Information Agents Handling Semantic Data as an Extension to Process Monitoring Systems

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Abstract. An approach to extend process monitoring with the help of information agents (IA) handling semantic data is presented in this paper. According to this approach, an operator of a process automation system can configure monitoring tasks that a group of IAs performs proactively. The monitoring tasks are assumed to be composites which refer to several process observations and their logical relations. The purpose of these composite monitoring tasks is to enhance the work of the operator by letting him to supervise process phenomena at a higher level of abstraction instead of following a large amount of simple measurement data. The monitoring agents operate as a multi-agent system consisting of agents with capabilities to combine both numerical and symbolic information from several data sources. The agents can setup and execute user configured monitoring tasks cooperatively. The approach is illustrated with test scenarios using data from an industrial paper making process.

Keywords: Process monitoring, information agents, semantic data.

1 Introduction

This paper is motivated by the increasing requirements of the work of process operators and possible solutions to these requirements with the help of new information technology. The volume of measurement data from controlled processes has increased which makes the monitoring task harder. Same time the need for cost reduction requires better monitoring performance. The monitoring work might be supported better by raising the abstraction level of the monitoring tasks implemented in automation systems [15]. The monitoring tasks could have a larger scope, i.e. refer to measurement and other related data in various separate systems, and more versatile monitoring logic, i.e. handling of logical relations between various observations.

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The purpose of this paper is to present an approach for extending process monitoring systems with agents handling semantic data. The aim of the approach is to facilitate automation of some monitoring tasks, which require combination of numerical measurement data with symbolic information about the controlled process. IAs based on the BDI-agent model [1], [4], [18] and utilization of semantic data models [4], [6] are proposed as a suitable implementation method for extended monitoring functionality. The BDI-agent model is used for modeling and executing the application logic of the extended monitoring tasks configured by the operator. Semantic data models are used for modeling symbolic information about the process and its state. Combination of symbolic data with numerical monitoring data is expected to provide better information for the operator about the state of the monitored process. This paper presents an overview of the whole of the approach. Details of the approach have been described in other publications [14], [16], [17], [19].

The paper is outlined as follows. Chapter 2 will discuss process monitoring and the possible role of semantic data and IAs as its extensions. A specification of an extension to a process monitoring system utilizing the mentioned techniques is presented in Chapter 3. Illustrating demonstrations are described in Chapter 4 followed by conclusions in Chapter 5.

2 Process Monitoring, Semantic Data and Information Agents

2.1 Process Monitoring

Monitoring the production process is one of the main tasks of process operators together with pre-planned control operations and disturbance control. The objective of monitoring is to evaluate if the process is behaving according to its objectives and detect possible deviations as early as possible. The requirements of this work have become harder in recent years due to ever increasing demands of cost reductions.

The main sub-tasks of process monitoring include selection of observed data, interpretation of results and decision-making about the need to act [15]. An important difficulty in data interpretation is the complex relationships between various phenomena in the process. Some deviations are difficult to observe and can only be noticed via inferences combining several information sources. The operators have expertise for performing these tasks. However, the large amount and low abstraction level of measurement data combined with limited human perception makes monitoring an error-prone task.

Process monitoring systems could be developed with capabilities to assist the data selection and interpretation sub-tasks of monitoring through so-called indirect management [9]. An essential idea in this approach is let the operator to configure a part of his expertise to the monitoring system and automate it. The data selection sub-task could be partly automated according to user defined rules which reflect his understanding of the expected behavior of the process. The low abstraction level of measurement data could partly be raised through creation of symbolic data from it [20]. However, this functionality needs to be designed carefully so that the user can trust it and the application can be maintained. It is also necessary to integrate it with existing monitoring systems.

2.2 Semantic Data in Monitoring

Semantic data models, e.g. ontologies represented with OWL [13] provide a mechanism to represent symbolic information that may be expected to be useful also in process monitoring. Semantic data can represent additional information about the process (e.g. about structure of the process, control activities, etc.) and offer a more abstract to view to observations detected from numerical measurement data.

The data handled in monitoring can be classified to three groups: numerical measurement data, symbolic data about the process and metadata about the services providing the data. Creation of symbolic data from numerical one can be useful when trying to interpret measurements [3]. Again, combination of both numerical and symbolic inferences may be useful in solving of complex problems [5]. Symbolic modeling of lower-level monitoring services can enable composition of higher-level monitoring functions [11].

Development of indirect management type of monitoring functions is likely to require combination of all the previously mentioned types of data. In situation interpretation sub-task of monitoring symbolic data inferred from numerical measurements is likely to be useful when creating an overview of a situation. While planning of data selection for monitoring symbolic information about the structure and behavior of the process and available data services could be used in order to ensure the scope and precision of observations.

2.3 Information Agents in Monitoring

IAs are a particular type of multi-agent systems whose purpose is to assist human users in accessing data that they need in their activities. IAs are expected to reduce the information overload that some users are facing [10]. They are expected to do this by proactively working for the interests of their users.

The functions of IAs in assisting their users have been proposed to include e.g. planning of information access operations and interpreting intermediate results. Eventually IAs could compose an answer to a query through a distributed problem-solving process [12]. Combination of BDI-agent model and ontologies has been proposed as one suitable implementation technique for IAs [4]. In monitoring IAs have been proposed to be applied to several functions, e.g. communication of process events to operators [2] and flexible definition of alarm conditions [9].

The properties of IAs seem to match at least partially the requirements of process monitoring. The operators need assistance in order to cope with the increased amount of monitoring information. Proactive operation of IAs could be useful for this purpose. However, in order to implement IAs for monitoring suitable methods for representing process data and handling it in IAs need to be designed. BDI-agent model and integration of ontologies with numerical data could be useful starting points for a design.

3 Information Agents Based Monitoring

3.1 System Overview

In this study the purpose of the IAs in assisting process monitoring is to improve the monitoring functionality available to operators through user-configurable extended monitoring tasks with higher abstraction level. An operator configures extended monitoring tasks according to his expertise and the IAs proactively run them and provide the user with abstracted feedback leaving out unnecessary details [16], [17].

The IAs operate as an extension to existing automation and information systems at a process plant as illustrated in Fig. 1. The information agents are intermediate agents that operate between the user interface and lower-level monitoring functions and other data sources. The operation of the IAs include conversation with the human user, composition of the extended monitoring tasks from the lower-level monitoring services and possibly cooperation with other IAs.

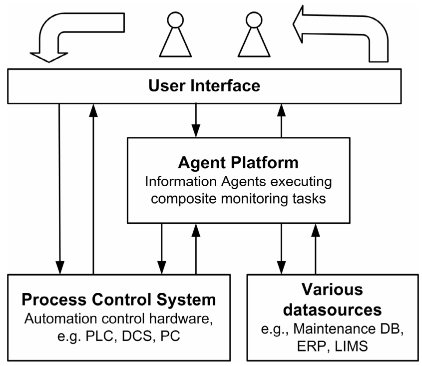

Fig. 1. Architecture of a process monitoring system extended with IAs

In order to be able to perform their tasks, the IAs are designed according to the BDI-agent model [1], [9], [18] as illustrated in Fig. 2. Data access and composition modules enable receiving and combination of data from several data sources. With further levels of data processing modules it is possible to create symbolic data from numerical one and make inferences from the received, combined and created data. The user configured monitoring tasks are represented as plans which are run parallelly by the BDI-interpreter. The plan execution is guided by goals, which represent the monitoring objectives configured to the monitoring tasks by the operator. The goal-oriented operation scheme is expected to select the focus of the monitoring tasks according to the intentions of the operator.

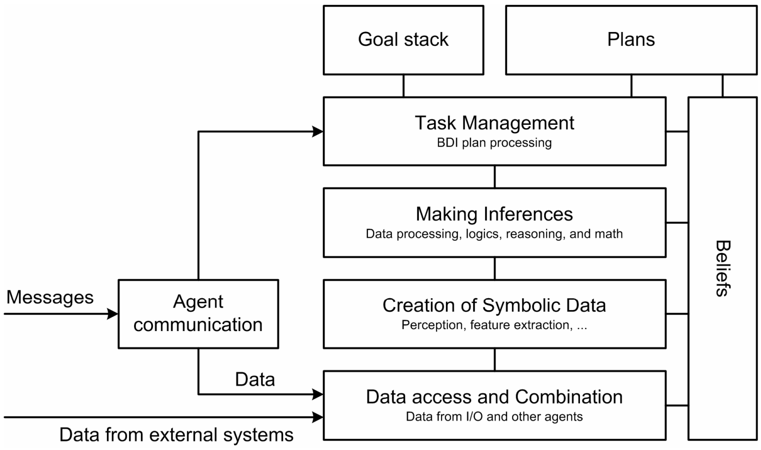

Fig. 2. Architecture of an IA

3.2 Data Access and Combination

The purpose of data access and combination is to collect data from separate external data sources and transform it into a suitable symbolic form for the monitoring tasks of the IA. This functionality is aimed for fulfilling the so-called location transparency requirement of information access in monitoring. For those data sources that naturally produce symbolic events, e.g., maintenance database and electronic diary for operator notes, there is still need to convert data to unite syntax and semantics. Ontologies representing the structure, events and behavior of the monitored process can be used for this purpose. A more detailed description of the data access and combination functionality is available in [14].

3.3 Creation of Symbolic Data

The purpose of creation of symbolic data is to transform a part of the numerical information, e.g., perceptions from physical world, into a symbolic form so that the monitoring tasks can combine it with other symbolic data and make inferences from it. This functionality is aimed for fulfilling the so-called format transparency requirement of information access in monitoring. The use of symbolic data is expected to make inferences less sensitive to noise which is always present in time-series data. Furthermore, symbolic and semantically meaningful data is needed to effectively integrate the whole production enterprise and it also might be produced by lower level devices in the future [7].

There are numerous ways to create symbolic data from the sensed inputs, e.g. using data mining, classification, and rule discovery techniques [3], and recently wavelets have been demonstrated to be effective in producing meaningful symbolic information [8]. Although there has been a great deal of research about methodologies of creating symbolic information, implementations to real life are not so numerous. This might be mainly because complex analyzing algorithms are too laborious to maintain, and therefore we try find out how to generate enough symbolic information requiring still as less maintaining as possible to keep the approach feasible.

3.4 Making Inferences

The purpose of inferences is to make observations, which are not evident in the data received from the external data sources, but which an operator would deduce from it. This functionality is aimed for fulfilling the so-called existence transparency requirement of information access in monitoring.

There are many possible ways in which useful new information can be produces from the data available from monitored process, e.g. user defined rules presenting relations between process values, relations from device type definitions, and correlations that data mining tools discover. In this research a particular type of making inferences, i.e. constraint networks, was experimented with (see Chapter 4.3 and [19] for details). Constraints are used to express logical criteria on the acceptable state of the process as configured by the user. The conditions can refer to any data available to the IAs. The IAs automate the consistency checking of the constraints. The constraints are expected to provide a relatively easily configurable method for expressing a part of operator's knowledge which he applies during monitoring.

3.5 Task Management

The purpose of task management is let users configure their monitoring tasks, run the tasks parallelly and provide them with necessary feedback through a suitable conversation. This functionality is aimed for fulfilling the requirement of flexibility in monitoring.

The task management can be designed according to the BDI-agent model in which the interpreter runs several extended monitoring tasks parallelly. The tasks are user configured combinations of data access and combination, symbolic data creation and inference making operations. The execution of the monitoring tasks is managed according to the goals they are fulfilling. It is expected that this kind of a control structure enables IAs to focus their attention to those monitoring tasks that are most relevant to the user taking into account the process state as described in the available data. More comprehensive descriptions of the task management functionality are in [16], [17].

4 Demonstrations

4.1 Monitoring of Maintenance Events

The first test scenario demonstrates the data access and combination capabilities of an IA [16]. Currently factories have various heterogeneous data sources containing important information about operational issues of a process. Especially, maintenance operations may dramatically change the functionality of the process, but as maintenance events are rather rare operators do not bother login to a separate system for checking them. Fig. 3 illustrates our first demonstration where an IA seeks maintenance events from a specified time period and uses a semantic plant model to link events to the corresponding time-series data.

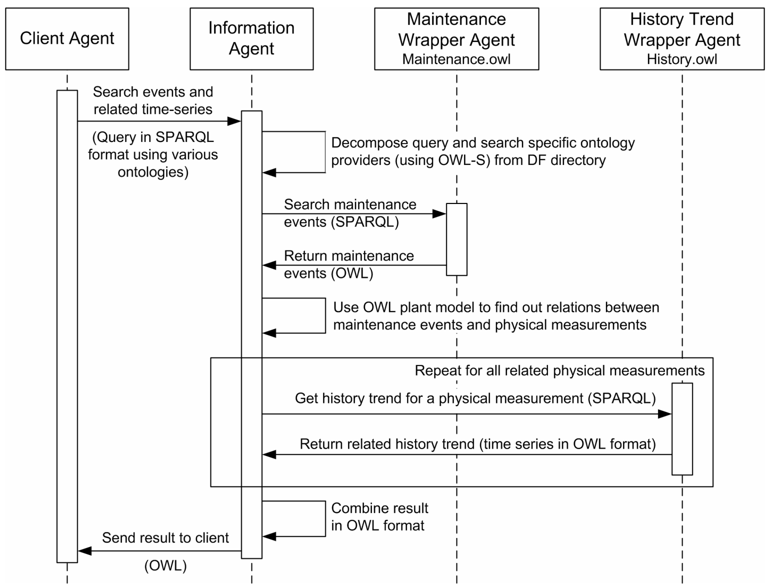

Fig. 3. Example where an IA decomposes a multi-ontology query into two sub-queries that *Wrapper Agents* (capable of answering to a single ontology query) are capable of answering. About SPARQL see [21].

Background for this scenario is that maintenance personnel registers maintenance operations to certain physical devices (address space relates to devices) and operators work with process measurements (control loop related address space) and there is no direct relation between these two. It is valuable for the user that an IA checks if there are registered maintenance events and links them to the corresponding time-series values using a semantic plant model. In short, the plant model used here expresses that maintained devices have some kind of relation to physical process quantities which again relate to process measurements.

4.2 Monitoring of Process Fluctuations

The second test scenario demonstrates the operation of one possible symbolic data creation capability of an IA. Within the normal operation of a specific process area it is desired that physical quantities are steady and near their normal operation points. Fluctuation from this steady state may be judged to be undesirable, and it would be beneficial for the operator to get information about the change events that happen in the process quantities.

With statistical methods it is possible to quite robustly detect change events from time series data, even when there is not so much a priori information about the characterization of the measured value. Figure 4 shows an example of real measurements where *change events* (level changes in this case) are detected with statistical methods.

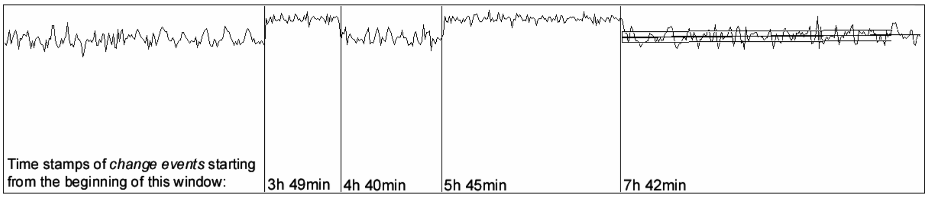

Fig. 4. Example of an IA using statistical signal processing to generate symbolic *change event* information (vertical lines in the figure) for time-series data measured from a physical process

After the symbolic change events have been generated for a single value, they may be used for various monitoring activities. For example, the user may request an IA to watch over some change event pattern within numerous physical quantities representing some interesting phenomenon in the process. Alternatively change events may be registered to launch more thorough temporal monitoring tasks.

Change events could also be used for navigation aid when user is trying to find interesting phenomenon from the time-series data stored in the history database. Currently, most history databases offer time or stored values as basis for navigation. If symbolic change events would also be available for navigation, user could jump to next or previous change event stored in the system. Depending on the characteristics of a process quantity this could be a useful shortcut to bypass steady, and usually not so interesting, time periods.

4.3 Monitoring of Measurement Consistency

The third test scenario demonstrates the inference and task management capabilities of an IA [19]. The test scenario concerns about the pH control in bleaching of mechanical pulp in a paper mill. The operator of the process has rules of thumb about the acceptable values of process measurements. Deviations may indicate malfunctions of pH sensors.

The operator configures the extended monitoring task by defining a set of constraints describing his monitoring logic, e.g. the flow of sodium hydroxide must be greater than the flow of sulphur dioxide (see [19] for details). The task definition is passed to an IA which identifies the needed data sources, sets up communication with them and builds data structures needed for checking the constraints (see Fig. 5). The communication and inferences of the task are activated by the BDI-interpreter of the IA when needed. Feedback is provided to the user if the constraints are not satisfied.

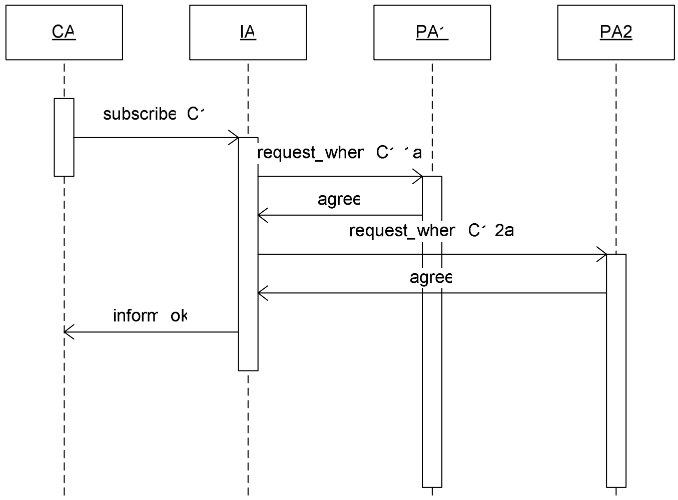

Fig. 5. Part of the operation in the pH monitoring test scenario in which an IA decomposes an user configured constraint (C1) to two simpler constraints (C1.1a and C1.2a)

5 Conclusions

In this paper an approach for extending process monitoring systems with IAs handling semantic data has been presented. The approach proposes the so-called BDI-model combined with processing of semantic data as a suitable implementation model for the extended process monitoring functions. It is stated that the BDI-model would be able to help gaining the flexibility and configurability that is needed in future monitoring applications. The approach has been illustrated with test scenarios using data from an industrial paper making process. The presented approach can be seen as a start for extended monitoring applications but more research remains to be done. Maybe one of the most crucial aspects for the future is the trust issue, i.e. how you can trust an autonomous system monitoring your plant.

In the future, the creation and utilization of symbolic data needs to be studied more thorough, e.g., detecting event patterns, producing better data combination and inferences. Novel studies are needed to show that we can produce useful results also with a limited set of symbolic data available in real world situations.

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