Objectively Assessing the Suitability of Digital Processes for Robotic Process Automation

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Abstract. Finding the most suitable process for Robotic Process Automation (RPA) is a cumbersome task that usually involves a manual process analysis from RPA experts. We propose a concept for objective and partially automated evaluation of the suitability of a digital process for RPA. This concept is based on the methodology of Desktop Activity Mining, a task mining framework that records all user interactions with software during the execution of a process. The collected information is used to answer general aspects that influence the suitability of the process for RPA and the assessment of individual events.

Keywords: Process Mining, Task Mining, Process Assessment, RPA.

1 Introduction

The ever-increasing national and international competition and the resulting digitalization of (business) processes lead to rising demand for automation. In the context of digital processes, automation using Robotic Process Automation (RPA) is one of the most common choices [1]. RPA is the automation of a digital process (activity) by using a software robot that imitates the interactions of a user with software applications and operates on the same interface as a real user would. Therefore, it usually requires little to no changes in the used software and can be applied on top of existing systems. However, despite this advantage, not all processes are suitable for RPA. Key requirements for RPA are the availability of structured data, e.g. databases or text documents, and a rule-based process [1]. Processes where human intervention and judgment are required are not suitable for RPA because robots cannot easily gain the experience an employee collected over years. Recent research is trying to overcome that obstacle by applying artificial intelligence and machine learning algorithms [2].

Before the implementation starts, the question arises as to which process should be automated. This is not a trivial question to answer as many different factors play a role in the selection of the most suitable process for RPA [3]. Hence, the implementation of RPA is usually done by company-external experts who are highly skilled in the usage of software robots but cause high costs and lack an understanding of the process to be automated. To improve this situation we propose an objective and partially automated assessment concept for digital processes based on Desktop Activity Mining [4].

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2 Background

This section provides background on the current state of the art in process assessment regarding their suitability for RPA. Furthermore, a brief overview of the methodology of Desktop Activity Mining is given.

2.1 Processes assessment regarding RPA suitability

There exists a variety of assessment methods that offer a selection mechanism for choosing the right process for an RPA project. Most of these methods are based on information that is collected using an interview or questionnaire. Therefore, the outcome and correctness of these methods highly depend on the quality of the collected data and the expertise of the interviewee.

Syed et al. extract a list of criteria from literature that summarizes the characteristics that a process needs to fulfill to be considered suitable for RPA. According to this list, a suitable process for RPA is highly rule-based, mature, manual, standardized, repetitive, fairly simple, and well-documented. Furthermore, it should have a high transaction volume and cost impact, structured digital data input, and few exceptions and connections to other systems which cause proneness to human error. [3]

This list is supported by several other publications which list similar criteria [5-7] and base their selection scheme on criteria from literature and interviews with RPA experts. Eggert and Moulen add the relief of employees as an additional criterion [5]. Fung also lists frequent access to multiple systems, decomposability into clear IT processes, and understanding of current manual costs as main requirements [6]. Plattfaut et al. group the already mentioned criteria into four different categories: (1) *exclusion criteria* (absolutely necessary), (2) *beneficial factors* (facilitate RPA), (3) *quality factors (*influence the efficiency and efficacy), and (4) *economic impact* [7].

Wanner et al. propose a selection method using quantifiable measures which can be extracted from software event logs [8]. They extract information like execution frequency, execution time, standardization, and stability from event logs and combine it into a quantifiable measurement system. Leopold et al. develop a selection method based on textual process descriptions [9]. They determine whether the textually described task is manual, an interaction of a human with an information system, or automated. Leno et al. search unsegmented UI logs for frequently occurring patterns that are candidates for RPA based on their frequency, length, coverage, and cohesion score [10]. Viehauser et al. propose a quantifiable method to identify and prioritize RPA candidates [11]. The used data, e.g. execution times and frequencies, rule-based nature, and error rates, is collected manually via observations of employees.

None of the presented works offers an objective process assessment regarding RPA suitability based on user interactions, but the majority relies on expert and employee knowledge about the process. Our concept tries to overcome this drawback by adding an objective layer to the existing known requirements. Furthermore, the data collection of our concept is partially automated by using Desktop Activity Mining. This overcomes obstacles like cumbersome and time-intensive employee observation ([11]) and dependencies on textual process descriptions ([9]) or existing log files ([8], [10]).

2.2 Desktop Activity Mining

The vast majority of methodologies and techniques in the field of process mining can be categorized as event data extraction, event correlation, or event abstraction. All of these approaches have in common that they are process-centric approaches that rely heavily on the application landscape and its underlying database systems [12].
In contrast to that, Desktop Activity Mining [4] is an approach that focuses on user interactions (i.e. mouse and keyboard events) with an IT system during a process execution. A chain of interactions makes up one activity of a process, i.e. one abstract process step. Several process activities together form a complete business process. For that purpose, a recording application tracks all user interactions during process execution on the level of mouse and keyboard events. In addition, information provided by the operating system is recorded. This includes unique identifiers of the used applications and UI elements, and screenshots to capture visual information. All information is combined into one process model with two levels of detail: a level of process activities (i.e. process steps), and a level of events (i.e. detailed click stream).
To increase the accuracy of the process model, several instances of the same process are combined into one model. This allows to capture many variants of the same process and construct a very detailed process model. Machine learning and artificial neural networks are used to compare and combine the separate recordings into one model [4].

3 Digital process assessment regarding RPA suitability

Based on the literature review, we propose a new concept for assessing the suitability of a process for RPA implementation. This concept consists of three layers that aim to evaluate a process from different perspectives. The goal is to improve the assessment by applying objective measures in addition to the qualitative surveys in literature. The first layer of the concept combines and structures criteria from related work. In the second layer, Desktop Activity Mining is used to collect information about the executed process and answer questions from the first layer. The third layer evaluates the automatability of single user interactions with the software in the process. While the first layer still requires some manual work, the second and the third layer are highly automated and only require the triggering of the process recording application.

3.1 First layer: General assessment

The conducted literature review led to a selection of criteria based on the rating and frequency with which they occurred in related work. We split the pool of criteria into two categories, *mandatory* and *optional.* [3, 5-7]

Mandatory requirements. We identified five requirements as mandatory for the implementation of RPA. The process in question has to be (1) a digital process using IT systems, (2) rule-based, (3) repetitive, (4) stable, and (5) use structured digital data. If one of these requirements is not met, an RPA implementation is not recommended.

Optional requirements. The identified optional requirements are separated into 4 categories: *favorable*, *unfavorable*, *volatile*, and *cost-benefit* criteria. *Favorable* criteria increase the benefits of RPA if they are present in the process. They include proneness to human errors, many different software systems, long human execution time, knowledge monopoly of one employee, and little employee capacity. *Unfavorable* criteria limit the success of RPA and include high process complexity, use of unstructured data (e.g., scanned documents), the necessity of human judgment and intervention, better performing alternative solutions, and sensitivity to process downtime. *Volatile* criteria are favorable or unfavorable for the success of RPA, depending on their concrete manifestation in the process and company. Acceptance and cooperation from employees, and implementation of data protection rules and regulations fall into this category. *Cost-benefit* criteria directly influence the economic success of an RPA implementation. These criteria include the transaction/execution duration and frequency, costs for IT-system changes and employees, and costs due to errors in the process execution before and after the process automation.

Based on the extracted *mandatory* and *optional* criteria, we created a questionnaire to gather information about the process that should be automated. This questionnaire is given to all involved parties in the process, which includes the employees who directly execute the process, but also supervisors and management parties. The diverse selection of interviewees ensures proper answers to the questions from all categories.

The questions regarding *mandatory* requirements are formulated as yes-no questions. All of them have to be clearly answered 'yes' to indicate a potential candidate for successful RPA implementation. The *optional* requirements are evaluated using a value scale from 1-10 with 1 denoting a complete non-fulfillment and 10 a total fulfillment. The values of all answers are combined and weighted considering whether the criterion is positively or negatively influencing the automatability.

3.2 Second layer: General assessment using Desktop Activity Mining

The second layer focuses on objectively answering some of the questions that are raised in the first layer. The answers of employees are often neither objective nor completely correct. Therefore, our goal is to remove this uncertainty from the selection of processes for RPA by using Desktop Activity Mining as an assisting, objective measure.

The prerequisite for using Desktop Activity Mining in the decision process for RPA, is the recording of several instances, of the process. The more variants of a process are recorded, the better the resulting process model and hence the selection process becomes. The following information can be extracted using Desktop Activity Mining:

Number of IT systems and applications. Desktop Activity Mining records the application in which an event that is relevant to the process is executed. This directly allows answering the question of how many different applications and IT systems are involved in the process and how many transitions between those applications are made.

Execution frequency and duration. How long one execution of a process takes on average can easily be determined by recording several instances of a process and measuring the real execution time of the process. Also, the execution frequency per month/year can be determined if the recording procedure captured all executions over a certain representative period of time, e.g., one week. Both values directly influence the *cost-benefit* criteria and the economic success of the RPA implementation.

Process complexity. The number of process variations and their frequency can be extracted based on the retrieved process model. The number and frequency of certain paths in the process model can serve as a good measure for the complexity of the process. A high complexity falls into the category of *unfavorable* criteria because it increases the difficulty of an RPA implementation.

3.3 Third layer: Assessment of individual events using Desktop Activity Mining

The third layer evaluates all single events of a process execution with respect to their RPA suitability on a scale of 1 (not suitable) to 10 (very suitable). The following event types are evaluated based on the information that Desktop Activity Mining captures:

Mouse clicks. The most relevant factor for automating mouse clicks is the possibility to clearly identify the correct UI element of the user interaction. As Desktop Activity Mining stores identifiers for the UI elements that were relevant in the event, we can leverage that information to check whether the identifier appears to be unique across the process and can therefore be used for a clear identification of the UI element. We additionally use computer vision techniques on screenshots to retrieve more information. Using detection/filtering algorithms and Optical Character Recognition allows us to get a region of interest for a mouse click, including e.g. the text on a button.

Keyboard inputs. Keyboard inputs are handled similarly to mouse clicks regarding the collected identifiers. However, the screenshot recognition cannot directly be applied because most of the time keyboard inputs happen in a text field that is visually not very distinct. Only extracting the white text field as the region of interest does not provide any additional information.

4 Current research and upcoming results

Our current research includes the integration of all three layers into one score that indicates the suitability of a process for RPA. The mandatory requirements from the first layer provide a stop-or-go decision for further evaluation. The optional requirements are partly answered by the described questionnaire and partly automatically by using input from the second layer. The resulting values (1-10) of all optional requirements are weighted and combined to one score. This score is then combined with the average score of all events from the third layer. The combination results in one score (1-10) that indicates the suitability of the process for RPA.

Furthermore, we work on extending the features of Desktop Activity Mining to include even more criteria in the second and third layer. This includes not only storing an identifier for the active UI element but more context-related information about the neighboring UI elements and the element tree in which the current event is embedded.

One of our major remaining goals is to evaluate the approach described here. For this purpose, we plan on evaluating real-world processes under the participation of process owners according to the presented method. To assess the validity of our concept we compare it to the approaches described in [7] and [11]. Furthermore, the resulting evaluations are then qualitatively assessed and compared by process experts.

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