Ergonomics Evaluation Using Motion Capture Technology

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Due to the increasingly high proportion of manual activities in production processes, there is a constant risk of musculoskeletal disorders or work-related injuries. The risk of these problems is exacerbated by the trend towards an ageing working population. European legislation is pressing for improved working conditions to eliminate the risks associated with health problems for workers. For this reason, the application of ergonomics in this field is growing. Musculoskeletal disorders, which are most often caused by inappropriate working postures, are a major problem. There are many methods for evaluating working postures.

Keywords: motion capture ; MoCap ; ergonomics

1. Introduction

Despite the opportunities presented by the introduction of automated solutions in industrial enterprises, most assembly and production processes are still carried out manually [1]. Today's progress cannot fully replace human flexibility and the ability to perform nonrepetitive lifting, assembly, and handling tasks. Physically intensive work and repetitive, uncomfortable working positions are causing musculoskeletal disorders or injuries that negatively affect workers' health [2]. European legislation, national regulations, and international standards force companies to analyse ergonomic risks in the workplace and implement measures to improve the physical and cognitive well-being of workers [3].

The ageing labour force will lead to growing demands on ergonomics. Designs to optimise work environments will have to be based on specific knowledge of the age-dependent performance potential of employees [4]. The basis for ergonomic solutions will be applied research targeting the ageing workforce [5][6]. With increasing age, major physiological changes occur, most organ systems present a physiological functional reduction, and the risk of coexisting diseases increases [7][8]. There is also a gradual decrease in work performance caused by reduced muscle strength and sensorimotor function. After reaching a power-performance peak for men and women in their 20s and 30s, muscle strength inevitably degrades. Last but not least, changes occur in the central nervous system and in the area of mental-cognitive performance [5]. Cognitive human factors include perceptual skills involving sensation, hearing and vision, perception, memory, and conceptual and discretionary skills, involving spatial skills, decision making, and problem solving [6]. All these factors represent a challenge for the design of tools, equipment, and workplaces. This is because there is no typical example of an ageing workforce; each person is affected by the ageing process in a different way. However, the challenge for ergonomics will be to develop a clear approach to developing solutions that meet user needs [6][9]. At the same time, the ability to work in advanced age depends substantially on the adverse factors to which a person is exposed during their lifetime. Ergonomics can contribute significantly to the elimination of risks caused by inappropriate interaction between the worker and the work environment and serve as a tool to delay human ageing [10].

The constant pressure from European legislation to improve the working environment in terms of ergonomics has a significant impact in comparison with the problem of an increasingly ageing population [11]. In most countries, the numbers of aged people and their percentage of the population have been increasing rapidly in recent decades. The process of demographic ageing is probably the most important social change of the 21st century [12][13]. Changes in living standards and quality of life, economic changes, social preferences, medical advances, and family policy are factors leading to changes in the age structure [14]. The continuing ageing of the population is a topic frequently discussed not only by demographers. Demographic changes are occurring in every sector of life, including economic growth, the labour market, health, housing, and migration [15][16]. The proportion of younger workers will decrease, while the number of workers over 50 will increase [17]. Economic prosperity is strongly dependent on the size and quality of the workforce. Businesses will soon have no choice but to pay more attention to the needs of older workers [15][18].

One way to avoid potential health problems of workers performing manual activities is to automate work processes in the context of the development of Industry 4.0 and modern trends. Automation, driven by major innovations in manufacturing, will play a key role in defining the future of industrial enterprises [19]. However, the implementation of robots and the creation of fully automated workplaces may result in a potential reduction in the number of jobs [20]. Therefore, enterprises tend to focus more on human–robot co-operation. This does not eliminate the human workforce, only reorienting it, maintaining work flexibility and efficiency and significantly increasing performance [21][22]. In some industrial countries, the introduction of collaborative robots would be a solution to the problem of a decreasing number of skilled workers [23]. Human–robot collaboration is now becoming a major technology of Industry 4.0 and is changing the character of manufacturing companies. Collaborative robots are an innovative industrial technology implemented to help operators to perform manual operations in so-called cyber–physical production systems, combining unique human capabilities with the power of machines [21][24]. When implementing collaborative robotics, the question of safety and ergonomics is very important; the worker is situated near a robot, for example, when collaborating on the same part or when there is direct physical contact [25][26][27]. A collaborative workplace not only improves economic performance, but can also improve overall ergonomics. With an ergonomic design and a proper segmentation of work activities, a robot can relieve a worker from an uncomfortable posture or fatigue from repetitive load handling [27][28]. The participation of ergonomists has proven to be a necessary condition for the design of collaborative technology and the importance of ergonomics, and its application in this field is growing [26].

However, even workplace ergonomics handled by experts has various pitfalls. Ergonomics uses many different ergonomic evaluation methods to determine workplace risks. Using these tools, it is possible to evaluate and assess the physical load considering the risk of biomechanical overload. Above all, the assessment goals are to find and eliminate the causes of musculoskeletal disorders, which are the most common health problem of workers in production [29][30]. Ergonomists have been using various observational methods or classifications for a long time, for example: for repetitive work—Occupational Repetitive Action (OCRA), for load handling—National Institute for Occupational Safety and Health (NIOSH) equation, and, for postural load assessment or other methods—Rapid Entire Body Assessment (REBA), Rapid Upper Limb Assessment (RULA), or Ovako Work Analysis System (OWAS). These methods are useful in industrial environments as they do not require too much equipment [31][32]. However, for example, RULA measurements based on self-report by workers or observation by an external assessor are subjective and suffer from low repeatability [30]. The current context of Industry 4.0 focuses on the importance of updating these observational methods and the necessity to develop and implement new objective ergonomic assessment methods [31]. For this reason, there is a growing interest in reliable, fast, and automatic tools for motion capture and analysis, not only in industrial environments, but also in the entertainment, medical, and sports fields [33]. Different types of motion capture methods have been developed [29].

2. Ergonomics Evaluation

In general, according to the research literature, it can be concluded that motion capture technology has a wide range of potential applications. However, most of the publications deal with the use of these technologies for ergonomic evaluation of working postures. This category includes articles from industry, in which researchers focus on ergonomics of manual material handling (**Performance evaluation of a wearable inertial motion capture system for capturing physical exposures during manual material handling tasks)**, work in warehouse environments, assembly tasks, etc. Due to the difficult conditions for capturing the movement of workers, new technologies are being developed to capture working positions, even in heavy industrial applications [34]. For example, in the paper **Innovative real-time system to integrate ergonomic evaluations into warehouse design and management,** the authors have developed a system based on inertial sensors with integrated magnetic interference compensation and long wireless connection specifically for this purpose [35]. Another important research set consists of articles from the construction industry. Workers in the construction industry are often exposed to physically demanding manual tasks with a high degree of ergonomic risk [36][37]. The rapid development of motion sensors in the construction industry enables proactive accident prevention by reducing the number of dangerous actions that commonly occur [38]. The authors of the articles **Experience, Productivity, and Musculoskeletal Injury among Masonry Workers** [39], **Data Fusion of Real-Time Location Sensing and Physiological Status Monitoring for Ergonomics Analysis of Construction Workers** [40], and **Stochastic Modelling for Assessment of Human Perception and Motion Sensing Errors in Ergonomic Analysis** [36] want to achieve consistent results. Using Inertial Measurement Units (IMUs) and video cameras, they reduce the risk of musculoskeletal disorders, injuries, and eliminate unhealthy work behaviour of workers [41][42][43]. Motion capture is used for a variety of purposes in healthcare, whether to evaluate working postures, for example at dental practices, or as a tool to support rehabilitation [29][44][45][46]. It can also include a medical study on **Motion tracking and gait feature estimation for recognising Parkinson's disease using MS Kinect,** which focuses on the use of Microsoft Kinect image and depth sensors for gait analysis and detection of Parkinson's disease symptoms [44][45][47][48]. Less common is the use of motion capture technology in the fields of sport, music, dance, etc. Athletes make all efforts possible to achieve maximum performance and to overcome not only their competitors, but especially themselves [49][50]. The article **Using Wearable Sensors to Capture Posture of the Human Lumbar Spine in Competitive Swimming** presented the possibility of using wearable inertial sensors for swimmers' training. Unlike visual analysis or video analysis, this system was able to provide objective measured data on the position of a swimmer's lumbar spine. The outputs subsequently provided coaches and researchers with valuable information on swimmer performance and technique in competitive swimming styles [51]. Another example of the use of inertial sensors is the study **Paddle Stroke Analysis for Kayakers Using Wearable Technologies**, which focuses on capturing the correct posture of a kayaker. Again, the proposed approach provides coaches and athletes with quantitative information that is crucial to achieving perfect performance and avoiding sports injuries [52]. The authors of the article **Folk Dance Evaluation Using Laban Movement Analysis** used the MoCap suit in a very interesting way, specifically to capture folk dance movements. After capturing the movements, a virtual reality simulator prototype was then created to teach them. Here, the user could view the dance segments and then repeat them themselves. The user's movements were captured and compared to a template and the dancer then received intuitive feedback [53].

From a research perspective, the importance of ergonomic assessment of work postures is increasing. Ergonomics increases worker comfort and directly affects work efficiency and productivity [54]. This fact is discussed by the authors of **A framework for interactive work design based on motion tracking, simulation, and analysis** and **Automatic risk assessment integrated with activity segmentation in the order picking process to support health management**. Both analyses apply motion tracking and ergonomic evaluation methods to improve the efficiency and quality of work in assembly, manipulation, and maintenance work. The authors aim to increase competitiveness and create a compromise between system performance and operator well-being, using digital human modelling (DHM) technology and motion capture devices based on the inertial measurement unit (IMU) [55][56]. A large percentage of studies related to workplace ergonomics investigate the use of modern technologies to prevent or eliminate biomechanical overload in workers. Physically demanding and repetitive tasks lead to work-related accidents, injuries, and musculoskeletal disorders. These risks can be completely avoided in the design of the workplace. For example, in the article **Ergonomic Design of a Workplace Using Virtual Reality and a Motion Capture Suit,** the authors created an innovative method of ergonomic workplace design using a motion capture suit (MoCap) linked to virtual reality [57]. The author team's research in this area was focused on manual assembly operations and the aim was to use motion capture to assess the ergonomics of these processes in virtual reality. A significant positive of this approach is the ability to apply this methodology in the design of a workplace before it is actually implemented in operation, allowing verification of ergonomic suitability and modifications if necessary to achieve better results. This allows cost savings to be made on changes to an already established workplace in operation. The disadvantage is that it is limited to manual assembly processes only; in the future, this methodology could be investigated within other types of processes. Position and motion capture are used not only in connection with workplace design, but also to detect and eliminate inappropriate work postures and optimise the current work environment. Evidence is provided by the articles **Innovative real-time system to integrate ergonomic evaluations into warehouse design and management, Physical risk factors identification based on body sensor network combined to videotaping, Measuring Biomechanical Risk in Lifting Load Tasks Through Wearable System and Machine-Learning Approach,** in which the authors use wearable sensors and other assistive technologies to capture motion and perform ergonomic analyses in different types of work environments [35][58]. Scientific progress is seen not only in motion capture methods, but also in methods of analysing the collected data. In the last of the three studies, a specific set of tools was developed and presented that processes the collected motion data and that provides an objective ergometric evaluation in real time [59]. Finally, the sources show that ergonomic evaluation does not only focus on a wide variety of work fields and environments, but also on specific age groups of workers. In the articles **Systematic review of Kinect-based solutions for physical risk assessment in manual materials handling in industrial and laboratory environments**, and **Ergonomics/Human Factors Needs of an Ageing Workforce in the Manufacturing Sector,** the authors highlight the increasing number of aged workers and provide information and perspectives on how industry will need to adapt to meet the needs of these workers in the future. For this purpose, the authors use Microsoft Kinect to characterise the aging workforce based on physical and cognitive factors [58][60].

The most widely used ergonomics assessment methods include Ovako Working Analysis System (OWAS), Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), Occupational Repetitive Action (OCRA), Snook and Ciriello, and National Institute of Occupational Safety and Health (NIOSH). Each of these methods requires different input data and focuses on assessing different aspects of ergonomics. Ergonomics assessment methods can be applied using tools that can be divided into self-report, observational tools, virtual simulations, and direct measurements. Answers to the question of the suitability of the use of the different ergonomic methods and the MoCap tool were provided by the studies [35]. Based on the examined sources, it can be concluded that the most commonly used ergonomic method is Rapid

Upper Limb Assessment (RULA), which is an internationally used and popular observational method that examines the kinematics of the upper body, that is, the neck, shoulder, trunk, and arms [61]. It is used to evaluate data captured by inertial sensors by the authors of **Combining Ergonomic Risk Assessment (RULA) with Inertial Motion Capture Technology in Dentistry-Using the Benefits from Two Worlds,** and **Physical risk factors identification based on body sensor network combined to videotaping** [58][62]. On the other hand, the authors of the study **Automatic risk assessment integrated with activity segmentation in the order picking process to support health management** highlight the shortcomings of the RULA methodology. This method is unable to assess the impact of improvement strategies on ergonomic risks because it is missing information about the activity. Together with posture risk, activity information is needed to accurately analyse the effect of the applied improvement strategies. A more comprehensive ergonomic analysis of the data obtained by MoCap is presented in the research paper **Innovative real-time system to integrate ergonomic evaluations into warehouse design and management.** The authors have developed an innovative whole-body system for real-time ergonomic evaluation of manual material handling in a warehouse. This system was created based on the most widely used RULA, OWAS, and OCRA methodologies and Lifting Index (LI) software subsystem, which can evaluate whole-body ergonomics. Due to the limitations and applicability of each method, the Selection Method module allows the user to directly select the most appropriate method based on the specific application [35]. The study **Wearable Sensor Network for Biomechanical Overload Assessment in Manual Material Handling**, again, highlights the absence of the possibility for whole-body ergonomic assessment when using a sensor network composed of inertial measurement units (IMUs).

The aim of the systematic reviews was also to analyse and evaluate the problems in the evaluation of ergonomics using motion capture technology and the feedback mentioned by the authors in their publications. These problems occurring during the application of motion capture technology in the workplace are discussed in several articles, which provide in their analyses improvements or compare data obtained with different technology, while highlighting their shortcomings or advantages of use. In the article **Evaluation of the Kinect™ sensor for 3-D kinematic measurement in the workplace,** the authors describe the inappropriateness of using existing motion-capturing systems for field work. They focus on the more optimal Microsoft Kinect method, comparing the obtained data with estimations from the Vicon system, and resolve the question of the feasibility, accuracy, and sensitivity of Microsoft Kinect used as a portable motion capture system at the workplace [42]. In comparison, the study **Filtered pose graph for efficient Kinect pose reconstruction** focuses on the problems of the frequently used Kinect. They highlight the high positioning requirements to obtain accurate positions. To improve the robustness of Microsoft Kinect, the authors proposed a new method for posture reconstruction based on modelling a posture database with a structure called a filtered pose graph. The study shows an improvement of the relevance of the positions and an improvement of the accuracy of the obtained data compared to the existing methods [63]. The paper **Experimental evaluation of indoor magnetic distortion effects on gait analysis performed with wearable inertial sensors** investigates the influence of magnetic fields on the distortion of outputs from a magnetic inertial measurement units (MIMU) system. Based on the gait analysis, it was found that some distortion occurs on the transverse planes of each joint and on the frontal plane of the ankle. Nevertheless, the measurements showed sufficient repeatability and the resulting data provide important information about the performance of the MIMU [64][65]. The authors of **Detecting the Hazards of Lifting and Carrying in Construction through a Coupled 3D Sensing and IMUs Sensing System** discuss the limitations of motion measurements under extreme lighting conditions and distortion. Their research proposes the design of a connected system that integrates and synchronises Microsoft Kinect with an inertial measurement unit (IMU) that is capable of providing reliable data, even under extreme conditions [66]. Research shows that there has been significant development in modern motion capture technologies used for ergonomic analysis. Methods of detecting and compensating for errors occurring in the measurement process and new systems allow for increasingly accurate outputs and the ability to objectively assess the optimality of the working environment [44].

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