ProAmbitIon: Online Process Conformance Checking with Ambiguities Driven by the Internet of Things

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Abstract
The ongoing digitization of processes in everyday life shows great potential for process automation, analysis, and optimization. However, digital traces of processes in the physical world, especially those involving human interactions, are often incomplete. This limits the possibilities for an automated process monitoring and analysis. *ProAmbitIon* proposes to use the Internet of Things (IoT) to bridge the gap between physical world process executions and their digital traces. In this project we leverage software-controlled sensors and actuators to enable a fine-grained monitoring and contextualization of process activities. Digital traces of executed processes can be created from and enriched with IoT data, and used for conformance checking to detect deviations–even at runtime and without relying on a Business Process Management System (BPMS). In developing new approaches for IoT-driven process conformance checking, we also address the issue of potential ambiguities originating from 1) informal process descriptions and 2) the lack of process-related data in IoT data. The project is conducted using real-world scenarios from smart healthcare and smart manufacturing.

Keywords
Process Mining, Conformance Checking, Explainability, Internet of Things, Ambiguous Process Models

1. Introduction

Processes and process-like descriptions are being increasingly adopted in every domain and aspect of everyday lives. They are used to instruct humans, computers, machines, robots, and all kinds of other resources how to interact and execute specific activities to solve a certain task. These real-world processes have become increasingly digitized [1]. Contextually, in recent years process mining became an important and mature discipline with broad adoption in industry.

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Process mining bridges process science and data science to extract event data about process executions stored in event logs for an automated analysis of processes [2].

Conformance checking is a process mining task conducted to automatically detect deviations of process executions (cases) from the prescribed underlying formal description (process model) [3]. Conformance checking assumes the existence of an event log describing execution traces. This assumption is realistic when the process is executed using a Business Process Management System (BPMS) or some other kind of process-aware control/monitoring system. However, in settings where process executions are not fully orchestrated or at least monitored by a single BPMS, the execution of certain steps may be outside the control of an IT system. Hence it might be challenging to obtain complete event logs. For instance, the digital traces of processes with a high degree of human involvement (e.g., in healthcare) are often on an abstract and coarse-grained level, containing human activities as black-boxes, incomplete activity sequences, and even erroneous data [4].

The gap between the physical execution of a process and its digital representation limits the possibilities of conformance checking for a detailed automated analysis with respect to deviations and exceptions [5]. As a result, these processes cannot be fully planned, predicted, optimized, or adapted in case of non-conformance. Additionally, most of the existing approaches and techniques related to conformance checking focus on the offline (a-posteriori) analysis of event logs [3]. This further limits the applicability of conformance checking for a timely analysis of processes executed in the physical world. Moreover, process descriptions for humans are often not provided as formal process models but in more informal ways such as guidelines, checklists or policies [6]. These informal descriptions may be interpreted in multiple valid ways, resulting in *ambiguities* of the process models and executions [7]. These ambiguities, as well as ambiguities from event logs (cf. [8]), must be considered for conformance checking.

We propose to use the Internet of Things (IoT) as an enabler for improved monitoring and conformance checking of real-world processes that may exhibit ambiguity. With the adoption of software-controlled IoT sensors and actuators, we are able to sense physical process executions and generate corresponding digital representations (traces), enabling conformance checking for those aforementioned settings where event logs are not available or incomplete.

The **goals** of the *ProAmbitIon*[1] project are to:

1. Investigate how to enable domain experts to enrich process descriptions with IoT-related execution aspects and use these for the monitoring of process elements (e.g., activities).
2. Investigate how conformance checking can be used in the presence of ambiguities to check the correctness of process executions and provide interpretable feedback to end-users.

Towards these goals, four research questions drive the project development:

- *RQ1*: How can domain experts be enabled to enrich informal process descriptions with IoT-related execution criteria for event abstraction and correlation?
- *RQ2*: How can stream analysis techniques be used to derive process event logs and event streams from possibly ambiguous IoT data?
- *RQ3*: How can conformance checking be used in both offline and online settings on IoT-based process event logs and streams that possibly contain ambiguities?

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- *RQ4*: How can end-users be provided with understandable feedback about conformance regarding process execution and with means for resolving remaining ambiguities?

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2. Project Objectives and Tangible Outputs

The project proposes to use the IoT as an enabler for an improved monitoring and conformance checking of ambiguous processes. The overarching objective is to develop a comprehensive framework that allows: 1) annotating informal process descriptions (e.g., activities) with monitoring points linking to IoT devices; 2) online monitoring and conformance checking of process executions through the associated IoT devices while managing ambiguity; and 3) providing interpretable and interactive feedback on the conformance.

The project will be conducted following design science research principles, and is expected to produce a number of artifacts:

- A framework for IoT-driven process event log and event stream generation based on annotated process descriptions.
- A domain-specific modeling language and tool to annotate and translate informal process descriptions with monitoring points following a low-code approach.
- A catalog of event patterns relating process activities with IoT data to support the annotation of process descriptions.
- A framework for the online analysis of IoT event streams to abstract to process events based on Complex Event Processing (CEP) [9].
- An approach for online conformance checking considering ambiguities and providing interpretable user feedback.
- Alignment techniques for process models and process event streams generated from IoT event streams in the presence of ambiguities.
- Mechanisms for providing interactive feedback about process conformance to show and resolve ambiguities.

3. Relevance of the Project

Several challenges at the intersection of the BPM and IoT research communities have been identified in the BPM-IoT manifesto [1]. With this project, we address multiple open challenges related to using IoT data to analyse the execution of business processes. We expect to advance the state-of-the-art of information systems engineering as follows.

Considering IoT devices as novel data sources for process activity detection (cf. [10]), we will be able to monitor and analyze processes executed even in the absence of a BPMS or other

Process-Aware Information System (PAIS) acting as the execution orchestrator or monitor. Additionally, the developed monitoring and analysis methods will be useful to complement BPMSs or PAISs, advancing the capabilities of existing systems and enriching process event logs with IoT data [11]. This will help closing the gap between the physical and digital world representations of processes, and bridging event-based and process-based systems [1].

To abstract IoT events to process events (cf. [9]), we will elaborate on the annotation of process descriptions with *monitoring points* associated with IoT devices and IoT event patterns [12]. The artifacts designed for defining monitoring points and the respective event abstraction procedures will simplify the generation of process event streams from IoT data. The IoT-based event patterns, in analogy to [13], will result in a patterns catalog that will be useful for system analysis in terms of patterns support and for the systematic development of event-based systems.

Considering processes with ambiguity, we will target the healthcare domain, which is characterized by high human involvement and expertise, and semi-informal process descriptions. We will develop procedures for checking process conformance that take ambiguity into account and provide interpretable feedback to the end-users. The project will relax the usual assumption that conformance checking is done in an offline setting and develop online conformance checking procedures to detect deviations also in the case of partial traces. This will require extending the notion of conformance (e.g., to *partial* [14]). Thus, with the project we will advance the state of the art of conformance checking with respect to concepts, procedures, and results presentation.

4. Current Project Status

The project explores novel approaches for IoT-driven conformance checking of ambiguous processes [10]. Two application domains are considered for the development and validation of these approaches: smart manufacturing and healthcare. Processes in these domains present significant differences, e.g., in terms of repetitiveness (resp. variability), structuredness, or degree of automation. Considering these rather diverse domains allows us to demonstrate the general nature of the solutions we will develop with this project. The first milestone for *ProAmbitIon* concerns the development of a suitable scenario for the smart manufacturing and for the smart healthcare domains. The achievement of this milestone is presented here.

4.1. Process in the Smart Manufacturing Domain

The domain of smart manufacturing is becoming increasingly penetrated with IoT technologies to achieve high flexibility and high throughput production processes. Production machines are equipped with a multitude of sensors and actuators producing high volumes of IoT data at various levels of granularity that can be accessed via open interfaces [15]. This data may range from low-level sensor readings to machine states to process-related information emitted from the PLCs (Programmable Logic Controllers) and MES (Manufacturing Execution Systems) controlling one or multiple production machines [16]. However, data quality and frequency may vary in production environments consisting of different types of machines and other IoT devices that are not controlled by one single MES. Legacy machines may only be equipped with a small number of sensors. Standalone devices such as robots or environment sensors may have their own PLCs or other forms of controllers that are not integrated with the rest of the production control. Moreover, despite the high degree of automation, manual steps and human-machine/human-robot collaborations may be a necessary part of a production process that can only monitored by sensors to a limited degree. Thus, deriving a consistent and homogeneous event log suitable for conformance checking from a typical smart manufacturing environment without having a central process orchestration–or at least process monitoring component–in place becomes a very challenging task [17, 18].

As a scenario we take an order-to-product process simulated using our smart factory model [19, 15]. A typical production process starts with storing new raw materials in a warehouse, and then receiving orders for a specific type of product identified by its color. The corresponding raw materials are retrieved and produced following a sequence of steps: *Unloading a raw workpiece from a warehouse – Check the quality of the raw workpiece – Transport the workpiece to an oven – Bake the workpiece – Transport the workpiece to a milling machine – Mill the workpiece – Sort the product – Check the product quality manually – Transport the product to pickup.* As this process follows a strict sequence of activities without a high degree of variability, we will adopt a BPMN-based approach to represent the process [15]. From this rather simplified simulation environment we will gradually move the process analysis to more sophisticated and realistic production environments provided by our associated project partners [20].

4.2. Process in the Smart Healthcare Domain

The healthcare sector is one of the most promising industries for BPM, with numerous undergoing endeavors as healthcare organizations strive for improved process effectiveness and efficiency [21]. Healthcare processes are typically challenging as they are knowledge intensive, loosely structured, mostly manual, and executed without the support of a PAIS [22]. Additionally, they require high flexibility to adapt to unforeseen emergency situations of individual patients. It is not realistic to orchestrate healthcare processes with a PAIS, and monitoring and conformance checking of processes in such a domain is challenging (e.g., due to privacy issues).

To identify a suitable scenario from the healthcare domain, we held a workshop with domain experts from the Division of Infectious Diseases & Hospital Epidemiology of the Cantonal Hospital of St. Gallen. The Division is particularly concerned with the adherence to hand hygiene guidelines, since health organizations have been calling for increased attention to hand hygiene as an effective means to prevent infections [23]. The scenario developed after the workshop was validated in a second workshop involving the same group of domain experts.

The scenario is based on a blood donation process, for which guidelines from the World Health Organization are available [24]. Focusing on the adherence to the hand hygiene guidelines from [23] in the context of the blood donation process, we consider a simplified version of the process composed of 9 steps in sequence: *Perform hand hygiene before touching the donor – Perform preliminary operations – Perform hand hygiene before aseptic procedure – Perform venipuncture – Monitor donor – Remove needle – Perform hand hygiene after potential exposure to body fluids – Perform final operations – Perform hand hygiene after touching patient's surroundings.* Here, the guidelines from [23] state indications for hand hygiene steps to be executed before or after the execution of some blood donation process steps: for instance, hand hygiene must be performed before touching a donor different from the one just touched (e.g., at the beginning of the process), or after a potential exposure to body fluids.

Following the guidelines, the process may look purely sequential; however, in reality the inherent characteristics of the healthcare environment demand for frequent and unpredictable disruptions to the prescribed flow. Such disruptions stem from unforeseen emergency situations (e.g., a donor fainting). They require the healthcare worker to deviate from the sequential execution, interleave the treatments of different donors (i.e., process instances), or perform additional hand hygiene steps before being able to proceed with the prescribed flow of operations. Detecting in particular unforeseen hand hygiene indications is a challenge we take on here. Additionally, often multiple instances of the process coexist in space and time, which makes the IoT-driven monitoring and conformance checking challenging, since certain IoT data–activity–process instance associations might not be obvious. For instance, from just the sensed position of a healthcare worker it might not be clear, which donor in the proximity is being treated.

4.3. Current Work

Currently, we are investigating the detection of process activities from IoT data using our smart factory model. A first approach following an interactive method that relies on domain expert knowledge has been published in [25] and extended in [26]. The method is based on the manual annotation of an IoT event stream with markings for the start and end of activity executions. These annotations define *activity signatures*, i.e., patterns over a multivariate time series that represent the activity execution in the IoT data [26].

Based on these first results, we are moving towards automating the activity detection exploring different approaches in parallel. On the one hand, given a non-annotated IoT data set, we are investigating how to automatically infer patterns for activity signatures based on unsupervised learning methods by finding the start and end times of activities as they occur. This is accomplished by dividing the activities into 'micro-activities'; information about the frequencies of micro-activities is then used to infer the entire activities. On the other hand, given an activity signature, we are studying how to automatically generate CEP-based applications for the detection of similar activities. Changes in the time-series of the signature are determined and translated into CEP queries in a CEP-based language [10]. The resulting CEP apps are deployed to a CEP engine for online activity detection where the CEP app matches the incoming IoT event streams with the sequence of changes encoded in the queries.

Additionally, we currently work on a formal conceptualization of IoT-driven process monitoring in the absence of a BPMS/PAIS. Here we define requirements for IoT-based events to support process monitoring and formalize a monitoring meta-model. These contributions will serve as a formal foundation for the framework for IoT-driven process event log and event stream generation based on annotated process descriptions (cf. Sect. 2).

We are also developing a laboratory environment to simulate the execution of the blood donation process in a controlled setting. We will deploy a set of IoT devices (e.g., presence and proximity sensors, touch sensors) to monitor the execution of the simulated process. We will also design a formal model for the process as the reference for conformance checking. To this end, we plan to adopt DCR graphs as a declarative event-based language [27]. This type of language is particularly suitable for processes requiring high degrees of flexibility. DCR graphs follow an alternative paradigm to the imperative one used for the smart manufacturing process, which is in line with our intention to demonstrate the general nature of the developed solutions.

5. Conclusion

Emerging IoT technologies promise to enhance the capabilities of Business Process Management Systems, in particular for real-world settings where digital traces are incomplete or unavailable. With *ProAmbitIon*, we are exploring novel approaches for IoT-driven online conformance checking of processes with ambiguities at different levels (e.g., in the process descriptions or executions logs). Here we expect several contributions to advance the state-of-the-art in information systems engineering. In the project, we consider scenarios from smart manufacturing and healthcare as two application domains that could benefit from the integration of IoT technologies with process execution and vice versa. The diverse nature of these domains will demonstrate the general applicability of the solutions developed in the course of the project.

First achievements include the definition and validation of two scenarios from smart healthcare and manufacturing. In addition, an interactive method to detect activities from IoT data has been developed. Research on how to automate the activity detection method is currently ongoing, along with a formal conceptualization for IoT-driven process monitoring. Further ongoing work concerns the setup of a simulation environment for the healthcare process.

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