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GETTER: An Innovation Applied to Manufacturing Environments

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Abstract. *Industry 4.0 term originated in 2011 from a German government high-tech strategy project. This expression was first noticed publicly in the industrial trade fair Hannover Messe in Germany in the same year. This information technology-based revolution has ignited a vision about a new upcoming industrial revolution that would consist in promoting intensive computerization of manufacturing. Since then, disruptive and emerging new technologies such as Artificial Intelligence, Computer Vision, and Internet of Things have been successfully applied into manufacturing environments providing tools to industries to improve their operating efficiency, productivity, safety, and quality. Open Source Computer Vision Library (OpenCV) is an open-source computer vision and machine learning library of programming functions mainly aimed at image processing, video capture, and analysis including features such as face and object detection. Extensively used in companies, research groups, and by governmental bodies, it includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. OpenPose is an efficient method for multi-person pose estimation with competitive performance on multiple public benchmarks. This technique detects real-time human body, hand, facial, and foot key points on single images. Given such definitions, this article proposes an application of the GETTER Artificial Intelligence approach in the manufacturing environment. Having such advanced computer vision libraries at its core, this solution is guided by Lean and World Class Manufacturing principles. Through extensive use of heatmap images, production cycle time analysis charts, workers movement (spaghetti chart), and displacement amount, GETTER provides insightful information that improves the operator's life quality, health, and safety by supporting their productivity enhancement. Besides, the solution provides the complete worker's postural screening analysis, having as scientific basis its respective clients' ergonomics protocol as European Avalanche Warning Services adopted. The relevant generated data is presented in operational dashboards, showing strategic key performance indicators to support Data-Driven decisions and Business Intelligence directions.*

Keywords: *Industry 4.0, Lean Production, Manufacturing, Productivity, Artificial Intelligence, Machine Learning, Ergonomics.*

1. INTRODUCTION

The applications of artificial intelligence in industry have grown exponentially since the "Industry 4.0" term disclosure, during the industrial trade fair *Hannover Messe*, in Germany 2011. Carrying the promise of developing highly-flexible manufacturing environments, through the use of technologies such as big data, internet of things, and machine learning methods, this revolution has brought an improvement not only in production, but also on workers' safety, health, and well-being. In industrialized countries, musculoskeletal disorders (MSDs) are the most common form of occupational diseases and have become one of the main focuses in the area of occupational disease prevention. According to Punnett and Wegman (2004), the physical ergonomic features of work cited as risk factors for MSDs include rapid work pace, repetitive motion, forceful exertions, and non-neutral body postures. Over the years, some survey methods have been developed to estimate ergonomic risk factors related to manufacturing operations, such as the Ergonomic Assessment

Worksheet (EAWS), the Rapid Upper Limb Assessment, the Rapid Entire Body Assessment, the Strain Index, and the Occupational Repetitive Actions methods.

Developed by Schaub *et al.* (2013), the EAWS method was created in Germany at the University of Darmstadt, in order to materialize international standards for manual handling of loads. EAWS is a first level screening for the evaluation of bio-mechanical overload risk, according to the International Organization for Standardization (ISO) 11228-1:2003, ISO 11228-2:2007, ISO 11228-3:2007, and ISO 11226:2000 standards. It has been developed for evaluating the physical human factors (postures, forces and manual handling), pointing out the main problems and offering, an opportunity to find design change solutions to overcome them. This method consists in filling-in a checklist composed by four sections. Symmetric and asymmetric static working postures are evaluated in section 1, action forces of the whole body or hand/finger system are evaluated in section 2, manual material handling is evaluated in section 3. Lastly, the load for upper limbs in repetitive actions, based on their frequencies, related to applied forces, are evaluated in the last section.

Despite the success of these survey methods for ergonomics investigations, the real-time measure of the specific joint angles that characterize the postures of the operators during the work activity, as well as its positions, become quiet challenging. This task is usually done by manually analyzing photos and videos captured in the production line to extrapolate the joint angles. As a result, ergonomic assessment is costly, time consuming and often affected by the auditor's sensitivity. In order to perform this task in an automatized way, several tools for digital human modeling (e.g. computer-aided design (CAD) software, digital enterprise lean manufacturing interactive application, HumanCAD and Jack) were evaluated; however this approach still does not allow real-world measures and it requires an expert user to assign the digital human mannequins (DHMs) proper posture settings.

GETTER is an artificial intelligence-based software solution aimed at ergonomic assessment containing several modules, such as Car Tracking, Pose, Ergonomics, Movement, Heatmap, among others. This paper will focus on Pose and Ergonomics modules. These components were developed to fulfill this painful task from manually analyzing joint positions in the manufacturing environment to a simple, elegant, and automatic way. Focusing on occupational safety and health, this solution provides modules containing not only real-time, but also real-world collection of posture data, aiming to mitigate unproductive and tiring ergonomic positions, according to EAWS methods. Through the use of human pose estimation algorithms, GETTER monitors unnatural and unplanned movements and provides indicators that might lead to changes in the workstation infrastructure or in the process itself. The relevant generated data can be presented in operational dashboard, reports or similar documents, showing strategic key performance indicators to support data driven decisions and business intelligence directions.

This paper proposes an application of the GETTER Artificial Intelligence approach in the manufacturing environment, giving relevance to the pose and ergonomics modules. These modules contain a motion analysis system to support ergonomic assessment based on EAWS methods.

The remainder of this paper is organized as follows. In Section 2, a brief overview related to ergonomic assessment techniques, such as DHMs, motion capture technologies and OpenPose are introduced. In Section 3, the adopted proposed methodology and the study case are detailed. Then, the analysis of the results of the proposed approach are presented in Section 4. Finally, the paper is concluded in Section 5.

2. RELATED WORKS

In this section, we briefly review some related tools to assist the verification process of repetitive activities performed during manufacturing operations, such as DHMs, motion capture and OpenPose.

2.1 Digital Human Modeling

Digital human modeling is a technique of simulating human interaction with a workplace in a virtual environment. This virtual evaluation process is useful in developing user-centered products by incorporating human factor principles at an early design phase. In respect to ergonomics investigations, the use of DHMs allow an early level of ergonomic assessment, even at the early stages of the design process, without the need for direct measurements on humans, since the tool performs the analysis task through a friendly three-dimensional graphical interface, as indicated in Chaffin (2005). DHM softwares are able to perform several ergonomic studies as it makes possible to emulate numerous manual handling tasks, such as lifting, lowering, pushing, pulling and carrying, all combined with computational tools to assist the designer. However, such simulations rely on software packages that contain requirements such as kinematic animation structures. In order to setup these packages, an ergonomics specialist is required due to the complexity of generating these movement tasks. Even though the software has semi-automatic control tools for some behaviors such as looking, reaching, walking and grabbing, it still requires pre-recorded motion through motion capture to improve the reliability of the simulation, as mentioned in De Magistris *et al.* (2013).

2.2 Motion capture technologies

Aiming to capture movements, several specific technologies are available. As mentioned in Mengoni *et al.* (2016), these technologies collect information through sensor and optical systems. According to Welch and Foxlin (2002), sensor systems are built using electromagnetic sensors, acoustic sensors and inertial sensors. These systems do not suffer from occlusion problems; however, they face accuracy issues regarding to the information collected. These sensors end up being intrusive, due to the fact that the operators are required to use extra equipment to be analyzed. Optical systems, on the other hand, contain two types of classes in which systems may or may not be based on markers. Although the expensive cost price and the requirement to install several cameras, systems that make use of markers have an excellent precision, as explained in Aromaa and Väänänen (2016). Systems that are not mark based, such as the Microsoft Kinect, has shown extraordinary accuracy in identifying skeleton points, but they are sensitive to occlusion. When certain parts of the body are obstructed, a reference loss occurs to the remaining unobstructed points of the skeleton, therefore, they are not suitable to track an operator seated and partially covered at a workstation.

2.3 OpenPose

In the work of Cao *et al.* (2018), researches at Carnergie Mellon University, in United States, created the first open-source real-time system for 2D multi-person pose detection, which was baptized as OpenPose. This system is able to jointly detect human body, hand, facial, and foot key-points on single images. The proposed method uses a non-parametric representation, which the original work refer to as Part Affinity Fields, to learn to associate body parts with individuals in the image. OpenPose is based on convolutional neural networks (CNN). An red, green, and blue (RGB) image is given as input into the neural network to extract the feature maps of the input. The feature map is then processed in a multi-stage CNN pipeline to generate the Part Confidence Maps and Part Affinity Field. Part Affinity is a set of 2D vector fields that encodes location and orientation of limbs of different people in the image. It encodes the data in the form of pairwise connections between body parts. A Confidence Map is a 2D representation of the belief that a particular body part can be located in any given pixel. Figure 1 shows the 18 body key point features detected in OpenPose system.

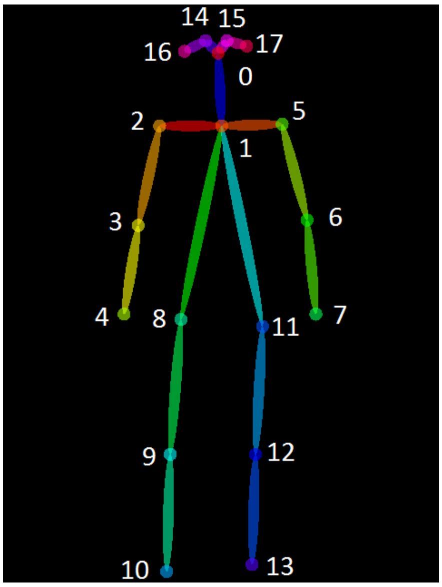

Figure 1. OpenPose 18 keypoints
(https://cmu-perceptual-computing-lab.github.io/openpose/web/html/.github/media/keypoints_pose_18.png)

3. METHODOLOGY

In this section, the methodology used to created the GETTER Pose and Ergonomics modules is discussed including the hardware and software architectures, as well as the data collection and processing procedures. At the end, a case study is also discussed.

3.1 Hardware architecture

GETTER Pose and Ergonomic modules hardware is composed by a single 720 pixel RGB Intelbras Dome Multi HD 3120D G6 camera. As shown in Figure 2, this camera output is transmitted in a streaming rate of 5 frames per second, through a parallel way, to a network video recorder (NVR) and to a Real Time Streaming Protocol (RTSP) as well. NVR aims to capture, store, and manage Internet Protocol camera images. This system is considered a more advanced option in capture standards, hence it is not used in analogical camera setups. In this module, video storage is needed due to the continuous improvement requirement of the human pose estimation model. RTSP aims to establish and control multiple synchronized video streams of continuous media belonging to a camera transmission. GETTER exploits this protocol to obtain real-time information about the production line. Finally, the aforementioned system is connected into a 32 Gb Random Access Memory (RAM) Intel Xeon server. This server also contains 2 Nvidia Quadro 8GB GDDR5 graphics processing cards, in order to obtain a faster processing of deep learning models.

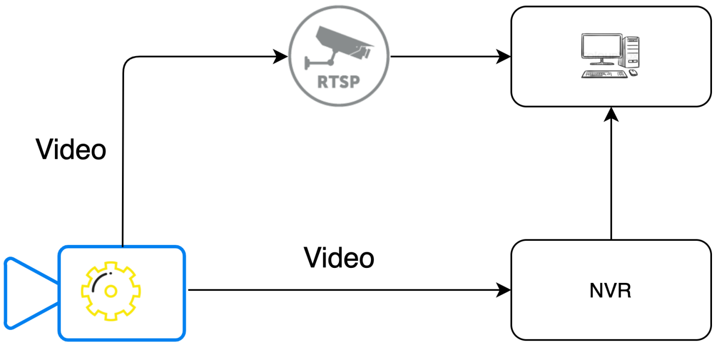

Figure 2. GETTER solutions hardware architecture

3.2 Software architecture

Figure 3 shows the GETTER solution software architecture. In this section, will be discussed, as well as each listed procedure.

3.2.1 Data collection

GETTER collects data from an application programming interface named Frame Capture. This application is built upon the open computer vision library: OpenCV (2000). It seeks to read data from the RTSP and convert this streaming into frames. In addition to this procedure, the Frame Capture compresses each frame into a array structure, and increases some metadata in respect to configuration in a dictionary format. Moreover, this application controls the streaming capture interval, in respect to working hours. This means that the Frame Capture does not collect frames during break intervals. Once frames are transformed into data dictionary structures, RabbitMQ (2007) is used to messaging purposes. This software is an open-source message-broker that is able to send and receive messages. This message-broker was a chosen due to the trade off performance with reliability and also to its ability to guarantee an specific order in messaging.

3.2.2 Data processing

As mentioned in section 1, EAWS was developed focusing on the automotive industry, which works with defined cycle times. It assigns load scores for unfavorable physical workload in a checklist composed by 4 sections and a visual evaluation is provided for each section, according to the 98/37/EC Machine Directive Council of European Union (1998). As shown in Figure 4, in case that the sum of all section scores is below 25, the procedure is labeled as a green zone, where no action is required. If the total score is between 26 and 50, the procedure is labeled as a yellow zone. In this label, a further risk assessment is conducted, taking into consideration other involved risk factors. The procedure may be redesigned if possible, or take other recovery actions to control the risk. Finally, if the total sum of points is greater than 50, it is considered as a red zone, in which actions to reduce risk area are required.

The objective of the GETTER Pose module is to support the determination of the EAWS scores, providing an estimate of the total period of time that the operator assumes certain inappropriate postures. To that end, GETTER makes use of OpenPose, which is responsible for estimate the workers' pose in a pre-defined region. GETTER Pose module is responsible by the estimation of pose positions; outsider operators removal, and average feet position collection.

In respect to the first mentioned responsibility, a single frame serves as the input to the system, returning a 21x3 array structure, containing human pose key points coordinates, human coordinates position, and lastly the accuracy of each one of these items. In addition to it, this function returns the same inserted frame, along with the predicted poses. Figure 5 shows an example of the output of this function.

According to the second mentioned responsibility, GETTER Pose module must ignore all undesirable operators, which are not in a specific area. This function has an person re-identification algorithm at is core, however it will not be discussed in this paper. Lastly, the average feet position of each operator is also collected. This function obtains a more precise location of the operator and it is also used for heat map generations, which also won't be discussed in this work.

Once GETTER collects the human pose key points coordinates, this information is broadcasted to the Ergonomics module. This module is responsible for ergonomics assessments, according to the EAWS method. The result of this module is a dictionary structure containing each individual EAWS position occurrences. Each dictionary key corresponds to the listed EAWS positions: walking, standing, bent, strongly bent, shoulder level work, and overhead work. It also contains how many times this position was identified.

GGscan is a file manager, developed by the authors, which aims to manage queues from the previous modules and store them. Lastly, the back-end process has the purpose to check the database. Once this verification is completed, it broadcasts the selected information to a dashboard, hosted on a front-end platform. Figure 3 shows the previously discussed software architecture used in GETTER Pose and Ergonomics modules.

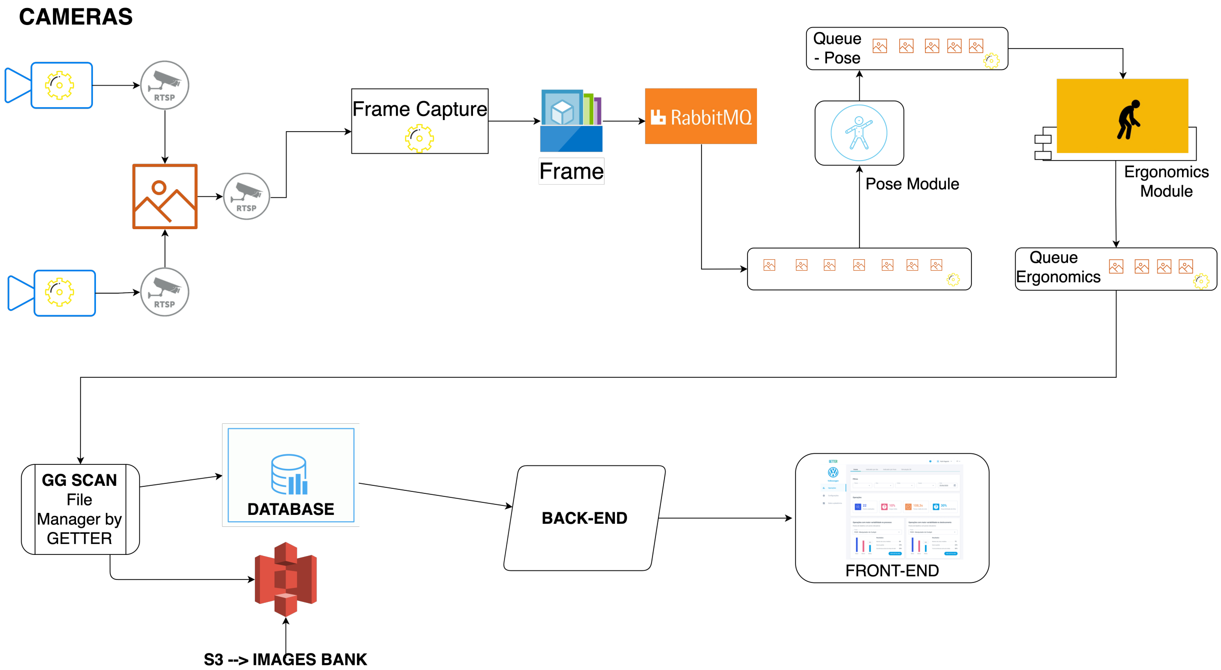

Figure 3. GETTER solutions software architecture

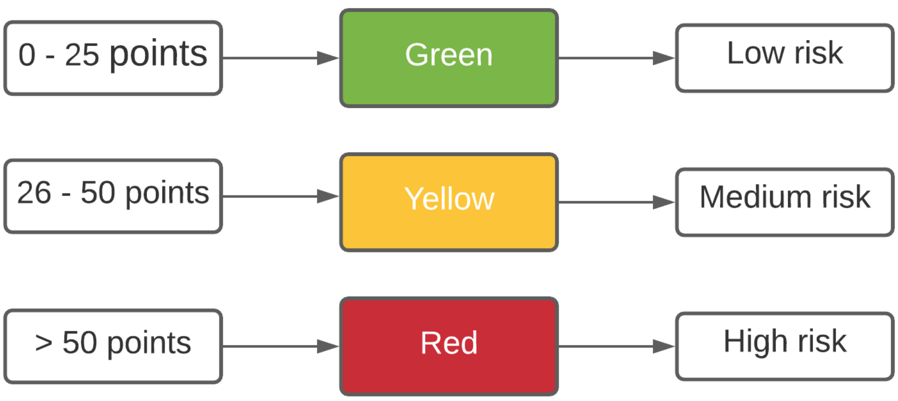

Figure 4. EAWS visual evaluation

3.3 Study case

Aiming to evaluate GETTER's performance, an automotive industry environment was adopted, where many operators perform a vast number of assembly operations. Composed by 16 distinct workstations, each one of them contribute for an object assembly in an average of 110 seconds. In this work, cycles are analyzed in a single workstation among the

Figure 5. GETTER pose module output along with the detected pose key points

remaining 15 ones. In the selected workstation, the operator performs tasks such as walking, standing, bent forward, shoulder level work, and overhead work. The arrangement of the objects to be assembled and the tools which the operator interacts with are organized as shown in Figure 5. The activities performed by the operators are characterized by a 5 step sequence. The first, fourth and fifth steps are related to manipulation of tools, the second is respect to part positioning and the third is related to part fitting.

4. RESULTS

In this section, we present the results metrics from the previous study case subsection. The validation samples were collected in a 1 hour processed video, containing the total average number of 30 cycles. According to Table 1, the total number of 5 cycles were randomly chosen to be evaluated. This table contains the total amount of time, in seconds, of detected risky posture styles, such as walking, standing, bent forward, strong bent forward, shoulder level work, and overhead work within a given cycle.

Table 1. Detection time of EAWS mentioned positions within a cycle in an automotive manufacturing industry.

Samples	Walking (s)	Standing (s)	Bent Forward (s)	Strong Bent Forward (s)	Shoulder Level Work (s)	Overhead Work (s)
Cycle 2	51.2	28.4	3.8	1.6	1	0.6
Cycle 3	40	47.6	6	0.8	7.4	8.4
Cycle 4	49.6	42.2	8	2.4	9.6	4.6
Cycle 5	47.8	45	6.2	1	9.2	5.2
Cycle 6	35.2	47.4	16.2	1.8	3.8	6.4
Cycle Average	44.76	42.12	8.04	1.52	6.2	5.04

As shown in Table 1, cycle 5 had the greatest amount of time, in respect to detected risky posture styles, compared to the remaining 4 cycles. In addition to it, cycle 2 had the lowest amount of time, hence it is considered the healthiest cycle due to the lowest unhealthier posture exposure. Finally, cycle 3 had the riskier task exposure. Containing a 7.9 second average amount of time between shoulder level and overhead works, this cycle detected 11.27% and 9.72% riskier task exposure compared to cycle 4 and 5 respectively, according to the EAWS method.

Regarding to the risk assessment, walking and standing tasks are considered as green zone (no risk) tasks. Bent forward and shoulder level work are considered yellow zone (medium risk) tasks. Finally, strong bent forward and overhead work are labeled as red zones (high risk) tasks. GETTER ergonomics module shows visually the aforementioned risk assessment, in order to support the expert's validation. As shown in Figure 6, the EAWS visual evaluation is clearly depicted in the worker's pose, in which walking is in green color, shoulder level work is in yellow color, and overhead work is in red color.

Table 2 shows the detected position time within a cycle. The attribute cycle time is respect to the duration of a cycle, the results attribute is respect to the total amount of time that a certain position was detected. Lastly, the total posture detection attribute is respect to the expert's calculation about when the operator is truly at a certain position, and about what the GETTER Ergonomics module predicted. The case study had an accorded validation margin of 75% between

Figure 6. GETTER Ergonomics module detected risks

both parts. As shown in Table 2, only in cycle 3 this margin was not achieved.

Table 2. Ergonomic expert analysis about the collected cycles

Cycle samples	Cycle time (s)	Results (s)	Total Posture Detection (%)
2	101.4	79.8	79
3	112	83.4	74
4	113.2	88.6	78
5	109.6	94.4	86
6	108.8	78.6	72

5. CONCLUSION AND FUTURE WORKS

GETTER Pose and Ergonomics modules are a new posture assessment system, in which exploits a real-time open-source multi-person detection library called OpenPose. In order to support the automatic detection of unproductive and tiring ergonomic positions, this is an automated, elegant, and user centered tool that effectively can assist ergonomic experts in ergonomic risk assessment in manufacturing environments. Developed accordingly to the EAWS method, this system contains an average of 77.8% precision, validated by ergonomic experts. The results show that this number can be increased by solving some occlusional cases, and also by solving some person detection issues. In some periods of the mentioned cycles, the operator is occluded and the system has some struggles due to this fact. In respect to the 5 cycles collected during the study case, cycle 2 is selected as the healthiest cycle due to the lowest amount of time of unhealthier posture exposure, whereas cycle 3 is the riskier one, containing 11.27% and 9,72% riskier task exposure compared to cycles 4 and 5, according to the EAWS method. Further analysis can be extended to other solutions provided by GETTER and other survey methods about ergonomics investigations, such as the Rapid Upper Limb Assessment and the Rapid Entire Body Assessment.

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