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On an evolutionary information system for personalized support to plant operators

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Abstract

Technological advances are gradually transforming industrial plants into cognitive cyber-physical systems. Such systems include heterogeneous assets which need to be adapted and supported throughout this transformation. However, operator support systems are still dependent on fixed guidance and paper-based instructions describing a standard procedure.
This paper presents an evolutionary approach for evaluating operators' feedback towards enriching and personalizing the instructions content on how to execute a certain activity. The feedback is provided through a web application and analyzed by artificial intelligence techniques. The proposed information support system has been applied on a case study about the maintenance of an industrial robot.

Keywords: Cyber-physical system; Artificial intelligence; Information support system;

1. Introduction

The emergence of cyber-physical systems and the introduction of their smart features in industry holds the promise of higher automation levels [1]. Regardless of the increasing introduction of smart devices and latest information and communication technologies (ICT), the human factor remains critical for a production system [2]. In this context, the active support of human operators on the shopfloor, addressing their individual profile and needs, is of major importance. Nevertheless, the provision of instructions for supporting plant operators efficiently during a task in industry is challenging.

The existence of information support systems in the industry is considered necessary for enhancing the capabilities of human operators in the current [3] as well as future context of industry 4.0 [4, 5]. Such systems are aimed towards supporting shop floor personnel in fulfilling their activities, such as in maintenance [6], repair, control tasks through multiple channel and context instruction sets. As a result, and throughout the years different technologies have been investigated and proposed, such as augmented reality [7], virtual reality [8] and even mixed reality [9, 10].

The problem of recommending items has been studied extensively and can be classified into two main categories; (a) Content-based, suggesting items similar to those a given user has liked in the past [11], and (b) systems designed to search and match a user's preferences to similar ones of other users in a system database [12]. The core functionality of a recommender system is the "prediction" of an item utility for a certain user. Recommender systems provide items of interest to a user based on certain characteristics that are evaluated by the algorithms that are implemented in their backend [13]. However, this approach does not support any dynamic interaction and tailoring of the information to the user based on his/her current state.

Towards providing personalized support, the acquisition and analysis of an operator's feedback is important. An algorithm for inferring user search goals with feedback sessions is discussed in [14]. Feedback sessions are constructed by clicking logs which are then mapped to user preferences and evaluated via means of an average precision criterion, that was produced by the authors. Moreover, the gathering, evaluation and management of customer' feedback during aircraft production is described in [15]. The feedback is a recorded change request which is evaluated through a KANO model [16]. A different feedback evaluation approach is presented in [17], where an improvement of the Rocchio feedback algorithm [18], is used taking into account the user's profile. The user profile is defined as a set of information describing the user [19]. It contains data that simulate the user preferences. In [20], a genetic algorithm-based recommender system is presented evaluating the similarity between users' preferences. A genetic algorithm is also used in [21] as the basis of the suggested recommender system.

With respect to the aforementioned, this study aims towards presenting an evolutionary method for enabling personalized support of shopfloor personnel in a dynamic way, through human-system interaction. The interaction is achieved by means of operator's feedback to the system and for the instructions received. The feedback is provided either in an explicit or implicit way. Then, it is used to update the user's profile. The profile is configured according to his/her provided feedback after the first time of using a specific instruction set. This is achieved through the introduction of an evolutionary algorithm customizing an instruction set according to the operators individual profile. The proposed approach has been tested in a case study about performing a maintenance activity to an industrial robot in a constrained environment.

2. Approach

In order to effectively support shop floor operators in their maintenance activities towards achieving increased satisfaction and potentially effective training, personalized support is required. This personalization should focus on current interests of the user and evolve as they change over time, due to various factors such as the sentiments, mood or age. In this approach the provided support in the form of instructions on how to complete a certain activity, would be adapted to personal characteristics of the operator.

The main flow of the proposed approach is presented in the figure below (Fig. 1) and analyzed in the following paragraphs.

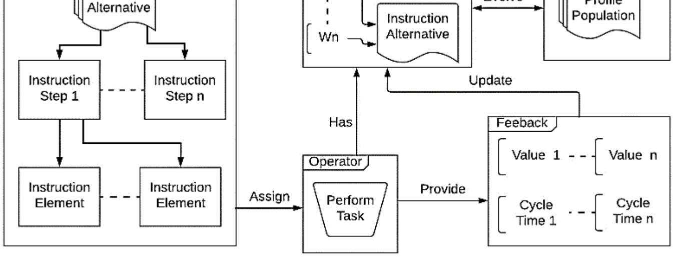

Fig. 1. High level representation of proposed approach.

The operator, represented in Fig. 1 by the operator component, is linked to an activity/task. To complete the task the operator is provided by a set of multimodal instructions, manually created and stored to a database.

There are two main entities, used for personalizing the instruction set content; profiles and instruction sets. The representation used for both entities is based on the vector space model [22] commonly used in information retrieval.

Every task corresponds to one instruction set which includes one or more alternative configurations. Each alternative may include multiple instruction steps each one having up to four instruction elements; text, image, sound and cycle time. In the vector space representation, instruction steps and queries are both represented as vectors. A distance metric which measures the proximity of vectors to each other is defined. To transform the instruction alternative into a vector space model representation, a weighted vector is used. The values of the weights are calculated using the frequency ratio accumulation method (FRAM) using a vector space mathematical representation of the instruction alternatives based on [23]. In this study, instead of categorizing text, the frequency ratios of the instruction elements with an instruction set are calculated for assigning weights. It should be noted that the alternatives' weights after being assigned do not change.

Each individual operator has a population of profiles, with one profile corresponding to one instruction alternative for a specific task. Each profile includes the operator's unique preferences to an instruction set alternative and a fitness value. The fitness is a measure on how successful the profile has been in the past in meeting user requirements. At the first time a profile is created the fitness field is assigned a non-zero default value. Also, default weights are assigned to each instruction element of the profile. The vector space model representation of a profile is like an instruction alternative. This common representation allows computing a degree of similarity between profiles and instruction sets for scoring the instruction alternatives. In order to find the proximity/similarity of vectors, the cosine similarity metric of the angle between the two vectors is used. In the current application, each profile searches a part of the database and scores all the available instruction alternatives. After the similarity computation, the instruction alternative which is finally presented to the user is selected from among the instruction alternatives which score well with respect to the different profiles.

Succeeding the task completion, the operator's feedback is captured. In runtime, the profile weights are updated according to the operator's feedback/preferences as well as the measured cycle time. The cycle time is the time interval for an instruction step to be completed by the operator and it is recorded by the system itself. The operator's feedback is considered for each instruction element.

The set of a user profiles, corresponding to the feedback received up to certain point of time for a few instruction alternatives, are used as an input to a learning mechanism. Purpose of this mechanism is to learn an operator's global preferences towards creating his/her personalized profile with respect to the supported instruction elements. As a result, a new operator global profile is created including a vector of weights revealing how important an element, such as text, is for a specific operator. The weights of the profiles are re-calculated through a genetic algorithm, according to the operator's profile updates, when providing new feedback for an existing instruction alternative, or additions, when executing a new task. Hence, the genetic algorithm controls the population characteristics and behavior in response to changing user interests. The genotype representation in this approach is a pair of profile and its fitness and consist the input of the algorithm. The genetic operators, namely crossover and mutation, refresh the weights of every global profile taking into account newly introduced weights in the set of genotypes.

3. Implementation

The proposed approach has been implemented into a software system as a web application following a client-server architecture (Fig. 2).

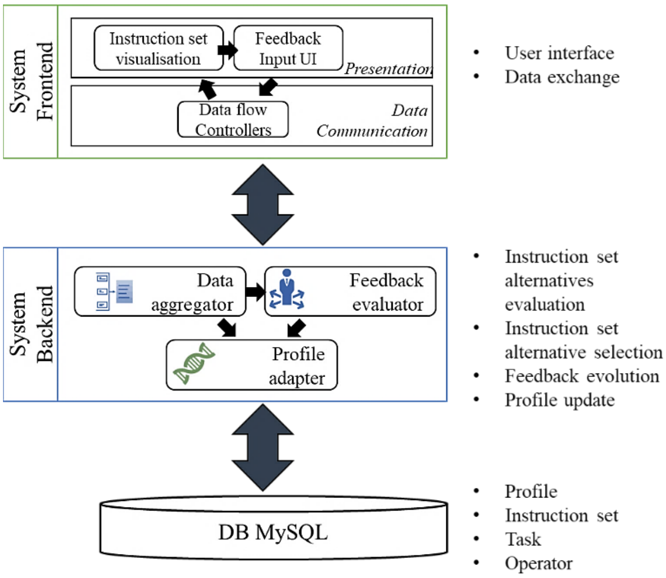

Fig. 2. High level representation of the implemented system's architecture.

The frontend consists of two layers, the data retrieval and the presentation layer. The data retrieval layer is responsible for implementing the data exchange to and from the backend through restful services. The presentation layer is in charge of displaying instruction sets and allowing the user to provide feedback. Moreover, a graphical user interface (GUI) has been implemented with AngularJS, a library written in JavaScript for web application development.

The backend was developed using Java and the Spring Boot framework. All functionalities of the backend are exposed as REST web services. The backend consists of four major components:

- **The data aggregator**: It manipulates data from the database and it routes them into the other components.
- **The feedback evaluator**: It uses the relevance feedback to enhance the performance of the system.
- **The profile adapter**: It uses a genetic algorithm for adaption and exploration of the operator's interests.
- **The database**: It keeps organized data on the disk.

The data aggregator component orchestrates the whole process, retrieving instruction sets and user profiles from the database and converting them to their vector space representations. Moreover, it is connected and interacts through information exchange with the profile adapter and feedback evaluator components. Finally, it re-evaluates the instruction alternatives of the specific task based on the entire profile population of a specific user, resulting to the selection of the highest score instruction alternative.

After the completion of the task, operator's feedback is provided manually through the system GUI for each instruction element. The completion time of each step is also measured by the system, as an additional feedback parameter. This time is then compared to the previously stored time interval in the database referring either to a default value, if it is the first time, or a previously recorded one.

The profile adapter and the feedback component consist the learning mechanism of the application. The profile adapter is based on a genetic algorithm, implemented in Java with the Jenetics library [24]. Through this library, an evolution engine was set up, being responsible for changing, respectively evolving, a given profile population received as input to the engine. The evolution is achieved by means of crossover, such as one point or two points, and mutation parameters which through the selected library can be highly configured. The population refers to a single task assigned to a user. Due to the application nature, the initial population is not randomly assigned, but retrieved from the database. This implementation uses a real number for saving the fitness value inside each genotype/profile. This real number is updated by user feedback and is assigned with the initial value of 0.5.

For data management and storage, a MySQL database was used for simplicity and for creating relationships between tables. The database keeps organized data for all entities such as profile, instruction set, operator, etc.

4. Case study

In order to test and evaluate the proposed concept, a case study has been performed in a constrained environment. The evaluated scenario involves an operator using the implemented system to get support for performing the replacement of gearbox to a robot. The software system is deployed in a local computer while the operator interacted with the system through an android tablet. A task entitled as Task1 and with a cycle time of 12 min is assigned to him, including the following steps:

1. Take new gearbox and screw driver from a rack, namely rack A.
2. Approach robot.
3. Remove protecting plastic cover.
4. Replace gearbox.
5. Put back plastic cover.
6. Return screw driver and replaced gearbox to rack A.

Initially, the user's profile is empty and instruction alternatives are scored zero. The instruction alternatives include only textual instruction elements Fig. 3. The initial selection is performed randomly.

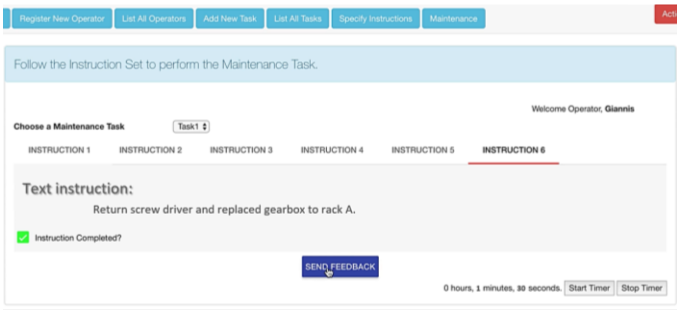

Fig. 3. Example of initial content for instruction step 6.

After the completion of each step the operator provided feedback through the system on which kind of customization is required. In addition to the feedback provided by the user, in the form of +/-1 the cycle time of each step is measured by the system itself as presented in the following table (Table 1).

Table 1. Instruction steps measured cycle time

Step	Image	Text	Audio	Expected duration	Actual duration	User Feedback
1	-	Yes	-	2.5	3	-1
2	-	Yes	-	1	0.5	+1
3	-	Yes	-	2.5	3.5	-1
4	-	Yes	-	2	1.5	-1
5	-	Yes	-	1.5	2	-1
6	-	Yes	-	2.5	1.5	+1

The evaluation of the operator’s feedback is the following:

- It takes a lot of time to the user to read the instruction step and carry out the instructions.
- User proceeds faster in the steps where there is audio or image instructions

In this experiment, the operator selected the addition of audio instructions and images in instruction steps 1 and 6.

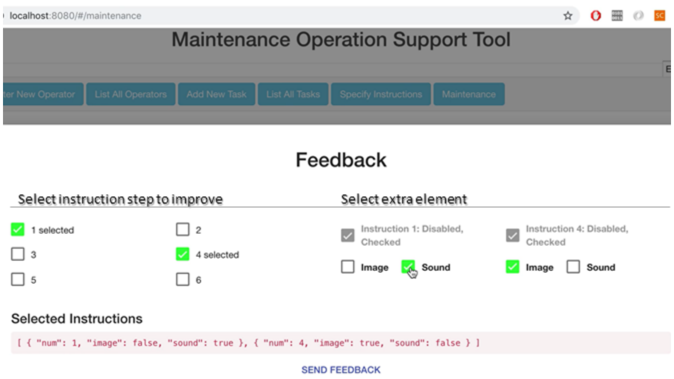

Fig. 4. Operator's feedback interface and selected customisation.

Thus, the feedback will update the corresponding profile by increasing its sound and image weight. It also will decrease the fitness value of this profile. The new profile now will re-evaluate instruction alternatives and one achieving the highest score will be linked to the specific operator’s profile and for the next time the same task will be assigned to him/her. The updated instruction step 6 is presented below in Fig. 5

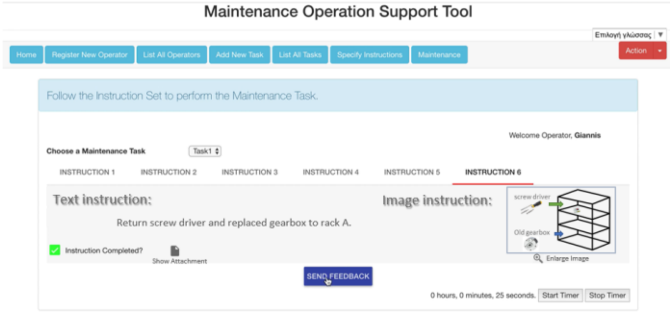

Fig. 5. Customised content for instruction step 6 based on operator's feedback.

Therefore, the system improved the instruction set that is presented to the operator by selecting a different instruction alternative from the database according to the provided feedback.

Additionally, and towards evaluating the evolutionary/learning part of the genetic algorithm, the same operator performed 5 tasks, hence creating a set of six profiles, corresponding to six instruction alternatives. The population of profile after the completion of 5 tasks is presented in the following table (Table 2).

Table 2. Profile population of the user

Profile	Image	Text	Audio	Cycle time
1	0.1	0.8	0.05	0.05
2	0.35	0.5	0.2	0.05
3	0.6	0.5	0.2	0.1
4	0.7	0.4	0.25	0.1
5	0.45	0.7	0.3	0.15

The learning mechanism and through the genetic algorithm, evaluated the 5 profiles to create the following global profile (Table 3).

Table 3. Operator's global profile

Profile	Image	Text	Audio	Cycle time
0	0.56	0.72	0.11	smaller

It should be noted that the cycle time field in the global profile gets a value of smaller or greater depending on the comparison of the evaluated cycle time of the profile with its expected value. Based on this comparison, the value assigned to the global profile is an indication of whether the profiles weights are expected to contribute to a smaller cycle time or the operator is expected to spend more time to fulfil an activity.

According to the global profile, the preferences of the operator are textual instructions with images, while it is indicated that providing instructions according to these preferences will result to a reduced cycle time for an activity.

5. Conclusion

This study was motivated by the need to support operators and users in a dynamic and at the same time intuitive way, meeting their volatile demands and preferences. The core idea proposed is the use of a software tool as a recommendation system and for establishing the communication and interaction with the user as well as receiving his/her feedback. A methodology has been presented for creating the user profile and dynamically updating it based on the feedback received. On top of it, a genetic algorithm is introduced to evaluate the user profile based on the feedback and update it accordingly. The update of the instruction set aims towards updating its content based on the available material in the tool's database towards either addressing individual's preferences, such as larger fonts, and/or activity-oriented requirements, such as reduce an activity's cycle time.

The preliminary system presented in this work shows promise for further advances that could enable personalized support for shopfloor operators. However, further research is required to make the system robust and investigate in greater detail the use of the genetic algorithm and its configuration. The evolution of the GA algorithm as well as the expansion of the use profiles and feedback mechanism will be considered. Moreover, this personalized support could be extended to cover applications outside of the manufacturing domain. This will also be part of the future investigations. Finally, it will be investigated the connection of the tool's database with external sources, such as the internet, as well as the enrichment of the feedback mechanism with natural language support and the implementation of a context engine.

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