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Process-Aware Internet of Things Model: A Discovery Method Using IoT Data and Process Mining Techniques

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Abstract— **The development of suitable systems for managing linked items and data has been made possible by the Internet of Things (IoT), which has completely changed corporate operations. An inventive method called "business process intelligence" combines process mining with process management to enable quick decision-making and real-time analysis. Nevertheless, there are difficulties in converting unstructured Internet of Things data into structured data, as structuring might lead to the loss of crucial information from the original data. In this research, a unique approach to automatically constructing IoT-connected business processes while preserving the original data richness is proposed. In order to transform enormous volumes of unstructured IoT data into data structures appropriate for process mining, the approach uses a model-driven architecture (MDA). The second stage involves semantic enrichment of process mining-generated event logs, which is achieved by annotating event log items with IoT-specific semantic concepts using ontologies.**

Keywords—Model Driven Architecture(MDA); Semantic Process aware IoT ; Ontology; Process Mining (PM)

I. INTRODUCTION

The Internet of Things (IoT) has created a new era of connectivity and intelligence, marked by the rapid development of connected objects. While this massive transformation of our everyday environment presents many opportunities, it also presents significant obstacles, particularly when it comes to managing business processes [1]. The creation of appropriate business process management systems is essential in this complex environment, where devices interact autonomously and generate huge amounts of data.

The emergence of Business Process Intelligence has attracted the attention of practitioners and researchers alike, as it brings a new dimension to the evolution of business process management [2]. The implementation of this innovative approach involves the integration of process mining techniques into process management, enabling an extensive and proactive understanding of business operations. Business Process Intelligence is emerging as an adaptive response to the complex needs of the IoT environment, thanks to process mining techniques. It extracts important information from the data generated by connected objects, offering valuable insight into how business processes evolve and interact in this dynamic ecosystem. By enabling real-time analysis and agile decision-making, this new approach transcends the traditional boundaries of process management. The purpose of the study was to determine how these works handle the transformation of event logs—a type of structured data—from IoT data so that process mining techniques may be used to create business processes. Our analysis has shown that the majority of studies focus on transforming massive, unstructured Internet of Things data into structured data, creating event logs suitable for the application of process mining techniques[3] [4] . This work has proposed innovative methods for managing the complexity inherent in Internet of Things data, organizing it in such a way as to provide crucial information for automatic process generation.

This transformation does, however, provide a recurrent challenge: while process mining may be effectively used to derive process models from structured data, the structuring process may result in the loss of important information about the original IoT data. This begs serious concerns about how well the process produced can retain the complexity and depth of the original unstructured Internet of Things data. So,in this paper, we have developed a novel method as part of our study to automatically generate business processes connected to the Internet of Things (IoT) while maintaining the richness of the original data. This method, which incorporates ideas from model-driven architecture and semantic enrichment of event logs, is divided into two main stages.

Phase 1: Optimal Data Transformation using Model-Driven Architecture (MDA) Proposal: During this first stage, we recommend implementing a model-driven methodology, namely a model-driven architecture (MDA), to effectively direct the conversion of vast amounts of unstructured IoT data into data structures appropriate for process mining. This method is based on building an abstract model that encapsulates the fundamental properties of IoT data, allowing for its change without compromising its original meaning.

Phase 2: Extending event logs with semantics: Our strategy's second stage is centered on the semantic enrichment of process mining-generated event logs. The implementation of a semantic layer depends on the annotation of event log items with IoT-specific semantic concepts using ontologies.

The rest of this paper is organized as follows: The primary ideas related to our work explained in Section 2. The primary concepts of relevant works pertaining to the semantic enrichment of event logs and the guidelines for converting data into structured format are presented in Section 3. An outline of the suggested methodology is provided in Section 4. Section 5 wraps up this report and looks forward to future research.

II. BACHGROUND REVIEW

In this section, we present two main concepts related to our work that are semantic process mining and process aware IoT.

A. *Semantic Process mining :*

Process mining is a set of methods used to manage business processes that are already in place and running in companies [5]. The event log created during the execution of business procedures is an essential element in the use of these methods. The type of process mining for which these event logs are used determines their exploitation. Process search methods fall into three main categories:

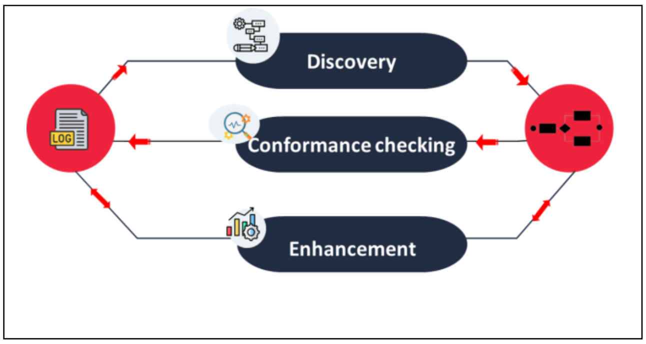

Figure 1. Process Mining Axes

- Discovery techniques can be used to create a business process model that describes the process behavior captured in the event log[5].
- Conformance checking verification techniques use trace data to find deviations in business processes from the current model [5].
- Enhancement techniques: use an event log to improve the existing business process model using actual process behavior [5].

Analyzing the syntax of event logs was the biggest challenge of process mining. However, event logs also capture knowledge of a particular business domain, which can be extracted and used to create discovered processes. In fact, semantic process mining was created to combine mining and semantic techniques. To extract semantic meaning from event log data, semantic process mining uses an ontology by introducing semantic annotations to link reference items in the event log to concepts in the ontology [6].

B. *Process aware IoT*

A business process that interacts with connected objects (IoT) is called an aware IoT process. These connected objects can collect real-world data, such as sensor, location, or usage data. This data is used by conscious IoT processes to make decisions, automate tasks, or increase operational efficiency. The key components of a process-aware IoT are:

Connected objects (Internet of Things): conscious IoT process data comes from connected objects. These may be drones, cameras, sensors, or other devices capable of collecting data in the real world [7] .

IoT data : The data collected by connected objects is known as Internet of Things data. This data can be used to make decisions, automate tasks, or improve operational efficiency. Crucially, this data is generally unstructured and voluminous [7].

A process model: also known as a workflow model, is a conceptual or visual representation of the steps, activities, and interactions involved in a specific process. It is a graphical abstraction that enables the sequence of actions or events that make up a business process to be understood, analyzed, and documented [8].

III. RETATED WORKS

To provide a better understanding of the use of process mining in the context of sensory data, our study focused on two key questions. The first question addressed was to examine the different methods used for the sensory data mining process. We tried to understand how these techniques and methods have been used to structure data and apply PM techniques.

The discovery that objects manufactured using these methods often lack the essential characteristics of connected objects (IoT) was the second issue in our investigation. In response to this finding, we considered how to enrich these events to create process-aware IoT. In the context of the Internet of Things, this innovative approach aims to integrate the missing (-) and existing elements in each approach to make the resulting processes more meaningful.

TABLE I. COMPARATIVE STUDY

Approch	Q1 : How to structure sensor logs to apply process mining techniques?					Q2 : How to enrich an event log to generate an process aware IoT	
	Event Correlation	Activity Discovery	Event Abstraction	Segmentation	Labelling	Task	Device
[9]	+	+	+	-	-		
[10]	-	-	-	+	+		
[11]					+		
[12]						+	-
[13]						-	+
[14]						+	-
Our Approach	+	+	+	+	+	+	+

Q1: How do you structure sensor logs to apply process mining techniques?

It should be noted that the methods mentioned in the table focus on the use of process mining to structure IoT data using different machine learning methods. For example, the segmentation method has been used, as has the correlation method. in approaches [9] and [11]. However, current literature often overlooks the essential aspects of IoT in creating an event log.

Q2: How to enrich an event log to generate a process-aware IoT

We have carried out an intense study of methods that have used an extension of the ontological model, whether through the device [14] structure or the task [12] [13] structure, with the aim of enriching the set of events we have generated.

IV. OUR APPROACH

Our approach is to automatically create an IoT-aware process. Process mining technology is used in this approach to facilitate the modeling and implementation of processes related to the Internet of Things. Our method is based on the following principles:

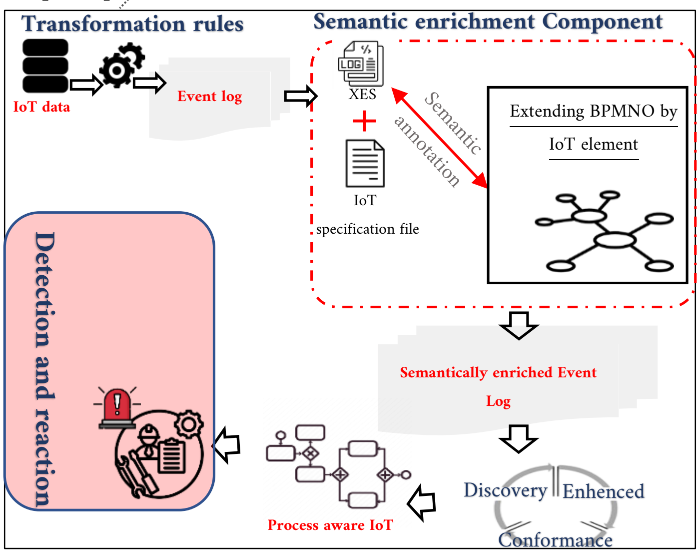

Figure 2. Our Approach to Automatically Generate Process-Aware IoT

Step 1: Model-Driven Architecture Component (MDA):

After generating an event log from IoT data, Architecture driven by the MDA model, which transforms each element of a sensor log into an event log, thanks to a set of mapping rules proposed by us [15].

Step 2: Semantic enrichment component:

The following step is to enrich the event log with IoT elements. We establish the semantic annotations that are to be integrated into the event log after data transformation. These semantic annotations will mention the ideas of BPMNO extension by IoT components [16].

Our ontology is based on the OWL ontology extension, enriched with elements specific to the Internet of Things (IoT). This IoT extension comprises three main elements: IoT data, IoT activity, and IoT resource.

Table 2 lists the elements involved as well as the attributes that will be added to the log. To refer to a concept in BPMN-IoT, we use the notation BPMN-IoT#ontology_concept.

TABLE II. ATTRIBUTES USED FOR SEMANTIC ANNOTATION WITH BPMN-IOT

Attributes	Targeted element in XES event log	Possibles values
IoT Data	Event	BPMN-IoT# Data-from-sensor
		BPMN-IoT# Data-from-reader
		BPMN-IoT#Data-from-collector
		BPMN-IoT# Data-from-actuator
IoT Activity	Event activity (org : activity)	BPMN-IoT# Actuatin-task
		BPMN-IoT# Collecting-task
		BPMN-IoT# Sensing-task
		BPMN-IoT# Reading-task
		BPMN-IoT# Actuating-task
IoT Device	Event Resource (org : resource)	BPMN-IoT# Sensor
		BPMN-IoT# Reader
		BPMN-IoT# Collector
		BPMN-IoT# Actuator

This step involves integrating the attributes defined in the log on the basis of the IoT element specification file. To do this, ON vas proposes an algorithm that captures the event log in XES and produces the semantically annotated event log using the Extending BPMNO by IoT element ontology.

Step3: Discovery of process aware IoT and reaction:

We will apply process mining techniques using an extended discovery algorithm after annotating event logs with IoT-related information. This extension of the algorithm aims to take into account the specifics of IoT objects such as devices, data and tasks. This will enable the creation of a more suitable process model that captures the complex interactions between the various components of the Internet of Things. The use of this extended algorithm will facilitate the analysis and understanding of business processes in an IoT environment, provide valuable information for predictive maintenance.

V. Conclusion

Finally, our extensive research on self-sustaining process generation in smart settings has brought to light the difficulties in converting large amounts of unstructured IoT data into useful business processes. Previous research has mostly concentrated on data structuring for the use of process mining tools; however, this approach has serious drawbacks, such as the loss of crucial information about Internet of Things data during the structuring process. Our novel method suggests a two-pronged way to tackle this problem. In the first stage, an abstract model that directs the transformation of IoT data while maintaining its original meaning is to be created using a Model Driven Architecture (MDA). In order to provide deep, contextual understanding, the second phase of the project, which is centered on the semantic enrichment of event logs, annotates log items with IoT-specific concepts using ontologies. Our method aims to address the problem of autonomous process creation in an IoT context by merging these two stages, providing a complete and reliable solution that maintains data richness all the way through the process. This contribution sets the stage for fresh research viewpoints to improve and broaden our methodology in order to promote noteworthy advancements in this dynamic and ever-changing sector.

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