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Nenad Filipovic *Editor*

Applied Artificial Intelligence: Medicine, Biology, Chemistry, Financial, Games, Engineering

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Preface

The book covers knowledge and results in theory, methodology and applications of Artificial Intelligence and Machine Learning in academia and industry. Nowadays, artificial intelligence has been used in every company where intelligence elements are embedded inside sensors, devices, machines, computers and networks. The chapters in this book integrated approach toward global exchange of information on technological advances, scientific innovations and the effectiveness of various regulatory programs toward AI application in medicine, biology, chemistry, financial, games, law and engineering. Readers can find AI application in industrial workplace safety, manufacturing systems, medical imaging, biomedical engineering application, different computational paradigm, COVID-19, liver tracking, drug delivery system and cost-effectiveness analysis. Real examples from academia and industry give beyond state of the art for application of AI and ML in different areas. These chapters are extended papers from the First Serbian International Conference on Applied Artificial Intelligence (SICAAI), which was held in Kragujevac, Serbia, on May 19–20, 2022 (www.aai2022.kg.ac.rs).

Nenad Filipovic

Contents

Advances in the Use of Artificial Intelligence and Sensor Technologies for Managing Industrial Workplace Safety

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Abstract. With technological progress, workplace safety standards have increased, so a growing scientific community focused on the application of technologies for improving workers' safety and well-being. In this study, we review recent advances in applying cloud technologies, artificial intelligence, and numerous sensors to assess various problems in safety science, ranging from reporting and management roles to improving the ergonomics of physical tasks. Particularly, we review studies focused on applying or combining cloud technologies, artificial intelligence, sensors, and robotics for studying or improving industrial workplaces. The emphasis was on topics covered with our recent project AI4WorkplaceSafety (http://ai4workplacesafety.com), where we were focused on: 1) developing a lightweight framework for easing the collection and management of safety reports (related to unsafe acts and unsafe conditions). 2) Automating of PPE compliance using computer vision, which represents specific cases of unsafe acts. 3) Assessing and detecting unsafe acts related to pushing and pulling (typical examples are workplaces in warehouses and transportation). 4) Finally, we briefly presented a modular and adaptive laboratory model (industrial workstation) design for a human–robot collaborative assembly task. It is concluded that ongoing technological progress and related multidisciplinary studies on this topic are expected to result in a better understanding and prevention of workplace injuries.

Keywords: Artificial intelligence, workplace, safety, engineering.

1 Introduciton

Industry 4.0 (I4.0) is a term used to indicate the global industrial transformation driven by rapid technological advances. According to the official Global Industry Classification Standard (GICS), there are 11 sectors, 24 groups, 69 industries, and 158 sub-industries [1]. Considering such diversity, it is nowadays more precise to talk about the I4.0 branches; such are: Quality 4.0 [2], Maintenance 4.0 [3], and Safety 4.0 [4]. So far, in many industrial branches, the major goal has been set towards automation which has

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brought tremendous progress in many manufacturing sectors (automotive, electronics manufacturing, welding, etc.). However, it is shown that in practice there are still many workplaces that cannot be adequately or fully automatized. Although there is a growing trend of supplementing laborious workplaces with (co)robots that can collaborate with human operators [5] - authorities agree that the further evolution of technology and industry will remain even more human-centered [6]. Thus, there is an increasing need for technologies that could help in improving the well-being of human operators in an industrial environment.

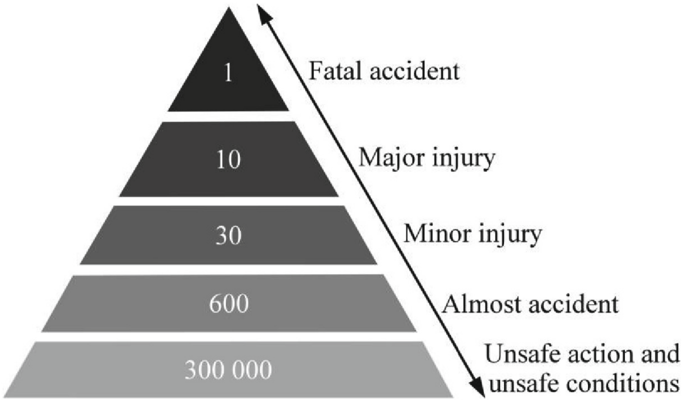

Fig. 1. Workflow of the digitalized management of unsafe conditions and unsafe events

1.1 Workplace Safety Management in SMEs

Risk and safety management is a broad topic [7], so the focus of this chapter will be restricted to occupational safety and health (OSH). Briefly, the OSH scientists and professionals aim to improve the safety, health, and welfare of people at work, with the end goal to the number of production injuries and accidents down to zero. To reach this goal, companies are focusing on proactive identification of the accidents' precursors to prevent accidents. According to Heinrich's pyramid (Fig. 1), proactive identification of unsafe conditions (UC) and unsafe acts (UA) have the biggest impact on safety [8]. Although there are recommendations set by regulatory bodies and international standards, traditional management of workplace safety has shown to be a slow, subjective, and complex task when it comes to industrial practice. In the rest of this chapter, the emphasis is put on reviewing research studies that cover SMEs' needs because of the fact that they generate most of the GDP and employment opportunities in developed countries. Moreover, it is more likely that compact solutions proposed in the literature will be first applied in SMEs on a smaller scale before being incorporated into enterprises' ICT systems. From the SMEs' viewpoint, enterprise solutions frequently are too expensive, especially when it comes to the incorporation of additional and/or nonstandard features specific to their type and size of business [9]. In these terms, cloud technologies and compact web frameworks have shown the biggest potential to improve safety management, along with computer vision techniques - as the recognition of UC/UA is a visual task.

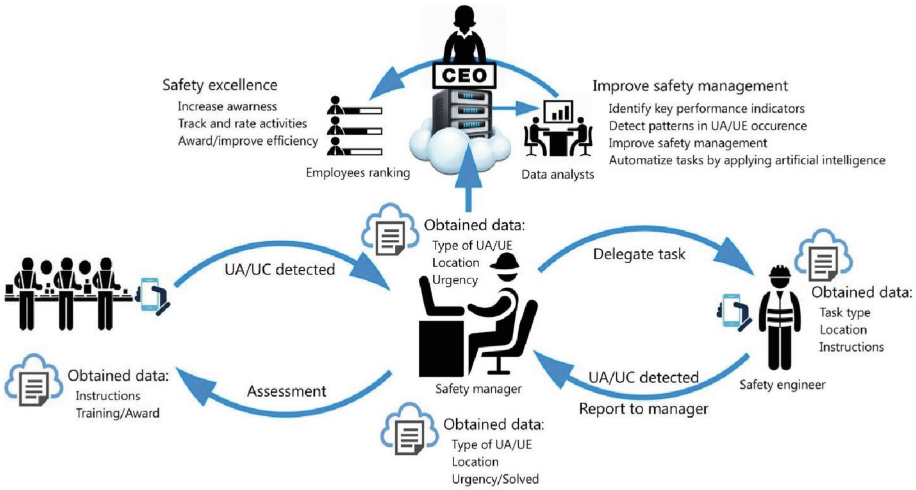

Fig. 2. Workflow of the digitalized management of unsafe conditions and unsafe events [10]

1.2 The Importance of Timely and Objective Identification of UC/UA

With the progress of the Safety 4.0 paradigm, traditional paper and manual reporting are being replaced with cloud-based applications and services run on smartphones and edge devices. One such solution is the SafE-Tag, a minimalistic framework released with the aim to enhance the collection of safety reports and delegation of corresponding tasks - with the end goal of encouraging employees to proactively contribute and learn about safety [10]. The graphical illustration of the concept proposed in the same study is given in Fig. 2. The composing parts of the proposed solution are a) central cloud server and b) remote mobile device - so that employees are allowed to collect and report UC and UA, as well as to receive and respond to assigned tasks. Along with an efficient collection of safety reports, the long-term benefit of digitalized safety reporting is to enable in-depth analysis of safety performances by employing business intelligence.

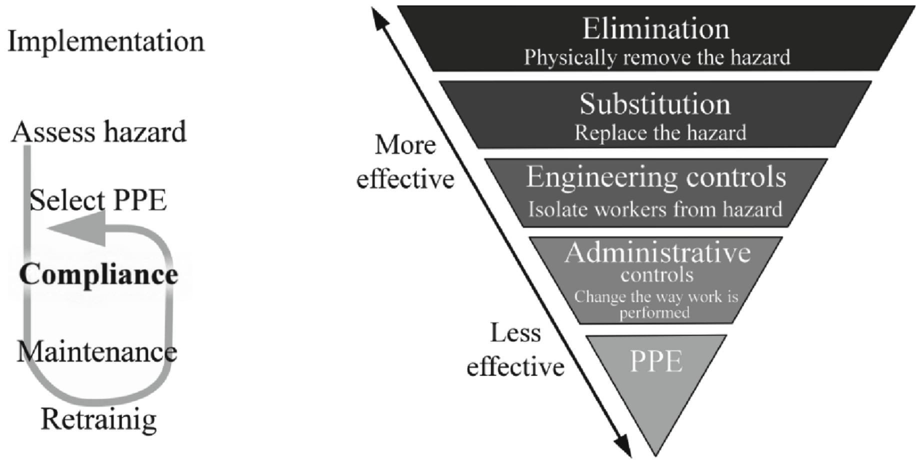

Fig. 3. Relation of workplace safety standards and PPE compliance

2 Misuse of PPE as the Use Case of Unsafe Acts

The Occupational Safety and Health Administration (OSHA) has proposed the five levels of OSHA controls (Fig. 3): 1) elimination, 2) substitution, 3) engineering, 4) administrative, and 5) use of personal protective equipment (PPE) [11]. In this sense, the use of PPE may be considered a first-line barrier between employees and hazards when applied. Despite the availability of PPEs, and corresponding PPE standardization and use guidance, the industrial practice has shown that misuse of PPE still represents a serious problem. Briefly, reports indicate that PPE misuse causes a number of injuries and large losses to national economies [12]. This is explained by supervisors' inability to timely and objectively notice PPE non-use in large manufacturing halls where the number of workers fluctuates [10]. Although PPEs are commonly stratified into four levels (A-D) [13], in related studies PPEs are commonly split according to physiological functions that they aim to protect. Initially proposed approaches are variants of radiomics-based detection of helmets [14]. Recent studies are based on the use of convolutional neural networks [15]. In terms of deep learning architectures used, the most frequently used detectors are YOLOv3 [16, 17], Fast R-CNN [18]. In a recent study, Nagrath et al. demonstrated the application of combining SSD and MobileNetV2 classifier for Covid19 mask detection [19].

There is a high variability of PPEs concerning appearance and design. Therefore, compliance of a head-mounted PPE is a very specific case. Moreover, sometimes it is required for an employee to wear multiple PPEs simultaneously (e.g., hard hats, safety glasses, safety masks, and earmuffs). Compared to previous studies that were running multiple classifiers or multi-class classifiers for the head- mounted PPE and mainly focused on hard hats and face masks, our goal was to assess the usage of object detectors in a more efficient approach and perform comprehensive validation by accounting for more PPE types that are relevant for wider industrial application of the computer vision-based compliance of PPE (Fig. 4).

Fig. 4. The concept of AI-driven PPE compliance [20]

In this chapter, we review our recent study which proposed a generic procedure composed of four steps (Fig. 5): 1) employee detection/identification of an in the workspace (Fig. 5a); 2) pose estimation for detecting body landmark points (Fig. 5b); 3) use of the pose landmark points to define regions of interest (ROI); and 4) classification of ROIs (Fig. 5c).

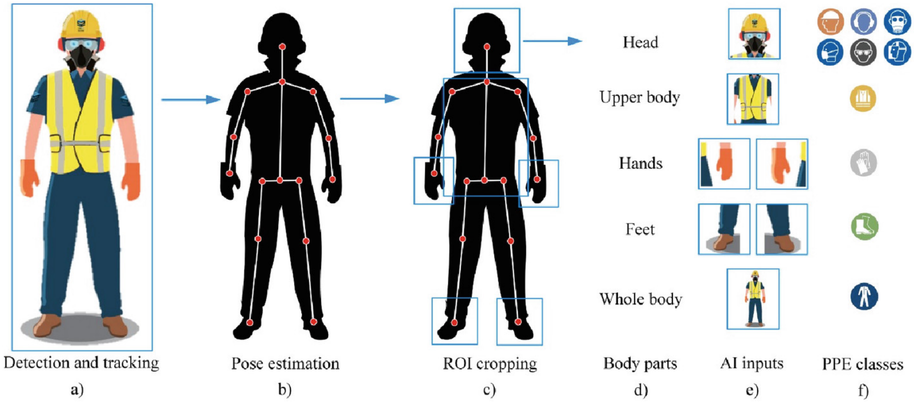

Fig. 5. Workflow of the proposed pose-aware PPE compliance [20]

Particularly, the procedure used HigherHRNet for pose estimation [21], which estimates body landmark points by using the high-resolution representation provided by HRNet [22]. The detected landmark points were used for defining regions of interest (ROI) around five body parts (head, hands, upper body, legs, and whole body). Since the PPE compliance was considered as a classification problem, previously cropped ROIs were subjected for the various deep learning classification architectures MobileNetV2 [23], VGG19 [24], Dense-Net [25], Squeeze-Net [26], Inception_v3 [27], and ResNet [28] - while the MobileNetV2 was the most optimal choice. Briefly, the MobileNetV2 is based on an inverted residual structure, where the input and output of the residual block are thin bottleneck layers, while the intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity [23]. The authors performed the transfer learning by using the model pre-trained on the ImageNet data set [29]. The training was performed using the Adam optimization algorithm [30] with the cross-entropy loss function and the following online augmentations: random rotation (±30°), random flip, random crop, and Gaussian noise. The data set used in this study was developed by combining web-mined images and public PPE datasets (from the Roboflow hardhat train data set and the Pictor PPE data set). The metrics selected for the evaluation and comparison of developed models were accuracy, precision, recall, and f1 score. Considering the current privacy regulations and costs/complexity of using AI, the solution is recommended for the use in controlled conditions, such as: 1) self-check points (when users are asked to confirm their identity by using e.g., RFID card, while AI is used solely for the PPE compliance but not for the purpose of identification and tracking), and on 2) monitoring of particular workplaces/machines with high risk from injuries (so that AI could ensure timely detection and mitigation of occurred risks). In Fig. 6, we showed a couple of use cases [20].

Fig. 6. Sample results of PPE compliance [20]

3 The Use of AI for Assessing the Safety of Pushing and Pulling Activities

The focus of this section is on managing workplace safety in workplaces that involve tasks of pushing and pulling (P&P), such as warehouses and transportation. Non-ergonomic

P&P causes musculoskeletal disorders (MSD), including pain in the back, arms, neck, etc. For employees, in addition to job loss (or forced retraining), MSD also has negative long-term consequences in the form of permanent disabilities and inability to perform everyday activities.

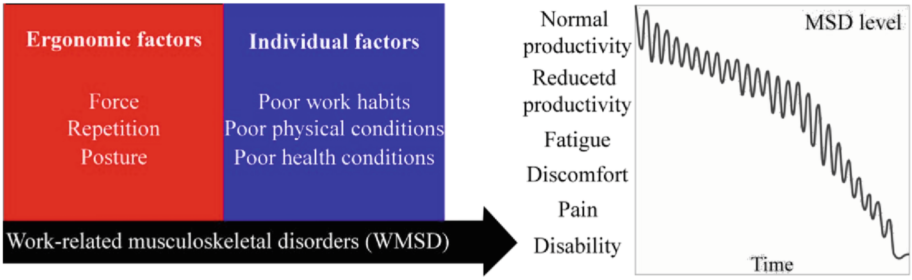

Fig. 7. Progress of the musculoskeletal disorders caused by repetitive non-ergonomics acts at a workplace

Industrial practice recognizes two categories of a cargo P&P: 1) with wheel-based tools (handcarts, forklifts, etc.) and 2) without wheels-based tools (rolling, sliding, and pulling) [31]. This chapter is focused on the first group; however, the proposed methods are applicable to the second group as well. Risks related to the P&P can be divided into ergonomic (workplace-related) and individual (poor health habits or poor physical conditions) [32]. The three key ergonomics risks, which are of interest for this study, are: 1) High frequency-repetition; 2) Excessive effort-overload; and 3) Incorrect (unnatural) body posture. When a worker is exposed to these risks over time, fatigue of the human body accumulates – and when the fatigue level overcomes the ability of the body to recover, regenerate and adapt – MSDs and injuries occur (Fig. 7). The risk assessment of P&P involves consideration of: 1) handcarts type and conditions; 2) weight of cargo; 2) operator's body posture; 3) P&P path shape; 4) distance to be covered; 5) condition of the floor; and 6) presence of obstacles. As may be noted, operators' habits do not directly determine most of these factors, or they do not change significantly over time. For example, the condition of floors and equipment is in the charge of maintenance engineers, process engineers are responsible for choosing the optimal route and mode of transport, management and procurement are responsible for the optimal choice of the type of handcrafts, etc. However, the position of the body during the P&P is extremely subjective and it is not easy to be improved or monitored during working hours. The current bottleneck of workplace safety practice is the assumption that a supervisor will notice non- ergonomic handling of handcarts and timely warns operators – which is very difficult to be managed manually. Accordingly, this study aimed to enhance this risk assessment task and facilitate safety engineers' precise preventive actions.

Fig. 8. Experimental setup for P&P task

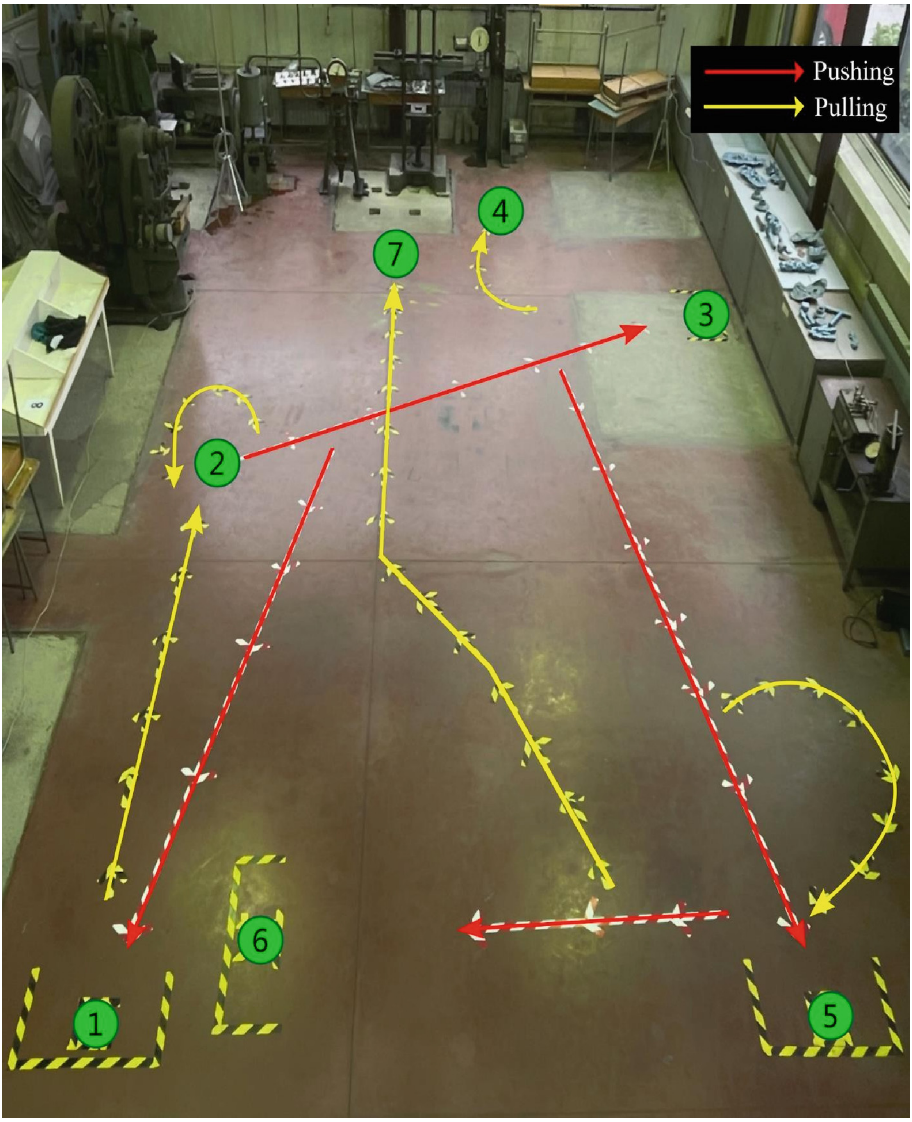

Fig. 9. Experiment environment and P&P path

Figure 8 and Fig. 9 show the experiment environment and pushing and pulling path used in the study [33] and our ongoing study. As may be noted, it is composed of complex turnovers and push/pull maneuverings. In the recent study [33], we aimed to use force IoT sensors to measure P&P force for various participants. Sample force diagrams are shown in Fig. 10, where different colors were used to separate left- and right-hand forces. From this sample diagram, there are considerable differences in signals measured from the left and right hand, as well as for vertical and horizontal components of forces.

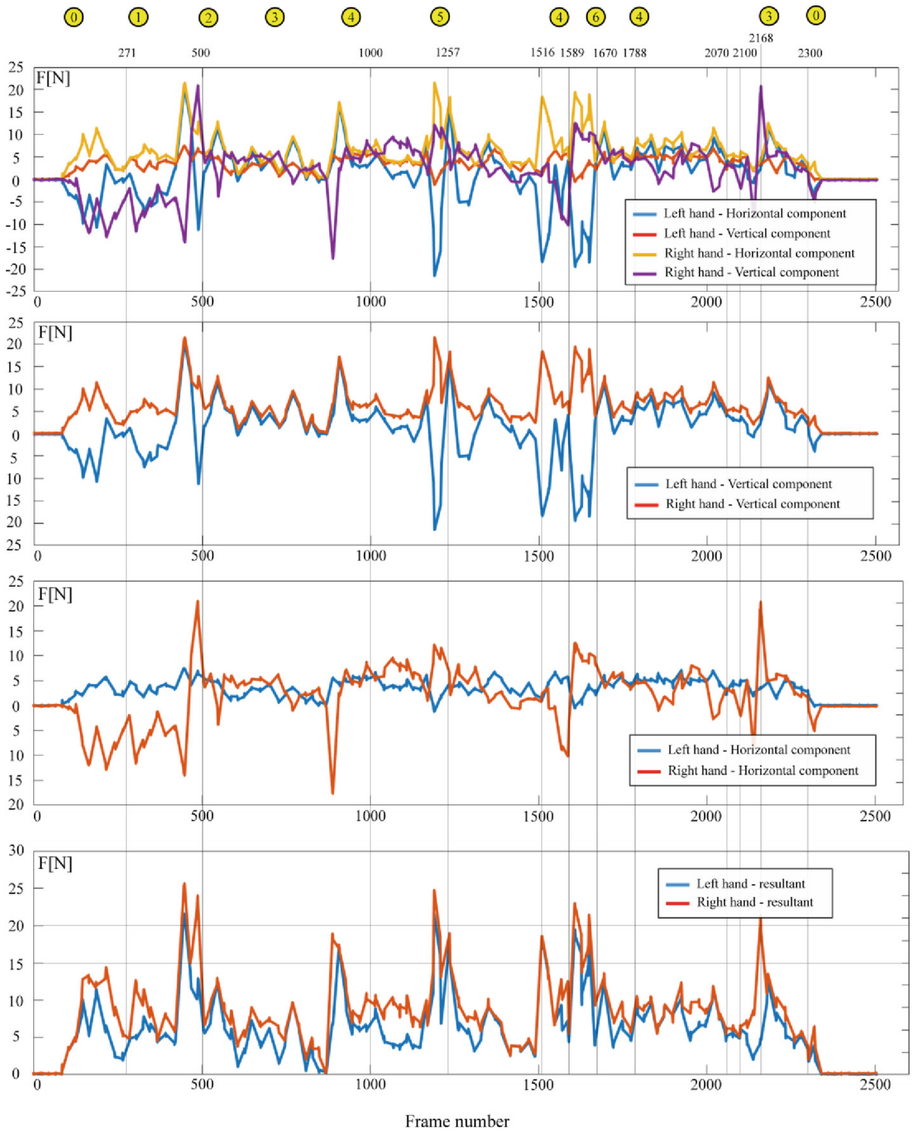

Fig. 10. Pushing and pulling forces for experiments performed in study [33]

3.1 Workplace Musculoskeletal Disorders and Injuries

There is an increasing need to improve the interface between human operators and new technologies while ensuring the implementation of the highest workplace safety standards and well-being of human operators in an industrial environment. Besides, new workplace safety standards declared zero injuries as an ultimate goal. To achieve this challenge, safety science and ergonomics aim to design and improve workplaces by minimizing discomfort, exertion, and stress and eliminating hazards and risks of injuries [34].

Previous studies showed that non-ergonomic execution of repetitive and physical tasks is among the major causes of work-related musculoskeletal disorders (WMSDs) [35]. It is important to emphasize the difference between difficulties in detecting and managing unsafe acts and unsafe conditions. For example, the misplaced tools, missing PPE, and unclear floors, represent typical unsafe conditions that can be instantly detected and mitigated [20, 36]. Contrary to that, unsafe acts that may be related to WMSDs need to be considered repetitive events resulting in accumulated negative effects [37]. The practice has shown that timely and objective detection of unsafe acts is essential to prevent WMSDs, and their accompanying negative consequences (disabilities and the inability to perform everyday activities) [38]. The costs and consequences of WMSDs are studied by international organizations such as World Health Organization [39] - which reports indicate that ~ 126.6 million adults in the US have a musculoskeletal disorder; while similar reports related to the EU population indicate that 33% of workers have unnatural body postures for > 25% of their working time [40].

In manufacturing halls, the key effort in implementing and follow-up of safety recommendations are performed by onsite safety managers and safety supervisors. Their roles are related to workplace monitoring with the aim of managing the worker's actions and to detects their distinctions from safety recommendations. However, the practice (large manufacturing halls and the number of employees that move across) has shown that the manual supervision of workers is ineffective and expensive. As a solution, a series of initiatives tend to propose computerized tools to automate or improve the detection of unsafe acts in both in-lab and industrial environments. The studies presented here are mainly focused on analyzing the task of pushing and pulling (P&P) handcarts, which was chosen as a representative, highly dynamic task whose variants are present in many industries (transportation, warehouses, healthcare, etc.). Another interesting task that will be covered is collaborative polishing with the help of a collaborative robot.

3.2 Computer Vision, Deep Learning and Workplace Safety

Detection and recognition of objects and (unsafe) actions is a well-studied topic in the field of computer vision, which has recently rapidly evolved with the breakthrough of deep learning [41]. In this section, we review studies in which computer-vision techniques were used to recognize unsafe acts in industrial environments. In a study by Han et al., a computer vision framework was proposed to identify critical unsafe behavior in construction, specifically ladder climbing [42]. Three actions were considered ascending, descending, and reaching far to a side (unsafe act). The detection of unsafe actions was performed by combining the results of both 2D pose estimation and 3D reconstruction and using the motion templates and skeleton models. The number of correctly detected actions was further enhanced with a more detailed human skeletal model (with more joints) applying the same methodology [43]. Another approach for safety assessment of ladder climbing tasks was presented, considering dynamic behavior as a static posture and using a mathematical model of the human skeleton to identify unsafe behaviors based on value ranges of joint parameters [44, 45]. Classification of postures regarding human back, arms, and legs (and their three levels - straight, bent, and bent heavily) were employed to ensure ergonomic posture recognition [46]. An RGB camera was used to capture skeleton motions, view-invariant features in 2D skeleton motions were selected, and the function that approximates the relationship between real-world 3D angles/lengths and the corresponding projected 2D angles/lengths was defined. Risk assessment for several outdoor jobs was performed using OpenPose [47] outputs and computing Rapid Upper Limb Assessment (RULA) scores from snapshots and digital videos. Monitoring construction workers is not a new concept, and procedures for detection that localize construction workers in video frames and initialize tracking have been developed [48]. Some authors suggested that applications of deep learning, even though more complex, could provide satisfactory results in the field of safety management. Seo et al. offered a comprehensive review of systems for safety monitoring on construction sites, categorized previous studies into groups, and emphasized research challenges [49]. A new hybrid deep learning model (CNN + LSTM) for automatic recognition of workers' unsafe actions was developed [50]. The approach was experimentally validated in several scenarios on the task of ladder climbing, where a combination of CNN and LSTM adequately examined spatial and temporal information. An improved CNN that integrates red–green–blue, optical flow, and gray image streams for activity assessment in construction are proposed [51]. It was tested on a dataset of real-world construction videos containing actions of walking, transporting, and steel banding. To prevent workers from falling from heights in construction, Fang et al. developed an algorithm using a faster region-based CNN for detecting the presence of workers and a deep CNN for determining if they are wearing a safety harness [52]. An interesting framework for risk management of railway stations generalizable to a wide range of locations and some additional types of risks was presented [53]. CNN was applied as a supervised machine learning model to automatically extract and classify risky behaviors (fall, slip, and trip) in the stations.

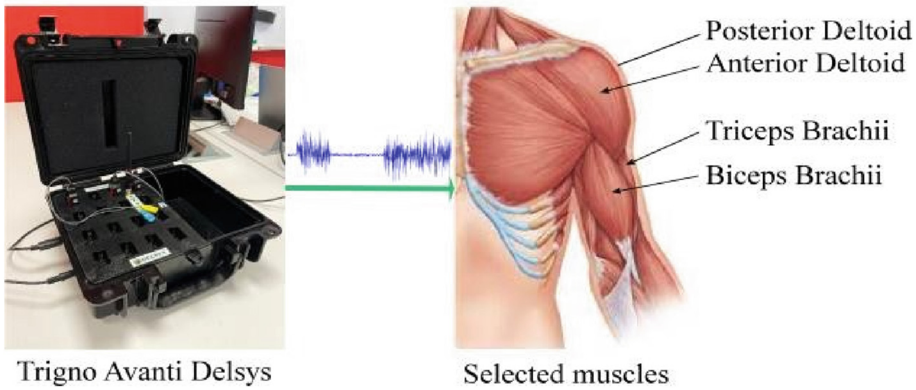

Fig. 11. EMG measuring equipment and selected arm muscles

3.3 The Use of Sensors for Analyzing Workplace Safety

As an alternative to computer vision, there are numerous methods for safety management and recognition of human activities using sensor data. Yan et al. proposed a wearable Inertial Measurement Units (WIMU), a based warning system for construction workers that guarantees self-awareness and self- management of risk factors that lead to WMSDs of the lower back and neck without disturbing their operations [54]. A smartphone application processes real- time data (quaternion data transferred into angles of flexion, extension, lateral bending, and rotation) captured by the IMU sensors fastened to the back of a safety helmet and the upper part of the back. Yang et al. presented a computationally efficient method for activity recognition as a lightweight classification using activity theory for representing everyday human activities, radiofrequency identification (RFID) sensor data, and penalized Naive Bayes classifier [55]. Hofmann et al. used ordinary smartphone sensor data and LSTM for human activity recognition and detection of wasteful motion in production processes [56]. The activities considered were walking, standing, sitting, and jogging, and the reported accuracies for each activity were above 98%. Ordóñez et al. proposed a deep framework for activity recognition - DeepConvLSTM (convolutional and LSTM recurrent units) suitable for homogeneous sensor modalities and multimodal wearable sensors [57].

EMG has the potential to guide our understanding of motor control and provide knowledge of the underlying physiological processes determining force control. It opens the possibility of acquiring insight into muscle activity (load) and better interpreting overexertion, thus preventing the threat of WMSDs and enhancing industrial workplace safety. Even though this idea is not new [58, 59], the scientific fields of biomechanics and biomedical engineering still need to be further investigated, and more effort needs to be put into analyzing industrial task execution. Detailed instructions for EMG measurement methodology have already been presented and widely used [60, 61].

EMG sensors were utilized, as a primary tool, in many recent studies that tried to analyze and assess the risk levels of WMSDs. An extensive study (more than 100 workers with and without a history of chronic pain) was conducted, testing lumbar paraspinal muscles as a predictor of low-back pain (LBP) risk [62]. The same participants were reevaluated two years later, and by examining some EMG variables, it was possible to successfully identify a subgroup of subjects with a higher risk of back pain. In-lab experiment on the risk assessment of non-fatal, cumulative musculoskeletal low back disorders among roofers was presented [63]. The effect of working on uneven rooftops, different working postures (stoop and kneeling), facing direction, and working frequency was evaluated using EMG measurements and 3D human motion data. An analysis of experienced and inexperienced rodworkers using EMG sensors and Xsens MTx Xbus system was conducted to examine the factors that affect the risk of developing lower back musculoskeletal disorders [64]. Working strategies of the two groups were compared, with the accent on levels of back moments L4/L5 and the time spent in an upright and flexed posture. A novel wearable wireless system capable of real- time assessment of the muscular efforts and postures of the human upper limb for WMSD diagnosis was proposed [65]. This real-time system that combines IMU and EMG sensors was tested on the task of repetitive object lifting and dropping, and the risk was estimated based on Rapid Upper Limb Assessment (RULA) and the Strain Index (SI). A biomechanical analysis was conducted in the solid waste collection industry investigating five occupational LBP risk factors for three techniques of waste collection, throwing and three garbage bag masses [66]. LBP risk factors were computed using a full-body musculoskeletal model in OpenSim, where muscle activity was estimated in two ways: using EMG electrodes (more accurate) and the conventional static optimization method.

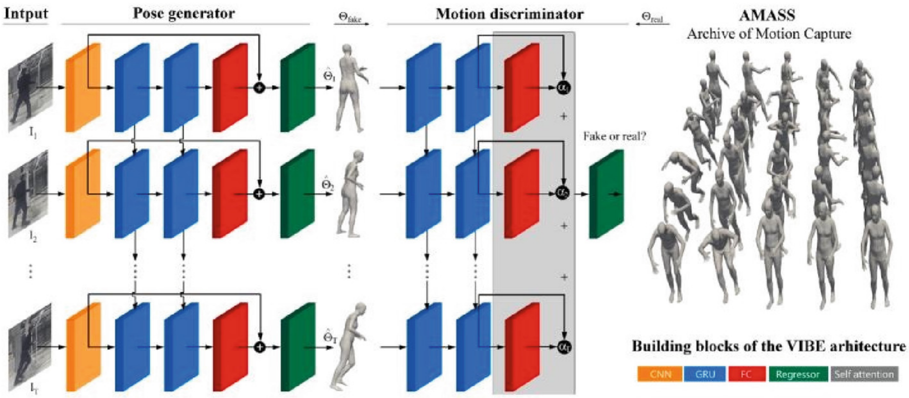

Fig. 12. VIBE architecture for 3D pose estimation from monocular images [33, 67]

3.4 The Use of 3D Pose Estimation and Human Body Models

The experiments were recorded using four DAHUA IPC-HFW2831TP-ZS 8MP WDR IR Bullet IP cameras with a DAHUA PFS3010-8ET-96 8port Fast Ethernet PoE switch. The host PC had an 1151 Intel Core i3-8100 3.6-GHz 6-MB BOX CPU. In our experiments, the Video Inference for Body Pose and Shape Estimation (VIBE) architecture [67] is used to solve the 3D pose reconstruction problem in an adversarial manner. VIBE is a video pose and shape estimation method. The first step of VIBE is a pose generator that extracts image features from video input using a pretrained CNN. Temporal encoder - bidirectional Gated Recurrent Units (GRU) processes these features to make use of the sequential nature of human motion, thus incorporating information from past and future frames which is beneficial when the body of the person is occluded or its pose is ambiguous in a particular frame. Then, the regressor predicts the parameters of the Skinned Multi-Person Linear (SMPL) body model [68] for the whole input sequence at each time instance to obtain realistic and kinematically plausible 3D body shapes and poses (motions). SMPL parametric model delivers a detailed 3D mesh of a human body composed of Quad4 elements with $N = 6890$ vertices and $K = 23$ joints. The SMPL model is composed of 82 parameters Θ, which are divided into: 1) pose parameters $\theta \in R^{72}$ (rotation of the 23 body landmark points), and 2) shape parameters $\beta \in R^{10}$ (the first 10 coefficients of a PCA space).

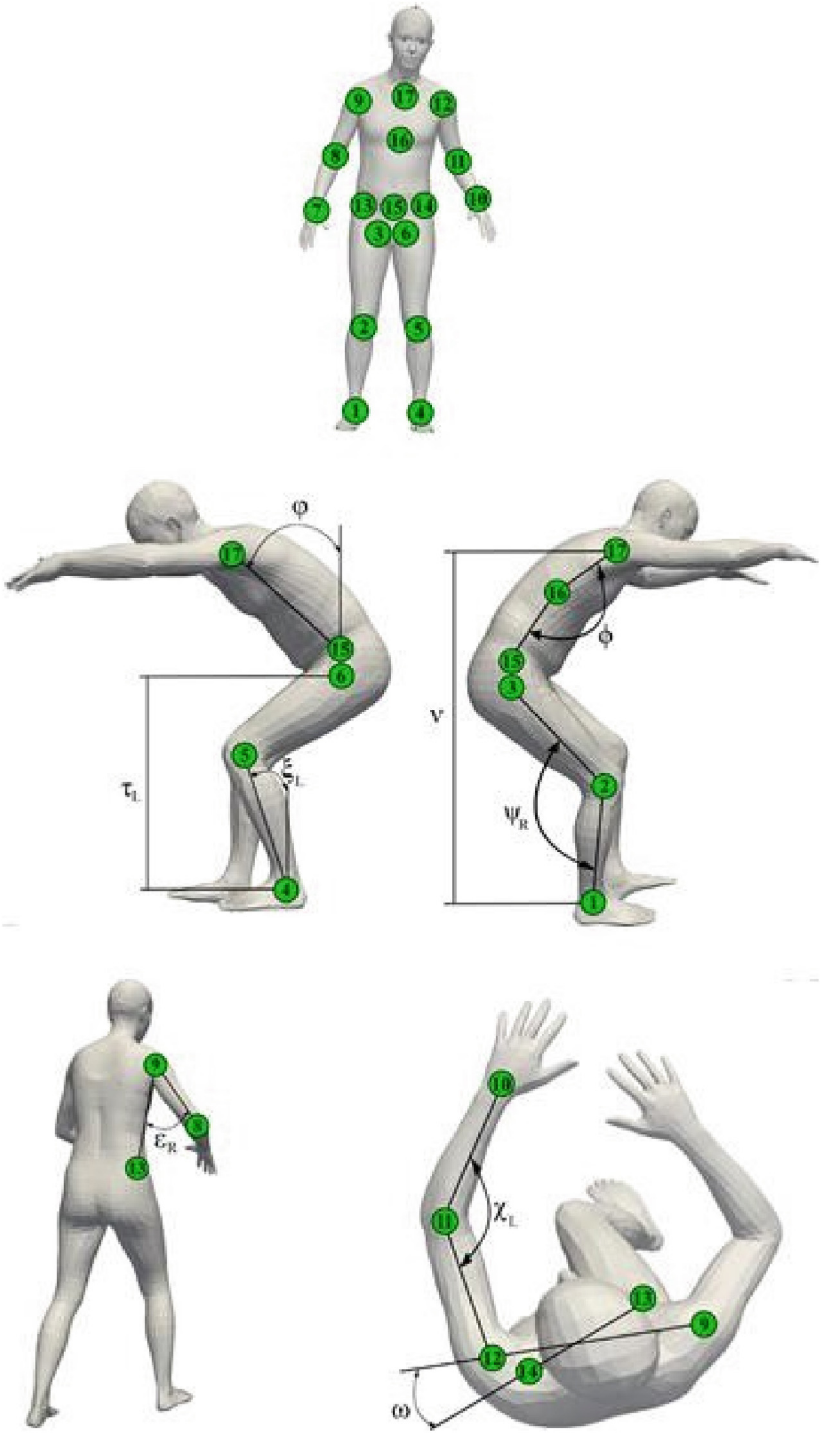

Fig. 13. SMPL model with ergonomic parameters

Accordingly, the SMPL model is a differentiable function, $M(\theta, \beta) \in R^{6890\times 3}$. The motion discriminator has the task of deciding whether the generated sequence of poses corresponds to a realistic or fake sequence. It uses a stack of GRU layers to process poses sequentially. Then the self-attention mechanism dynamically aggregates and amplifies the contribution of important frames. The motion discriminator is trained on AMASS database (~11,000 movements of ~ 300 subjects) [69], and it takes predicted pose sequences along with pose sequences from AMASS. If the motion discriminator cannot spot the difference between predicted poses and the poses generated from AMASS, then the predicted motion is realistic (adversarial approach).

From the reconstructed SMPL pose, we chose 17 landmark points and computed a series of 13 parameters (divided into three groups) that were used to assess P&P ergonomics (Fig. 13) [33]:

- Leg parameters - the angle of the left knee $\psi L(\triangleleft 1, 2, 3)$, the angle of the right knee $\psi R(\triangleleft 4, 5, 6)$, the angle of the left lower leg and the vertical axis $\xi L(\sphericalangle 1, 2, Z)$, and the angle of the right lower leg and the vertical axis $\xi R(\sphericalangle 4, 5, Z)$;
- Spine parameters - the angle of spine $\phi(\sphericalangle 15, 16, 17)$, the angle of the spine and the vertical axis $\varphi(\sphericalangle 17, 15, Z)$, the vertical distance between landmark points 1 and 3 $\tau|1, 3|Z$, the vertical distance between points 1 and 17 $\upsilon|1, 17|Z$, and the angle of torsion between the shoulder and the hips ω $(\sphericalangle 13, 14, 12, 9)$;
- Arm parameters - the angle of the left elbow $\chi L(\sphericalangle 10, 11, 12)$, the angle of the right elbow $\chi R(\sphericalangle 7, 8, 9)$, the angle between the left upper arm and the torso $\varepsilon L(\sphericalangle 13, 9, 8)$, and the angle between the right upper arm and the torso $\varepsilon R(\sphericalangle 14, 12, 11)$.

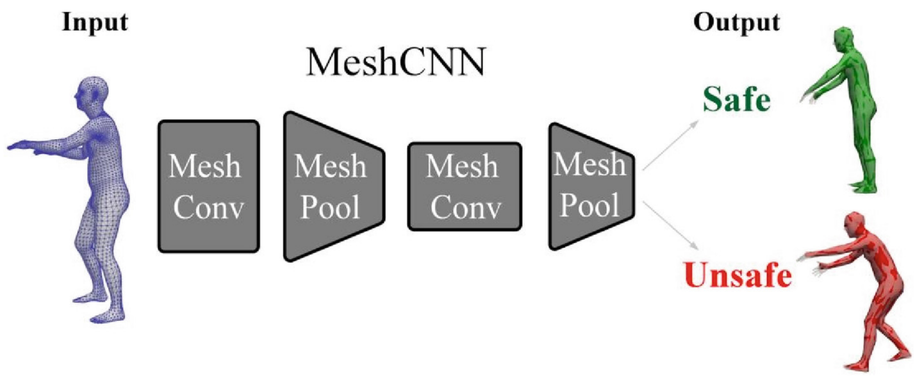

Fig. 14. Concept for MeshCNN pose classification

The polygonal meshes provide an efficient, non-uniform representation that approximates surfaces via 2D polygons in 3D space, explicitly capturing both shape surface and topology [70]. MeshCNN is a deep convolutional neural network designed explicitly for triangular meshes [71]. It comprises customized convolution and pooling operations tailored to operate with the 3D mesh edges. Convolutions process edges accounting for mesh geodesic connections, while the pooling layers preserve the surface topology through the edge collapse. MeshCNN spatially adapts and learns which edges to collapse, unlike classic edge collapse, which removes edges to minimize geometric distortion. Through the successive call of mesh convolution and pooling, the network iteratively generates valid mesh connectivity by learning to preserve and expand important features and discard and collapse redundant ones. The idea is to use 3D pose estimation algorithms, extract a realistic 3D model of a human body, and perform a classification to safe and unsafe acts using irregular structures directly as inputs of a deep neural network (Fig. 14).

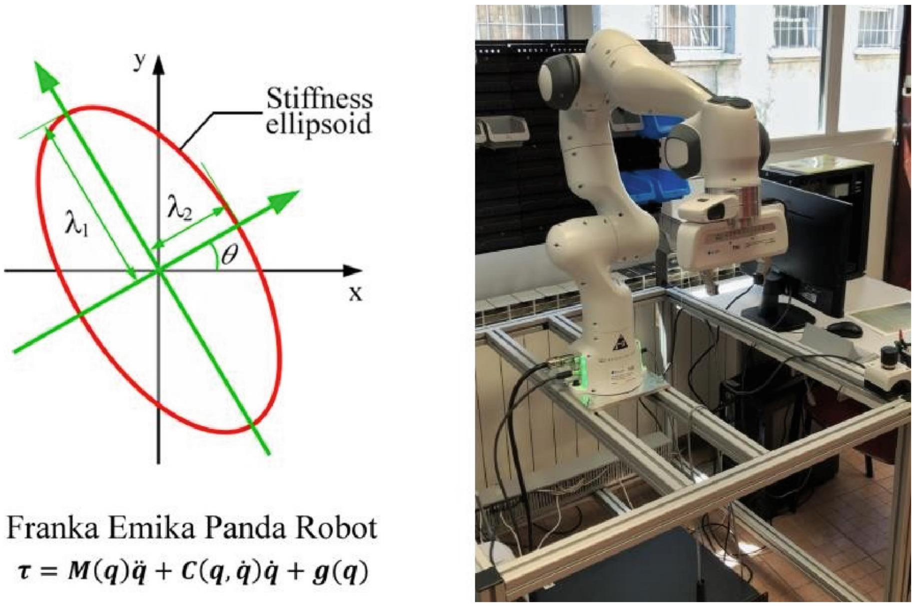

Fig. 15. Collaborative robot and its laboratory setup

4 Assessment of the Human–Robot Collaborative Polishing Task by Using EMG Sensors and 3D Pose Estimation

Our recent study presented a method to improve human–robot collaboration in the industrial setting [72]. The proposed method can be a tool to enhance ergonomics during complex dynamic interactions between a human and a robot, and it can enable the worker to be replaced by a collaborative robot capable of achieving workers' level of performance. The inspiration came from the vision of the factories of the future, where humans and robots will work alongside. This goal is still far away, and more analyses are required from the perspective of collaborative robot control, motion planning, safety, and ergonomics. Previous studies focused on numerous aspects of human–robot collaboration, and a unique framework is proposed for robot adaptation to human motor fatigue in collaborative industrial tasks [73]. KUKA Lightweight Robot was equipped with a Pisa/IIT Softhand and controlled in hybrid force/impedance mode, and EMG measurements were providing information about muscle activity. In order to improve ergonomics, several configurations for collaborative power tooling tasks were tested using an MVN Biomech suit (Xsens Technologies BV) and a Kistler force plate [74]. Conclusions about preferable human poses were obtained based on the analysis of overloading joint torques and muscle activities. The same group of authors introduced the joint compressive forces to enhance the previously proposed model more precisely [75]. Finally, to account for multiple potential contributors to WMSDs, the set of ergonomic indexes are defined, and more extensive experiments were conducted in a laboratory setting [76]. None of the aforementioned solutions incorporated knowledge from the field of computer vision nor performed 3D pose estimation using conventional cameras.

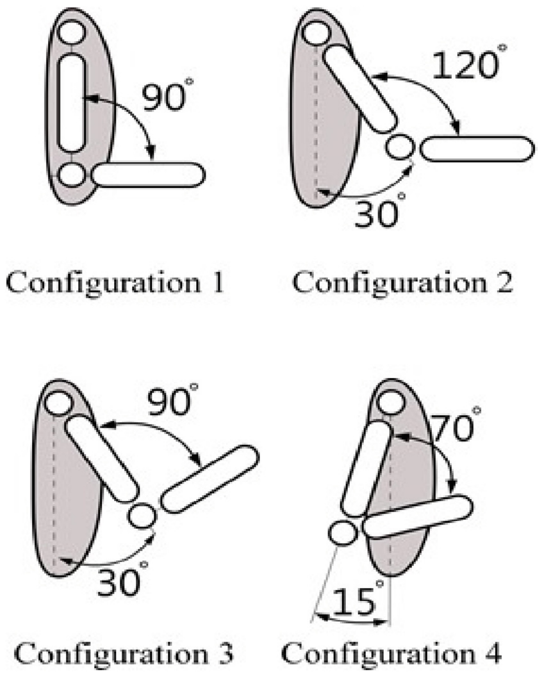

Fig. 16. Four different task configurations adopted by human co-worker

In our previous work, we conducted a laboratory study for human ergonomics monitoring and improvement in a human–robot collaborative polishing task. The data regarding the human whole-body motion, the force exerted on the working piece, and the human muscle activities were recorded through the experimental sessions to investigate the trend of human muscular activity and its correlation with body posture configurations and acting force during the collaborative task. Each subject was instructed to adopt four different body postures (Fig. 16) and to perform the polishing task (using a 1.2 kg polisher) in each configuration for 2 min, exerting a constant force of 10 N and

20 N, respectively. For the analysis of human muscle activity, dominant muscles for the polishing task were selected: Biceps Brachii (BB), Triceps Brachii (TB), Anterior Deltoid (AD), and Posterior Deltoid (PD), and four EMG surface electrodes (Trigno Avanti sensors by Delsys) were placed on the subject's skin (Fig. 11). The EMG signals were processed following the same methodology described in detail in our previous work [77]. The robot (Franka Emika Panda Robot (Fig. 15)) was controlled in impedance mode, and its task was to bring the board to the human and place it in different positions and orientations in the workspace for each experimental session. The board was provided with a force torque sensor to measure the interaction force between the tool and the working piece.

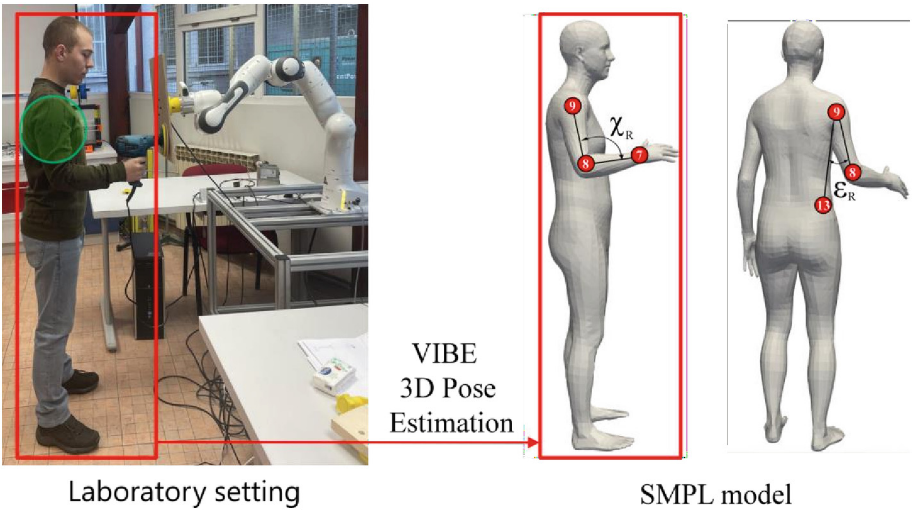

Fig. 17. The concept of the proposed solution - laboratory setting with robot and EMG sensors setup; and SMPL model with selected postural angles

The 3D pose reconstructions were obtained by using the VIBE deep learning architecture, and the poses were represented with the Skinned Multi-Person Linear (SMPL) parametric body model. Following the previous study [33], we extracted a series of ergonomic parameters and selected two postural angles that are important collaborative polishing task - χR and εR, defined on the SMPL model with key points 7–8-9 and 8–9-13, respectively (Fig. 17). Furthermore, human arm manipulability $w = \sqrt{det(J(q)J(q)^T)}$ [78] was taken into account.

The results indicated that for this collaborative task, muscles with dominant activity are the Anterior Deltoid and Biceps Brachii, while the activity of Triceps Brachii and Posterior Deltoid is almost insignificant (below 10% of maximal voluntary contraction for all configurations). Configurations 2 and 3 have overall higher muscle activity than configurations 1 and 4. A similar result can be found in previous work on this topic [74]. With the increase of exerted force, a notable increase, especially in Anterior Deltoid and to some degree in Biceps Brachii activity is observed. Configuration 2 provides the lowest arm manipulability capacity, which affects task productivity and makes it even less preferable than configuration 3. To conclude, preferable poses that are safe and ergonomic and should be adopted by a human coworker in the collaborative polishing task are configuration 1 and configuration 4. The results of 3D pose estimation, more precisely the estimation of two considered postural angles, suggest that there is a potential for successful pose differentiation that opens the possibility of performing accurate pose classification of these four configurations. Pose classification can lead to the adaptation of the robot behavior to assist and guide the human partner to conduct the collaborative task with less effort and in a more ergonomic way.

Fig. 18. mBrainTrain EEG measurement devices [81]

5 The Use of EEG for Workplace Safety Assessment

In the late 1920 s, Hans Berger, a German psychiatrist, invented the electroencephalogram (EEG) to assess the electrical activity of the cerebral cortex. Briefly, EEG is a recording method of the macroscopic electrical activity of the surface layer of the brain using small metal discs (electrodes) attached to the scalp [79]. Recently, a lot of effort was put into investigating the use of EEG in the industry (as it can reveal other useful information, e.g., emotions [80]) - opening a new scientific discipline called neuroergonomics. Monitoring workers' attention and brain cognitive activity during repetitive tasks has been studied using EEG. The potential of EEG to measure the cognitive workload of human operators in the chemical process control room was evaluated [82], and a multi-feature EEG- based workload metric with detailed insight into the evolution of the operator's mental models during training was developed [83]. Deep learning algorithms were used to investigate goal-directed context-dependent and context-independent behavioral patterns as neurological terms and goal-directed decision-making based on a correlation of brain regions' activity [84]. Detection of cognitive overload in highly controlled, specially designed tasks was also explored [85]. In order to develop future fatigue countermeasures and reduce fatigue-related accidents, EEG frequency bands and four different algorithms were used to detect fatigue [86].

5.1 Development of Modular and Adaptive Laboratory Set-Up for Neuroergonomic and Human–Robot Interaction Research

Our recent study presented a modular and adaptive laboratory model (industrial workstation) design for a human–robot collaborative assembly task [87]. The goal was to analyze the task from the perspective of neuroergonomics and human- robot interaction: to explore current industrial workers' problems, including performance, well-being, and injuries, and to create a solution that meets the operator's anatomical, physiological, and biomechanical characteristics. The workstation (Fig. 19) was comprised of several specific components: Poka–Yoke system (six lines that supply six different components), collaborative robot station, EEG system (EASYCAP GmbH, Wörthsee, Germany and SMARTING, mBrainTrain, Serbia (Fig. 18a)), EMG sensors (biosignalsplux muscleBAN), and touchscreen PC screen. Initial conclusions were that it is possible to improve the physical, cognitive, and organizational aspects, thus increasing workers' productivity and efficiency through transforming standard workplaces into the workplaces of the future by applying ergonomic research laboratory experimental set-up.

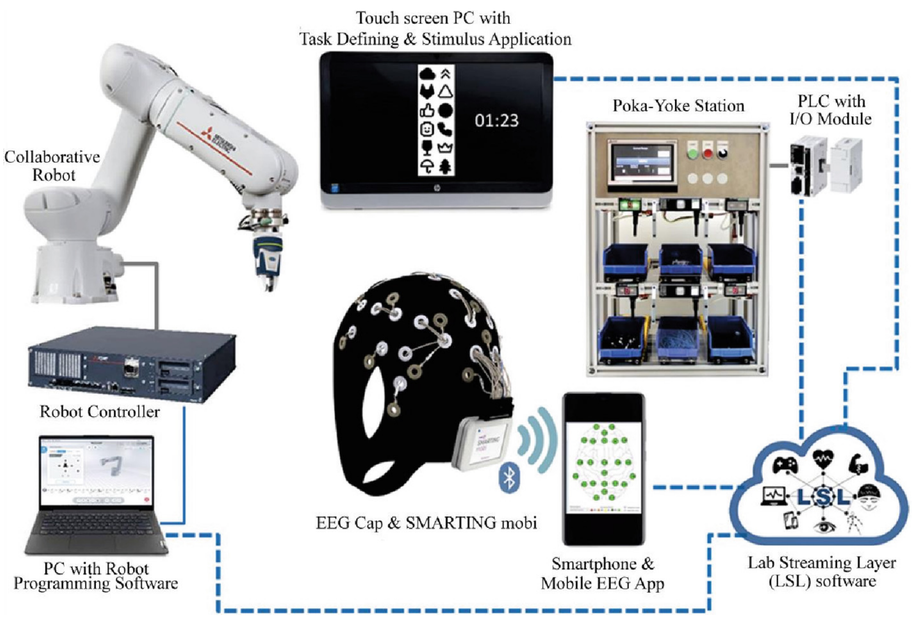

Fig. 19. Lab Streaming Layer integration of key measurement set-up elements [87]