Process Management Enhancement by using Image Mining Techniques: A Position Paper

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Abstract: Business process modeling is a well-established method to define and visualize business processes. In complex processes, related process models may become large and hard to trace. To keep the readability of process models, process details are omitted. In other cases, process designers are not aware which process steps should be modelled in detail. However, the input specification of some process steps or the order of internal sub-steps could have an impact on the success of the overall process. The most straightforward solution is to identify the cause of reduced process success in order to improve the process results. This can be challenging, especially in flexible process environments with multiple process participants. In this paper we tackle this problem through recording image data of process executions and analyzing them with image mining techniques. We propose to redesign business process models considering the analysis results to reach more effective and efficient process executions.

1 INTRODUCTION

Companies use business process models to visualize and control internal workflows describing the necessary process steps for each process participant to reach a company goal, for example manufacturing a certain product. Such process models may contain hundreds of modeling elements leading to large and hardly traceable process models (A. Polyvyanyy, 2008b). Besides, though there exists modeling recommendations regarding general aspects like correctness or comparability (J. Becker, 2000), there is no concrete rule or guidance how detailed a process has to be modelled. Thus, it is quite obvious that processes are often modelled in an abstract way to keep up clarity and traceability. Sometimes also missing knowledge about process details prevents a process modeller to add more detailed (sub-)steps. This high level of abstraction leads to the fact that detailed information of process steps are omitted (R. Bobrik, 2007), (A. Polyvyanyy, 2008a). Two typical examples illustrate the observation from above.

In a first case, diverse liquids have to be filled into a casting mold. Due to missing knowledge or due to keeping the process description simple, the process modelers describe this process step on an abstract level as “add all ingredients”. Looking into process details reveals that three ingredients have to be added. So the process could also be refined into three process (sub-)steps ”add blue liquid”, ”add red liquid”, and ”add green liquid”. Process participants are free to choose the execution order of low-level process steps which are not modelled but contained implicitly, leading to an excessive flexibility in the execution step. In some other cases, process modelers are not aware of the optimal execution sequence of process steps. For instance, they allow that two steps are executed independent from each other, i.e. in arbitrary order. However, the execution sequence does have an impact on process performance, regarding the execution time and/or the quality of process outcomes. Following the example above, the addition of the red liquid as second step instead of third step results in a mixture with reduced binding capability, i.e. this execution sequence is finally not desired. This affects the overall process success since the result of any subsequent task depends on the quality of the mixture.

In a second case, parts have to be disposed on a pallet. Again, due to missing knowledge or due to keeping the process description simple, the process designers are not more specific about placing the parts on the pallet. Furthermore, some tasks are hard to describe or important details can’t be described with established process modeling languages. In this palleti-

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sation scenario this may include (i) information considering the position of objects in the product environment, (ii) information that is related to special movements. If modellable, such information can only be integrated in a process model through a large number of process modeling elements. Especially if different alternatives are allowed, the number of modeling elements strongly increases what contradicts the ideal to keep business process models traceable through preserving a certain level of abstraction. Although there are approaches that deal with that challenge, e.g. (Wiedmann, 2017), (M. La Rosa, 2011), (A. Polyvyanyy, 2008b), they assume that knowledge about the correlation between this details and the process success already exists. To guarantee the success of a process and to enhance its execution, necessary details of activities that are not contained in the business process model have to be discovered while satisfying the following three conditions:
1) Process analysis has to be done automatically since participants are not aware that execution details may influence the process success. Also in the case that the process model is executed for the first time, no prior or expert knowledge exists. Furthermore, the analysis should be done with a minimum interference in the regular working process to ensure correct results.
2) The analysis should be able to identify the cause of reduced process success by extracting necessary information and developping suggestions for improvement.
3) The extracted information has to be represented in the process model in an appropriate way.

Although quality control and process monitoring are popular topics in research, existing approaches (e.g. (D. E. Lee, 2006), (T. Prykäri, 2010)) focus on the identification of deviations in process results but do not meet the listed requirements. In this paper we suggest to tackle this problem by recording and analyzing image data of activity executions. We propose to apply image mining techniques in the process management context to enhance business process models and ensure process sucess.

In our work, we extract necessary process steps and related information from image data which is not yet contained in the existing process model. In order to identify these missing details, we propose to use established image mining techniques. The process model is then enriched by this content through adequate techniques. We therefore go beyond the limitations of regular process modeling languages.

In general camera systems are cost-efficient sensors which often already exist in small- and medium-sized enterprises and industrial working areas. Recorded image data created in such process environments contains valuable information which is often not fully analyzed. Image data can either contain static information, like the input or output of a task or dynamic information, like the task processing itself. Both may contain necessary information for process enhancement. In our conceptual approach, we therefore dinstinguish between the analysis of images and videos. Images are related to snap-shots of the execution while videos capture the whole execution of the task including related subtasks.

Our overall system meets all three requirements as described above. Furthermore, the image analysis results of our conceptual approach may serve as input for recommendation systems to support given recommendations. For example, our system reveals the best execution of an activity and therefore identifies the most suitable process participant for this task. In contrast to previous work that relates images to process context, we focus on the process execution step and analyze recorded image data that contains real information of the process environment.

The remainder of this paper is structured as follows. The following section summarizes background information and gives an overview of important related work. Section 3 presents our conceptual approach to reach process enhancement through analyzing image data and points out our contribution. We conclude our work and give a recommendation for future work in Section 4.

2 BACKGROUND AND RELATED WORK

In general, images can be understood as complex data collection. Depending on the context in which they are created, the knowledge about this context and other associations, images may contain meaningful information if analyzed and interpreted correctly. How to achieve an effective extraction of this information is the research question in work that is related to image mining. According to (J. Zhang, 2001), *image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the image databases*. Among others, different methods from computer vision, data mining and machine learning are used to process low-level pixel representations contained in raw images or image sequences in order to identify high-level spatial objects and relationships. The overall image mining process is well described in (M. Hsu, 2010). Summarized, the process can be divided into three parts:
Pre-processing: In order to reduce the cost of the analysis step which can be high in time and space,

images have to be preprocessed. Therefore unnecessary or unrelated data is cleaned up and quality reductions due to noise are eliminated through filtering operations. This step may include image-thresholding, border-tracing an wavelet-based segmentation.

Feature Extraction: Algorithms are used to detect features such as shapes, edges or other basic elements in the images. Therefore the image content is reduced while unimportant features can easily be discarded. A promising feature extraction approach can be found in (P. G. Foschi, 2002), where a combination of the features color, edge and texture is suggested.

Image Mining Technology: Image mining techniques are used on the extracted feature vectors to reveal, evaluate and explain high-level knowledge. Several methods have been developped which realize this procedure in different ways: Image classification, clustering, indexing and retrieval, object recognition, association rule mining and approaches that work with neural networks.

The techniques are used in many different real-world applications, like for example the analysis of paths and trends of forest fires over years in satellite images in order to enable firefighters to fight fire more effectively (J. Zhang, 2002). Another work uses images gathered from the Web for learning of a generic image classification system and enables a Web image mining approach for generic image classification (Yanai, 2003). Image mining was introduced by (Ordonez and Omiecinski, 1998) as new approach for data mining. The fundamental concepts of discovering knowledge from data stored in relational databases are transfered to image databases.

Related to this idea and the fact that process mining builds on data mining, also the association of image mining with process mining techniques or rather the application of image mining in the context of business process management is reasonable. However, the application of image mining techniques or in general the integration of images in this field is not yet fully explored. The work of (Wiedmann, 2017) and (R. Schmidt, 2016) suggest two different approaches to introduce images and related mining techniques in business process management. In the thesis of (Wiedmann, 2017), the business process modeling language BPMN is extended to a more intuitive modeling language which allows to annotate tasks with multimedial content like images or videos. This approach enables to add non-formalized descriptions to a process task and enriches the process model with additional information. During the execution of this task, process participants can follow the referenced execution in the video. The work of (R. Schmidt, 2016) confirms the potential of image mining for business process management. The process management lifecycle according to (M. Dumas, 2013) is presented and the application and intregation of images and suitable image mining techniques for each phase are discussed. This approach focuses on image data which is created in each phase. The authors differentiate between documents, drawings and pictures, while documents contain textual information and are analyzed with optical character recognition methods. Drawings and pictures are analyzed by using one of the image mining techniques as described above. Furthermore, the authors present a protoype for object recognition of business process models which detects modeling elements like gateways, activities etc. from images.

Altogether, both authors explain how images contribute to support the overall process. Particulary interesting is the suggestion of (R. Schmidt, 2016) to analyze pictures, taken with phones or tablets, which contain information of the production environment. Covering the process monitoring and controlling step, these images are analyzed subsequently in order to find possible process improvements. This proposal corresponds with our approach, while we share the idea that any issues that may reduce the overall process success could revealed through monitoring the process execution.

In contrast to the work of (R. Schmidt, 2016), we suggest a concrete approach that aims to process improvement through an overall system that solely bases on the image data that is produced in the process execution step (cf. Section 3). Our system is restricted to images or videos which contain real information of the production environment or capture actual states of a product. We go further by restoring the analyzed improvements in the existing process model. For this we propose to translate them in the considered process modeling language or to use media annotations like suggested by (Wiedmann, 2017). Compared to classical machine vision approaches that control the quality of a product like (Manigel and Leonhard, 1992), (H. Paulo, 2002) or (E. Saldana, 2013), our concept starts one stage earlier and identifies the causes of defects in products if they are related to human task executions. However, such systems can easily be integrated in our overall concept while the implemented techniques can be used in the image analysis step of our concept.

3 CONCEPTUAL APPROACH

We illustrate our conceptual approach by a running example. In this example, a certain product has to be manufactured according to a process model *PM*. We

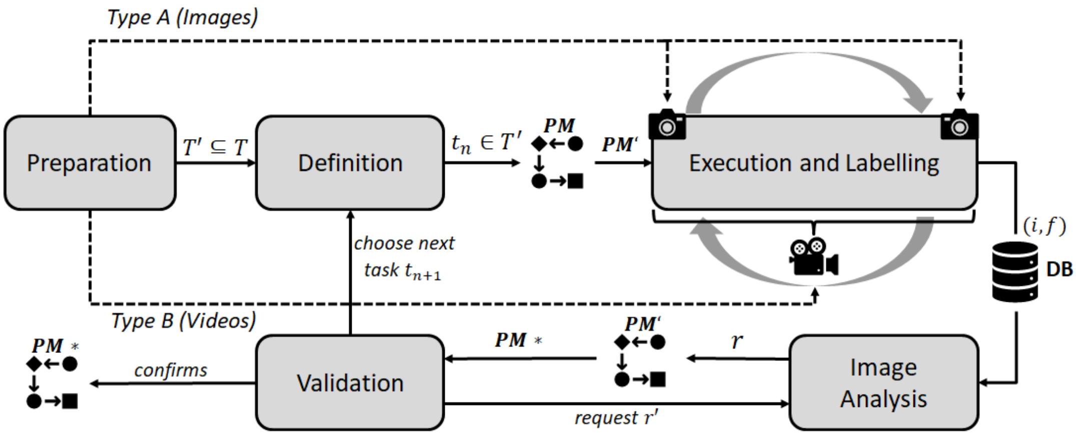

Figure 1: Our overall concepts consists of 5 high-level steps while in one cycle, task t_n of all process tasks T is taken into account. Furthermore, the existing business process model *PM* is adapted to PM' and the database *DB* serves as storage for pairs of recorded image data (images and videos) and related feedback of each process execution (i, f). Based on the validation of the calculated reference data r, either *PM* is extended with missing information to $PM*$, or new reference data r' is evaluated or $t_{n+1} \in T$ is taken into account.

assume that *PM* contains all tasks T of the process necessary to create that product. Although all (most) process executions were successful, i.e. the manufacturing processes were completed correctly, the final products were revealing quite different quality. Since the process model is already in place and process executions did not show errors, the assumption was that not all process steps were modelled – and thus finally performed – optimally. The process experts presumed that either (i) some of the process steps were not modelled in enough detail, i.e. are too abstract since internal sub-steps are not specified sufficiently (process steps of Type A); or that (ii) the input specification of some process steps were not modelled prescriptively enough (process steps of Type B). Focusing these two flaws in this paper, our conceptual approach comprises the following 5 steps (cf. Figure 1).

1. Preparation.
By examining the process model, the process experts identify all tasks of Type A and Type B as candidate steps that might lead to disparate production results. Although, at this point in time, the process experts still do not know whether this assumption is correct and in case it is correct how the solutions would look like. All tasks that meet these conditions are summarized in a task list $T' \subseteq T$. To continue our overall example, we assume that we analyzed *PM* while identifying exactly two tasks t_1 ("add all ingredients to the glass") matching *Type A* and t_2 ("place all machine parts on the palette") matching *Type B* with $t_1, t_2 \in T$ out of overall n tasks ($|T| = n$) leading to $T' = \{t_1, t_2\}$.

2. Definition.
In this step, all tasks contained in T' are analyzed incrementally. That means that any task $t \in T'$ is selected and prepared for further examination. Therefore *PM* has to be redesigned to PM' while the definition of t has to be adapted as follows. If t belongs to *Type A*, the new definition of this task has to contain the information that its execution has to be monitored by recording videos of the execution. If t belongs to *Type B*, the task has to be redesigned so that an image has to be taken. Depending on the context, the image has to be taken at the beginning, before starting the execution or after finishing the execution of t. Furthermore, a camera system has to be provided and installed in order to enable the recording of image data. In our example, the process experts perceive that task t_1 is composite. However, they are not sure what the sub-tasks are at all. So, they should monitor the upcoming executions of this process step by videoing it. Additionally, the process experts see that task t_2 requires a complex input configuration. Thus, it is proposed that process experts take pictures of the input configuration of upcoming process executions. Due to the presumption of the process experts that t_2 might have more impact on the overall process sucess, they decide to start with the analysis of t_2. Therefore *PM* is redefined in the way that an image is taken after placing all machine parts on the palette.

3. Execution and Labelling.
In this step, the redefined process model PM' is executed and image data (images and videos) is generated as specified in the model. At the end

of each process execution, the data is labelled, i.e. process experts evaluate the process success through giving feedback considering different criteria. Traditional criteria that are related to process success are the production time, cost and quality of the result (A. Collins, 2004). We suggest to implement the feedback step at the end of the overall process execution in order to identify the influence of the considered task on subsequent tasks in the process model. Depending on the situation and the issue, giving feedback directly after the execution of the considered task possibly does not reveal correlations within the process like we will see later in the example. However, if the feedback is given directly after the execution, the considered task is analyzed related to classical machine vision approaches but provides more flexibility. For both alternatives it should be ensured that all feedback refers to the same criterion in order to enable comparability between them. Any feedback f and the related image data i that has been recorded during the execution step are stored as pair (i, f) in a database DB. Each set of image data referring to one execution is hence associated with an evaluation of success. This procedure is repeated until DB contains enough data to serve as basis for a meaningful analysis. In our running example, we assume that PM' is executed 100 times under the assumption that we know that 100 executions provide a sufficient data basis for analysis. This means that 100 images are recorded, which show the resulting palette after an employee placed all machine parts on it. Together with the associated feedback 100 pairs (i, f) are stored in DB.

4. Image (and Video) Analysis.
In this step, all entries in DB are analyzed by using image mining techniques including all 3 parts of the image mining process (cf. Section 2). Depending on the type of i that is stored in DB, different objectives are defined and therefore different methods have to be applied. In all cases, the overall goal is to analyze the differences between all entries and to relate them with the feedback in order to identify which differences cause good or insufficient process results. Based on the analysis results, reference data r is created which serves as input for the validation step and the camera system. This data can be understood as the image data which is recorded in the context of an ideal execution and is used as guideline for further executions.

If DB contains images (i.e. i is from Type A), it holds entries capturing the same state of each process execution. To somehow compare these images and to find relevant features that differ them, image retrieval techniques as well as image classification and image clustering are suitable methods. But also the application of neural networks is quite promising, especially in finding an adequate reference image. The most promising image, i.e. the arrangement that is rated best after feedback evaluation, is stored as guideline in r.

If DB contains videos (i.e. i is from Type B), it holds several recordings of the full execution of the same task. As described above these executions may differ in the order of underlying subtasks. Therefore all subtasks has to be identified in a first step and then the order of them has to be analyzed and compared in a second step. These requirements could be reformulated as challenge to extract event logs and therefore process models from videos and to find techniques to compare them. The order of the subtasks that has the most success is finally stored in r.

In our example, the 100 entries in DB are analyzed, while it turns out that the positioning of the machine parts on the palette seems to have an impact on the overall process sucess. The image data which refers to an ideal execution is stored in r and is prepared as input for the camera system.

5. Validation.
The instructions identified in phase "Image Analysis" are incorporated into PM' resulting in $PM*$, while t is modified to match r. Therefore PM can be extended by additional modeling elements to include necessary subtasks or other detailed information. Alternatively we suggest to follow the concept of (Wiedmann, 2017) and to use media annotations. This approach enables the integration of image data and allows the use of a more powerful process modeling language what supports our idea of process enhancement.

Afterwards, this new process model version $PM*$ is further executed. Observing and measuring process success determines whether this new version of a process is accepted or further investigation have to be undertaken. In the latter case, the whole process improvement process has to start from its beginning.

To realize this procedure, t is still taken into account and image data is recorded while $PM*$ is executed. In contrast to the previous execution step related to PM or PM', process participants now execute an estimated more successful version of t. Furthermore, the camera systems recognize deviations, leading to an interruption of the execution if the recorded image data differs from r.

Figure 2: The image i recorded after executing a task (left), the reference image r (middle) and the calculated difference image (right). Black areas in r refer to pixel colors that deviate from each other, while white areas indicate same pixel colors.

If it does, the execution has to be adapted until it matches r including a predefined threshold. In this step, again image mining techniques are used to identify this deviations. Just as in the previous execution step, pairs of image data and feedback are collected and analyzed in order to validate if the restriction to executions that relate to r really lead to process sucess. If the validation fails and DB still contains negative feedback, either r has to be recomputed based on a larger number of entries in DB or t was not the task that led to the unsatisfying process success and the procedure has to be repeated for the next task $t' \in T*$ while $T* = T' \setminus \{t\}$. If the definition of r as guideline leads to more successful process executions, the modified process model $PM*$ replaces PM.
Applied to our example, we assume that the process model is adapted as described above. We further assume that during the execution of t_2, deviations are detected because a machine part was placed wrong on the palette. For this we implemented a prototype and built up a small scenario according to t_2 as shown in Figure 2. While there exist several approaches to find the difference in two frames, one of the easiest ways is to determine the pixel differences. In this technique the number of pixels that change in value more than some threshold are counted (cf. (Boreczky, 2006)). By comparing i and r it can be seen that two of three machine parts differ in their position and orientation leading to their reoccurences in the difference image. In this example we assume that the validation step fails. The process experts decide to further examine t_2 instead of taking t_1 into account. Therefore further process model executions are performed in order to reach a larger data set for DB and to identify a better reference image r'.

The presented example shows how our concept can be applied to enhance processes through using image mining techniques. Our approach enables the identification of process model execution details that have an impact on the overall success of the process. The existing process model is only extended by information, which is identified as necessary in the analysis step. Therefore the predefined abstraction of the process model is preserved but details which improve the overall process are included.
Since the presented idea considers the overall success, it is possible to reveal complex interrelations and dependencies between tasks that are not contained in the process model but influence the process result. Quality assurance approaches only evaluate the result of a single (mostly non-human) task execution. Therefore they are only able to analyze the direct correlation of a task execution with its output. In contrast, we suggest to consider the overall process success and to focus on all tasks, where the input is not fixed or multiple executions are possible. Our concept therefore enables to analyze the effect of a task on a subsequent task which leads to a reduction of the process success. In most cases, all single tasks were executed according to their rules defined in the process model while an direct evaluation of the task execution result would confirm process success. In contrast, the result of the overall process might not be satisfying. At this point, existing approaches reach their limitations since they are not able to identify the cause of the reduced process success sourcing in the dependency between tasks. Like described above, our concept tackles this issue and provides a more general process execution analysis.
Our approach is based on the analysis of image data while we therefore introduce an innovative application of image mining techniques in the process management context. Image data serves as valuable source for complex analysis since it has high information content, provides several features and supports the flexibility of our approach. This flexibility reflects in the possibility to deal with static as well as dynamic information related to the process environment.

Concluding, our system does not only extract relevant features from images but identifies process execution dependencies affecting the process success and suggests reference data related to optimal executions. We want to point out that the intregration of this information in the existing process model is important to ensure process success in future executions, while we suggest media annotations presented by (Wiedmann, 2017) as adequate technique.

4 CONCLUSION AND FUTURE WORK

In this paper we present our idea to use image mining techniques in order to enhance business processes. We suggest a flexible approach which is based on monitoring process executions while image data related to the process environment is collected. This image data is labelled and analyzed to identify execution-specific features that have an impact on the overall process sucess. We further show how this information can be integrated in existing process models to enhance future executions without reducing the traceability of process models. The review of existing approaches confirms that the application of image mining techniques in the process management context is an open research gap.

As for future work, technical aspects have to be discussed which include the evaluation of existing image mining techniques depending on the use case. Furthermore, we plan to implement an overall prototype and to proceed evaluations with simple examples. Finally, we intend to further investigate the realization of our idea in real process environments. We will collect broader use case scenarios and explore suitable application areas.

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