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Automated work cycle classification and performance measurement for manual work stations

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ABSTRACT

The increasing demand for highly customized products requires flexible, reactive and adaptive manufacturing systems. Accurate and up-to-date information about the processes is a strict requirement to meet these needs. Real-time data capturing technologies, such as RFID, have already been used for some years in manufacturing environments, mainly for inventory management, planning and quality control. However, these systems fail to generate information on the performance of the operator in the system. This paper presents a video-based system that automates the analysis of manual assembly line work stations and generates near real-time information to support workers in their pursuit of continuous improvement. A work cycle classification method was developed to detect anomalous and problematic situations in the work flow. Besides the classification of work cycles, the method also generates performance indicators to analyze the performance of the operator in the system. These performance indicators are visualized in an operational dashboard, which reveals the improvement potential of the work station.

1. Introduction

In the last decades, manufacturing companies had to deal with an increasing demand for more customized products. This shift from mass production to mass customization has increased the complexity of both manufacturing processes and their support systems. In order to stay competitive, these companies are forced to continuously monitor, analyze and redesign their processes. One of the major challenges is the collection of reliable and detailed data about the current process. Existing work measurement techniques are still relying on stopwatch measurements and manual video analysis, making them prohibitively time-consuming. More advanced and automated techniques are therefore required to support improvement of the continuously evolving contemporary production facility.

The progress in data capturing, storage and communication technologies has facilitated the use of video images in a vast variety of applications. Video content analysis has the ability to automatically analyze a video and detect and determine certain events. Well-known applications are found in sports analytics software [1] and video surveillance [2]. In manufacturing environments, motion capturing is mainly used for quality control [3], monitoring automated production lines and measuring and simulating the ergonomic load of workers [4]. In this research, this technology is used to capture information about the operators' behavior and work method.

This paper proposes a vision-based automated method to support manufacturing companies in monitoring, analyzing and redesigning their manufacturing processes. The system monitors workstations with one or more operators, and has two main functions: providing basic performance measurements and detecting problems or inefficiencies by recognizing abnormal operator behavior. The non-intrusive character of vision technology is one of the main assets of the system. Because of the fact that the system does not interfere with the operator, it is able to generate unbiased data and information over a prolonged period of time, unlike the manual analysis tools used today.

The system makes use of multiple cameras to track the movement of the operator within his work station. The captured work cycles are clustered and classified in order to detect abnormal behavior or anomalous events. The system identifies these events and returns the video footage of the concerning work cycle to the user. By accurately tracking and indicating these problematic situations, the system significantly accelerates the analysis and redesign process of assembly line work stations. Besides searching for anomalous events, the system also calculates the necessary performance indicators (KPI's) to assess the performance of

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a work station and more specifically the worker in the system. These performance measures are visualized and summarized in an operational dashboard. This dashboard provides a very visual and comprehensive view on the performance of the work station and could therefore allow operators to self-monitor their work in real-time. Moreover, the potential to automatically generate work instructions makes this system an important part of any operator information system.

This paper continues as follows: Section 2 describes what systems are currently used in industry to automatically analyze and improve manufacturing processes. Section 3 explains which methods are used for classifying the work cycles and how the performance measures are calculated. In Sections 4 and 5 the experimental setup is described and the results of these experiments are discussed. Finally, our conclusions are presented in Section 6.

2. Related work

Contemporary market demands require highly flexible and adaptive manufacturing systems. As opposed to conventional automation systems, humans have the capability of learning and adapting their behavior based on what they observe. These cognitive capabilities of highly skilled assembly workers are still the keystone to provide the level of flexibility, adaptability and reliability needed in a modern production environment [5]. In order to maintain the flexibility while maximizing the efficiency of the process, workers should be supported by automated systems that provide them with real-time information about the process and pinpoint opportunities for improving efficiency and profitability. Cognitive automation in an assembly line context supports decision-making in order to increase the quality of products [6]. The positive effects of an increased level of Automation (LoA) are widely reported in literature [7,8]. Most of the existing cognitive automation systems focus on providing the operators with real-time data about work instructions in order to decrease the number of errors and improve quality. Examples of such systems are described by [9,10]. Our research aims to extend these systems by providing information on how these tasks are performed in order to facilitate continuous improvement in the work station.

Constant capturing and tracking off accurate real-time process data is thus a necessity. The rapid evolution and development of wireless communication technologies such as Bluetooth and RFID have created new opportunities for monitoring new parameters throughout the whole lifecycle of a product [11]. Real-time data capturing systems based on RFID technology are already used in manufacturing applications mainly for inventory control [12], quality control [13] and job floor process control [14,15,16]. In assembly work stations, RFID readers have been used to monitor progress in order to inform workers about inspections and required test procedures and to automatically update the central production database [17]. These new technologies are part of industry 4.0, where cyber-physical systems communicate with each other and humans over the internet of things in so called smart factories [18]. Most of these systems generate loads of accurate real-time data about the process, however very little of this information is directly relevant for the workers.

Gröger et al. [19] proposed an Operational Process Dashboard for Manufacturing to support the operator to improve processes. They identified four main areas of process-oriented information that is relevant for operators:

- Process context: information about the context of both the overall process and specific process steps in order to create a general understanding of the entire process.
- Process performance: metric-based performance measures that supports the workers during their decision making process.
- Process knowledge: information on the actual execution of process steps and opportunities for process optimization.
- Process communication: transfer of information between all participants in the process.

This research mainly focusses on measuring performance and capturing knowledge. By generating performance measures that are directly related to the operators' performance, detection of inefficiencies and failures, capturing best practices and document this with video data, the system creates a vast amount of data and information that is directly relevant for assembly line workers. The use of human motion capturing techniques in assembly environments has been reported in literature. Examples found in literature aim to capture human motion to and use this data to improve the prediction of human motions in virtual simulation models. These methods rely on marker-based motion capturing techniques [20] or systems that use Kinect data [21], together with force and tool embedded sensors [22]. Multi-camera vision systems have been used to monitor the operator's safety in a human-cobot collaborative work cell [23]. Prabhu et al. proposed a method to simultaneously monitor and record human-workpiece interaction using a Kinect camera. The aim of their research is to create a better understanding of these interactions and obtain useful information for enabling automation scenarios [24].

None of the aforementioned monitoring systems feed the captured information back to the operator. This research aims to extract information for the human motion data and present this information to the operator directly in order to facilitate continuous improvement of assembly processes.

3. Methodology

3.1. Image processing

The system uses multiple cameras to track the operator during his work. The position of the operator in the video streams is calculated by generating a 3D-model of the operator from the synchronized footage of these multiple cameras as described by Slembrouck et al. [24]. The trajectory of the operator is then reconstructed by taking the 2D-projection of the operators' body of mass on the ground plane of the workstation in every video frame (50 ms). To create the 3D model of the operators' body, a visual hull is generated for every video frame. First, foreground-background segmentation is used to generate a mask that visualizes the position of the operators' silhouette in the 2D camera view for each camera. The physical space is divided in cubes of 2 cm × 2 cm × 2 cm, called voxels. For every camera, these voxels are mapped to their 2D projections (pixels) in the camera view. Voxels for which their 2D pixel projection belongs to the foreground mask are considered as occupied. These voxels create a so called generalized infinity cone with the operators' as the base and the camera as the apex. Performing the same procedure for each of the five cameras, results in five different infinity cones. Only voxels that belong to each of these infinity cones are kept to create the 3D model of the operators' body [25]. Fig. 1 visualizes this concept for a system with 4 cameras. Starting from the infinity cone created by one single camera (top left), the 3D model is systematically refined by carving away the voxels that don't belong to the infinity cones of the added camera views. The outline of the visual hull algorithm is given in Fig. 2.

The objects center of mass is then projected onto the ground plane to calculate the operators' position in every frame of the video image (50 ms). Every data point is given a timestamp. This way, the trajectory the operator follows during his work cycle is reconstructed. The output of the voxel carving method for one video frame is shown in Fig. 3.

One of the main difficulties when using vision technology in industrial environments is occlusion. Static objects such as conveyors and racks can block the view of certain cameras and make reconstruction of the workers' posture using the visual hull algorithm rather difficult. Therefore, a self-learning algorithm that is able to build an occlusion map for each camera from a voxel perspective, is developed. This in-