. Operational information can be used as extra input for the algorithms used by the application or system in order to optimize their outcomes, potentially resulting in improved decision making, better planning, cost reduction and optimization of processes, among others.

Systems and application can gather contextual information through sensors (e.g. location of the user and/or the device, status, time, nearby locations, other devices, etc.) in order to filter, search and relay relevant information or services. Contextual information can be classified according to its complexity and how it can be combined with additional data. As such, primary context refers to raw data, captured directly by sensors and used independently from other known information sources. Secondary context, on the other hand, refers to the fusion of primary context sources for a more global appreciation of context [10].

The NIS Project (Núcleo Investigação Sistrade) consists in the development of solutions for usability, adapted to the Industry 4.0 challenges, by exploring the elaboration of methodologies and rules for the improved development of Human-Machine Interfaces and web-design of adaptative interfaces. In the research for augmented reality (AR) solutions for the industrial environment, we aim to present an architecture for such a system that will be able to consider historical information about the user (such as profile, expertise, among others) and combine it with contextual information regarding their location and previous tasks in order to determine how to best guide the user in the following tasks.

This paper is structured as follows: (1) Introduction, wherein the applicational context and the project were presented, (2) Context Awareness and User Profiling, providing a short review of the concepts involved in the project and specifying domain dependent and independent data to be used, (3) Proposal, wherein we present the architecture, adaptational model and technologies and (4) Conclusions.

2 Context Awareness and User Profile

The interface (graphical or otherwise) is the main interaction point between the user and any system. The information it shows must be able to adapt to each specific user, and its meaning and relevance will always be in regards to its context and location [11]. When the information is made available is also a relevant factor: the user must not be overloaded with so much information they cannot make sense of it. Therefore, the user's context is an important factor when it comes to selecting the appropriate information to show [12].

There are several different approaches to implementing User Models, of which four categories can be extracted: knowledge-based, rule-based, behavioural and stereotyped-based [13, 14].

Knowledge-based approaches rely on the amount and quality of the information the user possesses over the application's domain and how it is obtained [5]. This information is generally forward by the users themselves through forms, enquiries or studies. Behaviour-based approaches, on the other hand, rely on the monitorization of the user while it performs tasks in the system [7], and different behaviours can be used for the formation of groups of users or heuristic extraction.

Models based on rules can be defined either automatically or semi-automatically through the use of machine learning algorithms or be formalized manually by domain experts. These rules can be used to infer new knowledge about the users, finding frequent application in scenarios where it is important to predict the users next move or anticipate possible errors.

Finally, stereotype-based approaches allow for the formation of possible groups of users through a relatively short number of relationships. They define, in a first step, which stereotypes are expected, attributing them a set of characteristics. These may include different layers for each user group, such as performance levels and expertise in their tasks [5, 13, 15].

2.1 Domain Dependent Data in Context-Awareness

Consider an AR system to be used in an assembly line, in which several tasks must be performed in sequence. Each task is therefore dependent on the one that precedes it and relies on different machinery. Additionally, if different products can be made on the same line, the same machinery can be used for a number of tasks. The system has support information regarding all possible actions that can be performed in the line but must decide which information to show the worker when a new order is being processed.

As such, when a given worker is at their workstation, the following contextual information can be captured: the location (and corresponding machinery), materials available and current order.

Information regarding available machinery can be used to establish which actions are possible in that area; i.e. by knowing the location of the worker, it is possible to filter the number of tasks that can be done by excluding all the actions that can only be done in different locations [11]. This gives us a subset of tasks and, therefore, a subset of support information that can be shown to the user. However, of these, not all are relevant: by knowing which product the worker is currently working on, it is possible to extrapolate a sequence of actions they can perform, filtering the support information further. This filtering process takes an even more relevant role when inserted in an AR environment where, on top of a risk of sensory overload to the user, there is a risk of complete occlusion of the environment the user is operating on. Impeding the user from properly concluding his tasks may have an unwanted impact either on security issues, or operational and financial losses. As such, even the tasks that are relevant to the current context need to be properly evaluated as to justify its inclusion in the interface.

Additionally, not all support information is equally relevant; knowing more about the specific worker allows us to understand their ability and, therefore, how much support they need in performing their tasks, i.e., for the same location and tasks, different levels of support can be given. The importance of these needs to be assessed.

2.2 Evaluating Performance in User Profile

The system must know the characteristics and context of the user in order to be adaptable. Such characteristics depend not only on the user's stereotype but are also affected by other factors such as the user's performance. The system then must use information regarding actions – i.e., to possible tasks and sub-tasks – defined in the user's model in order to assess which contents are relevant to the current stereotype; data regarding performance is therefore used to adapt the content to the user's needs.

As the users execute their tasks, their behaviour will depend in the degree of confidence shown in performing their tasks: an experienced user is more likely to be more confident and to fulfil their tasks successfully, while a less experienced user may take a more cautious approach, needing more time and/or guidance [4, 16]. Keeping an historic record of past performances of a given user for each task is a simple way for the system to assess their confidence level and decide which information must be put in the forefront and which one is not particularly relevant. E.g., for an inexperienced user, it may be enough to provide a navigation system that allows the user to query about the task's general procedure. Exposing an inexperienced user to a higher amount of information may be a small price to pay when compared to a bad performance in a given task [4]. On the other hand, overloading an experienced user with huge amounts of information may do more harm than good, as they probably don't require the same amount of assistance [16]. Adaptation, therefore, happens through the omission or displaying of information based on the user's specific characteristics.

3 Proposal

Manufacturing Execution Systems and Enterprise Resource Planning systems hold and generate large amounts of data: more often than not, it is hard for users to establish which of it is relevant for their particular situation. By incorporating contextual information and the user's characteristics, we can develop algorithms that are able to give the users only the most relevant information according to their user profile. We propose that this information is delivered to the users through AR, with the aid of Hololens devices [17]. Which information is to be presented, and how, must be according to the context of the user and their personal needs.

The user's profile must therefore not only include the user's characteristics, but also temporal and environmental contexts, in a way that a broader, more dynamic model can be achieved in order to map the user's behavior in the different possible scenarios. I.e. the user's model will include information regarding preferences, interests, desires and/or needs.

3.1 Architecture

We will propose a stereotype-based approach, in which contextual information regarding the (i) user's expertise, (ii) their location, and (iii) available options will be used to determine which information will be available to the user at a given time.

Figure 1, below, illustrates how the adaptation mechanism depends on these different inputs:

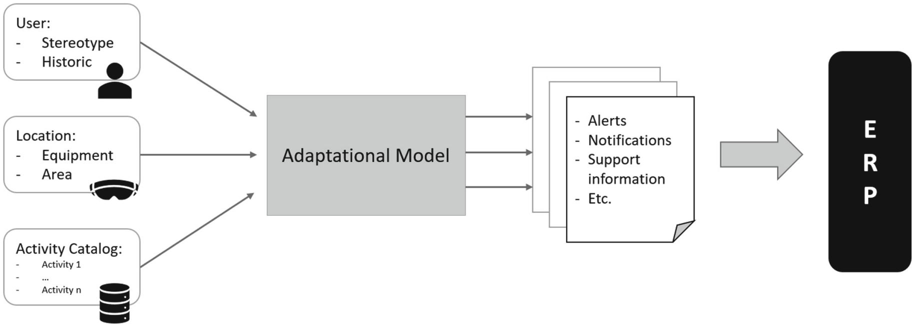

Fig. 1. System's main workflow diagram

User data, as previously mentioned, will identify the stereotype they belong to and, therefore, their characteristics. Additionally, it will also bring historical user data regarding past actions and the specific user's performance.

Information regarding the user's location will be supplied by a Hololens device, featuring data that identifies the space/room the user is currently in and identifying available devices.

Finally, we consider the existence of a catalogue containing all system's possible actions and helpful, support information regarding them that can be supplied to the users to help in the execution of said tasks.

3.2 Interaction and Adaptational Model

For any given moment and context, the goal of this Adaptational Model is to deliver only the most relevant information to the user. By searching through the catalogue containing all possible activities, the adaptational model will, on a first step, use location data to start the filtering process. As previously mentioned, this process will select a subset of information that is relevant to the location and usage of available assets.

As such, all the available contextual information can be used in a filtering pipeline, as illustrated in Fig. 2:

Considering that the filtering process may result in more than one task being possible under the current conditions, a ranking mechanism must be employed in order to assess which one is the most likely to be in execution. An expected activity flow and the user's action history can be used for this end. In a next step, information regarding

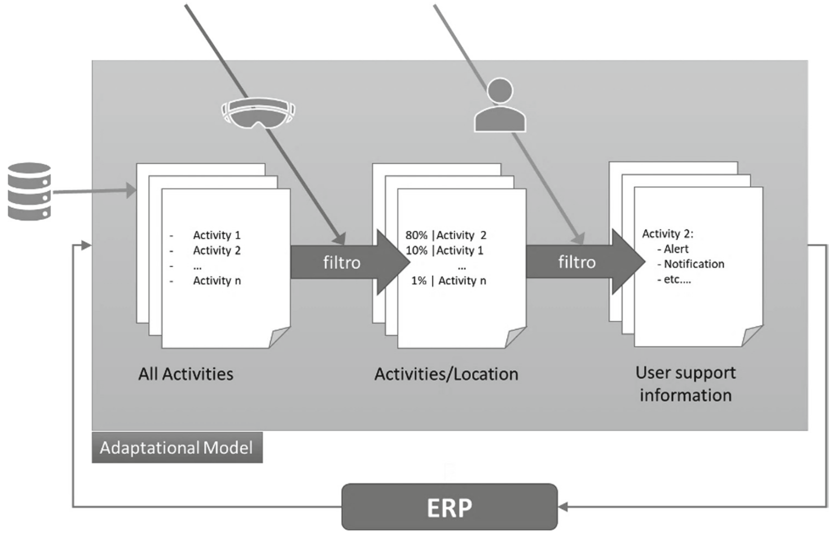

Fig. 2. Adaptational Model filtering process

performance will be used to assess which visual elements, such as menus, alerts or notifications, must be displayed either through the Hololens or other devices. However, identifying which task is currently being performed by a user is an uncertain and unprecise task. Even observing the user's recent activities may lead to a wrong conclusion, as the interpretation of their actions may not be an objective process. Bayesian Networks are commonly applied to scenarios where uncertainty is a factor [7, 18, 19], by providing a probabilistic model that allows reasoning over uncertain knowledge. In these acyclic graphs, each node represents a concept or a parameter, and each arch the direct, unidirectional influence between them. Each node has its own conditional probability table, quantifying the influence of the previous nodes over it.

In the context of this proposal, the Bayesian Networks define the relationships between activities, with each node being associated to one of the parameters identified in the User's Profile: be them the user's performance on a given tasks, or the steps that compose it.

For each user stereotype there's a Bayesian Network that represents all the tasks associated with it and relationships between them. Additionally, it includes relations between tasks that, while not exactly related to the stereotype, influence the tasks the user must perform. In Fig. 3, an illustrative subset of possible actions pertaining to Production Orders that can be executed by a Production Manager and their respective probabilities is shown:

Here, the nodes represent the possible tasks that can be performed by a Production Manager, how they influence each other and how likely the user is to perform them at a given moment. The probability tables are conditioned by previous interactions of the user with the system and evolve over time in order to better reflect their actual activities.

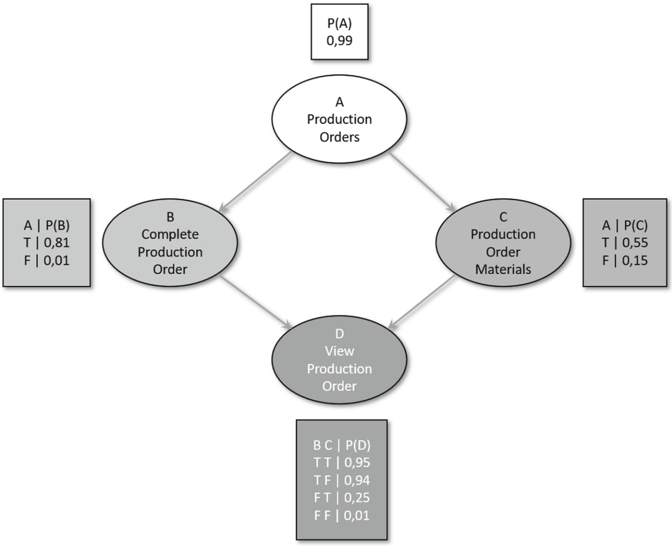

Fig. 3. Bayesian network of a Production Manager

4 Conclusions

How humans and machines interact is increasingly more relevant, as the informatization of services and industry grows; and systems that support the users as they perform their tasks, by adapting their interfaces to the person using them, become a necessity. Establishing a user model that encapsulates the expected behaviour and features of the users is only one of the pieces that will allow for such adaptative interfaces. In order to be as relevant as possible, other contextual information must be considered.

In order to show the user information regarding the tasks they must perform – which will depend on their location and available tools – it is necessary to combine context awareness technologies with user profiling information.

In this paper, we proposed an architecture that starts by modelling different user features through stereotypes, to which other contextual information is added, such as the location, available tools, previous tasks, among others. The combination of elements allows for the filtering of support information provided by MES and ERP systems, effectively showing the user the information that is most relevant not only in their current context, but more suited to their personal needs. The architecture presented is being implemented as three separate modules, including (1) the localization system, determining areas of interest in shop floor environment, (2) and the definition of the Bayesian network regarding the activities of the specified stereotypes. Following this implementation, the next step should be to use the outputs of the modules through the filtering pipeline in order to test the architecture in a proper industrial environment.

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