Instrument-based ergonomic assessment: A perspective on the current state of art and future trends

Sara M. Cerqueira[1], Alexandre Ferreira da Silva[1] and Cristina P. Santos[1]

***Abstract*— The majority of occupational disorders result from Work-Related Musculoskeletal Disorders (WRMSDs). Consequently, through the years, a substantial level of effort has been placed on developing new tools for ergonomic assessment, and nowadays, three major methods can be identified: self-reports, observational methods, and instrument-based. The present paper presents a brief review of the current methodologies for ergonomic-risk assessment, focusing on the instrument-based tools already developed. Additionally, an analysis is conducted on the potentials and future prospects of wearables in the industry 4.0, where the symbiosis between humans and machines is the heart of the concept.**

I. INTRODUCTION

WRMSDs sometimes referred to as repetitive strain injuries (RSI) represent the major contribution for occupational diseases, namely in Europe [1]. These disorders result from working conditions that expose workers to risk factors like high loads, repetitive motions, contact stress, static loading (lifting), vibration and poor posture, among other reasons, all of which are major risk factors [1]. In the last years, more attention has been drawn to this issue as it is one of the main concerns and research priorities of the European Agency between the years 2013 and 2020, not only due to the health effects on individual workers but also because of the economic costs involved such as insurance, medical and administrative costs, sick leave costs, early retirements and the reduction of the productivity levels [2], [3]. In fact, it is estimated that the costs derived from WRMSDs approach about 0.5% to 2% of the Gross Domestic Product (GDP) [4]. One of the main causes, besides heavy lifting and/or carrying and whole-body vibration, is sustaining an awkward body posture, namely excessive bending and twisting, which increases spinal stress and could result in injuries in tendons and muscles [5]. The present study aims at surveying the current tools developed and used for ergonomic assessment, highlighting their advantages and disadvantages, and a foresight of future trends and wearables' relevance in the Industry 4.0.

*This work has been supported in part by the FEDER Funds through the COMPETE 2020 – Programa Operacional Competitividade e Internacionalização (POCI) and P2020 with the Reference Project EML under Grant POCI-01-0247-FEDER-033067, and through the COMPETE 2020 – POCI – with the Reference Project under Grant POCI-01-0145-FEDER-006941.

[1]Sara Cerqueira, Alexandre Ferreira da Silva and Cristina P. Santos are with the Center for MicroEletroMechanical Systems (CMEMS), University of Minho, 4800-058, Guimarães, Portugal a75268@alunos.uminho.pt, asilva@dei.uminho.pt, cristina@dei.uminho.pt

II. METHODS FOR RISK ASSESSMENT

The literature presents several methods for risk exposure assessment and to evaluate the need for ergonomic intervention. These tools can be classified as self-reports, observational methods and direct methods [6], being that, while some methods attempt to correlate the fatigue with the duration, posture, and lifting range of each task, others only evaluate muscular fatigue [7]. The self-reports collects risk exposure data from the worker, both physical and psychological, through interviews and questionnaires. However, even though its application is direct and initially inexpensive, it is dependent on the worker perception, which usually is imprecise and unreliable. Also, in order to guarantee a representative data, a large number of samples is needed, which ends up raising the costs [6], [8]. Observational methods aim to detect workplace risk exposure by observation on the field or replaying videos, and can be subdivided into simpler and advanced. The simpler ones, also called pen and paper methods, are performed on job site by an ergonomic expert. Common used observational methods for upper body evaluation are Rapid Upper Limb Assessment (RULA), Ovako Working Posture Analysing System (OWAS), Occupational Repetitive Actions (OCRA), Postural Ergonomic Risk Assessment (PERA), Rapid Entire Body Assessment (REBA) and the NIOSH lifting equation. These methods evaluate different parameters, such as posture, frequency, duration, load/force, recovery time, among others. Despite being affordable and non-invasive, the simpler observational techniques are highly dependent on the analyst expertise, diminishing repeatability, precision and objectiveness [9]. In fact, the ergonomist hardly will notice a difference of $10°$ in the worker posture, when observed in real time. On the other hand, the advanced observational techniques are based on video recording, followed by a dedicated software analysis. Hence, its results are more precise. Yet, its costs are substantially higher, requires a highly specialized staff for work posture characterization and are time-consuming [6]. Finally, direct or instrument-based methods can acquire, in real time, the ergonomic level risk. Actually, the use of modern measuring devices, placed on the user's body, could lead to objective and more accurate results, reducing the time needed for an ergonomic evaluation and allow the assessment of dynamic tasks. However, instrument-based tools are frequently expensive and complex, once the data interpretation demands effort from the analyst and can bring discomfort and alterations to the workers' behaviour [10]. Recently, researchers have been developing this type of systems, aiming to provide an automatic and objective assessment of the ergonomic risk to which the worker is exposed, during his task's performance [11].

III. INSTRUMENT-BASED METHODS

The existing systems for direct assessment of the human body posture can be categorized into: (1) Goniometric-based, such as the Lumbar Motion Monitor, a tri-axial electronic goniometer that measures of the displacement angle of the thoracolumbar region in relation to the pelvis [12]. However, its usage is uncomfortable and can modify the normal postural behavior. (2) sonic-based, which use ultrasonic waves and are constituted by transmitters and receivers. Once the sound propagation on body tissue is constant, the distance between both sensors can be calculated and, therefore, measured the spine flexion, emulating the Schobert's test [13]. An example is the system developed by [13], which integrated four pairs of ultrasound emitters and receivers with an inclinometer, a device that measures angles in relation to the gravity line, for evaluation of trunk inclination and spine curvature. However, these systems present some drawback such as sampling rate, since distance measuring depends on the velocity of the sound in the body tissue. Also, the thickness of the subcutaneous fat and air noise and properties (e.g. temperature, air density) can influence the results, which limits the usage to laboratory conditions and to subjects with low body fat percentage [9], [13]. (3) Accelerometer-based, a sensor that measures acceleration variations for further angle computation. An inclinometer constituted by four tri-axial accelerometers was developed by [14], aiming the assessment of posture and movement of upper limbs, trunk, and neck, with the line of gravity as reference and two degrees of freedom. The system was able to measure the degree of arm elevation, although it was relative to the vertical line of gravity and not to the trunk. It also could not measure rotation or distinguish arm adduction from arm flexion. (4) Motion capture (MoCap) technologies, which includes optical marker-based, optical marker-less, and inertial. These technologies provide a digitalization of the subjects' motion, a promising technique for posture evaluation that has been exploited by researchers in the last years [11]. Regarding posture strain and muscular fatigue evaluation, the most used method is electromyography (EMG), a technique based on the measurement of the skin's electrical potential through the use of electrodes. There are two types available: intramuscular and surface EMG. Due to the fact that the first one is invasive, sEMG sensors are preferred for ergonomic assessment experiments [9]. These last two methods, the MoCap technology and the sEMG, have been very popular among the researchers for ergonomic risk assessment and, therefore, worthy of a deeper analysis.

A. MoCap technologies

The marker-based motion tracking systems have been extensively used due to its precision, reproducibility and possibility to analyze the whole body at the same time. However, these systems require the use of markers, which are reflective (passive markers) or light-emitting (active markers) surfaces, by the subject. One example is the Mac Reflex, a system composed of video cameras with infra-red overlaid and reflex markers, that can measure the Euler angles of the rigid body [14]. Commercially available OptiTrack, CODA and VICON are also frequently used [15]. These systems are very precise and accurate, enable the capture of multiple subjects movements and allow a high acquisition rate. Marker-less MoCap is based on depth cameras and computer vision algorithms to estimate body position and assess its kinematics. A popular choice for research projects is the Kinect, developed by Microsoft Corp in 2009, due to its low cost [16]. The first generation of this sensor has been used for ergonomic risk assessment, acquiring data for implementation of methods such as OWAS [17]. However, this generation was not capable of measuring joint rotations, which was improved in the second generation of Kinect, and, therefore, allowing the computation of scoring risks through RULA, NIOSH, REBA and EAWS criteria [11], [16]. Another approach for the use of this sensor was the development of a smart workplace that could adjust the table height to the worker when an awkward position was identified. However, the system presented a low efficiency as the height chosen by the system only matched the one that was suitable for the worker in 15% of the cases [18]. As for the Inertial MoCap, they use inertial measurement units (IMU) attached to the human body. These sensors combine accelerometers, gyroscopes and, in some cases, magnetometers. They can measure acceleration, angular velocity and magnetic field when the magnetometer is present. However, the magnetic field is influenced by metal objects, which are very common in industrial context. IMUs can obtain orientation on the transverse plane, which was not possible with accelerometer-based systems. Commercial systems like the MVN from Xsense and the IGS-180i from the Animazoo have been used for inertia data acquisition and computation of 17 body joint's, allowing ergonomic assessment based on RULA, OWAS, LI, and OCRA methods [19] or quantification and evaluation of the trunk postures for workspace redesign purposes [20]. Notwithstanding, these systems are expensive, which constitutes a barrier to its implementation. Consequently, researchers developed low-cost systems, on a DIY approach, like the arm motion tracking developed by [15], that used one IMU on the upper arm and one potentiometer aligned with the elbow joint axis, or by using the built-in sensors from the smartphones [8]. Additionally, the knowledge of the potential of posture feedback to the user led the developers to incorporate warnings when the predefined angle thresholds were exceeded [10], [21]. In [22], IMUs were embedded on the personal protective equipment with the same aim. In fact, the experiments' results showed that the subjects did improve their posture in the following days. Posture recognition has also been addressed, based on a state machine algorithm [23]. Seeking to overcome each sensor limitation, [24] proposed a coupled system that synchronizes a Kinect camera with an IMU, with the first acquiring the initial position and building a reference for the IMUs recorded information.

B. sEMG

Small-sized and wireless surface electromyography sensors have been exploited for ergonomic assessment. These sensors are non-invasive and provide a direct and objective measurement of physical load exerted on muscles without intruding in the worker's normal activities. Consequently, it has been exploited for assessment of the muscular efforts required by the performed task and for computation of NIOSH lifting equation with the EMG information [25]. Moreover, a combination of sEMG sensors with IMUs networks have been proposed, aiming to complement kinematics data with force exertion for evaluation of the ergonomic risks associated with manual rebar tying typical positions [26] and the biomechanical overload study in a car assembly line [27].

IV. DISCUSSION

Optical Motion caption systems suffer a few drawbacks such as the need of a large, dedicated and light controlled environment, the cameras' limited field of view, the possibility of occlusion by the surrounding objects that can result in an inaccurate 3D representation of posture, and the fact that data processing is time-consuming [28], [29]. Additionally, even though the marker-based optical MoCap is often seen as the gold standard for human motion analysis, it has a high initial cost and imposes the use of a special suit with embedded markers [30]. On the other hand, Marker-less optical MoCap like the Kinect, dismiss markers and, therefore, the use of special suits and calibration is not needed. Also, they are less expensive than the other MOCAP options [31]. However, due to the restrictions imposed on the workspace area and conditions, the use of camera-based technology is often limited to laboratory condition. In turn, marker-based MoCap is commonly used as ground truth for the validation of new projects. Unlike the abovementioned systems, IMUs do not suffer from occlusion, light conditions or misrepresentation of real motion conditions [31]. In terms of comparison, IMUs are more reliable and robust than the Kinect. In addition, its small size and lightweight allows its integration on wearables that can be used for ergonomic assessment on the actual workplace with no mobility restrictions, contrary to the optical MoCap technologies. sEMG can also be used in wearables and allow the study of the muscles involved in the task execution. However, IMUs and sEMG present limitations. Regarding the first ones, it lacks reference and surrounding environment data, an information often helpful for better identification and analysis of endangering tasks [31]. sEMG sensor' shortcomings are related to electrode-skin impedance, noise, crosstalk between muscles signals, along with the knowledge requirement about anatomy and electrophysiology [32]. In terms of academic work, a trend for wearable and inertial-based systems was identified.

V. PERSPECTIVE ON FUTURE TRENDS

Currently, observational-based methods remain the most used ergonomic assessment tool. Notwithstanding, as revised above, through the years, researchers have been putting effort into testing existing devices, initially developed for other purposes (e.g. MVN Xsense), and developing their own system for posture recognition and quantification of the ergonomic risk associated with the workplace or task, aiming the workplace redesign or posture improvement, through the feedback integration on the device. The industry is marching to its 4th revolution, searching for the smart and skilled operator 4.0, that uses the interaction between humans and machines to potentialize his productivity. However, a productive worker must be healthy, and the use of wearables in an industrial context is a step-further to this vision [33]. The possibility of acquiring the operator's kinematics and continuously monitoring his posture on-site offers many possibilities. Besides the already implemented strategies of providing warnings to empower the worker with posture self-awareness, namely, the related risk level and the possibility to correct it, other approaches are possible. Such include recording the operator's posture during the work shift and keeping a historical track, which can be used for pattern recognition through the use of artificial intelligence algorithms. As a result, the identification of tired workers would be possible and, therefore, plan rest-pauses and work-shifts or send a warning to switch tasks, according to the identified patterns. Furthermore, based on the industry 4.0 perspective, the workplace could adjust itself, like the table height, to the worker in a concept similar to the one implemented with the Kinect camera [18]. Also, the acquisition of the operator kinematics could help human-robot collaborations by live streaming the workers biomechanical information to the robot, which would adjust its assistive behavior to reduce the operators joint overload, when detected [34]. Moreover, the addition of sEMG sensors to the IMUs network in the wearable would provide important data regarding the muscular strain. For example, sEMG data can be a leverage for the identification of lifting intents [35]. The intention prediction could also be fed to the collaborative robot, which would aid the operator to lift the object. In addition, feature extraction from kinematics for gesture recognition and posture classification, which has already been subject of study [36], could be an asset towards the human cyber-physical production system, a concept that aims a dynamic interaction between humans and machines [33]. Nevertheless, such proposition is still difficult to accomplish. First of all, in order to the worker accept to use the wearable daily, its design must be comfortable, lightweight, non intrusive, and grant a friendly user interface. Secondly, a stable network connectivity shall be guaranteed, assuring that data is not lost, and the usual process is not stopped. Additionally, the battery life must last the work shift and the decision making shall be performed in real time and on-site [37]. Also, IMUs acquires lots of data. When many sensors are used, both the large amount of data transfer and storage, as the high computational resources required for its processing, pose as a barrier. The issue of reducing data storage has been addressed, with the use of supervised motion tensor decomposition for inertial data processing and posture prediction. The stored data presented a reduction of 90%, but further work must be developed to improve the system's accuracy, especially when predicting transitional postures [38]. In conclusion, wearables present a massive potential and certainly will take a major role in the upcoming industry. However, hardware and software developments are still required to achieve this end, constituting a relevant research opportunity for the scientific community.

REFERENCES

[1] M. Aghilinejad, N. S. Azar, M. S. Ghasemi, N. Dehghan, and E. K. Mokamelkhah, "An ergonomic intervention to reduce musculoskeletal discomfort among semiconductor assembly workers," *Work*, vol. 54, pp. 445–450, jul 2016.

[2] EU-OSHAS, "OSH in figures: Work-related musculoskeletal disorders in the EU-Facts and figures," tech. rep., 2010.

[3] E. Rial-González, S. Copsey, and P. Paoli, "Priorities for occupational safety and health research in Europe:2013-2020," tech. rep., 2013.

[4] Direção-Geral da Saúde, "Lesões musculoesqueléticas melacionadas com o trabalho: Guia de orientação para a prevenção," tech. rep., 2008.

[5] W. J. A. Grooten and E. Johansson, "Observational Methods for Assessing Ergonomic Risks for work-related musculoskeletal disorders. A Scoping Review," *Revista Ciencias de la Salud*, vol. 16, p. 8, jun 2018.

[6] G. C. David, "Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders," *Occupational Medicine*, vol. 55, pp. 190–199, may 2005.

[7] E. Spyropoulos, E. Chroni, P. Katsakiori, and G. Athanassiou, "A quantitative approach to assess upper limb fatigue in the work field," *Occupational Ergonomics*, vol. 11, pp. 45–57, 01 2013.

[8] N. Nath, R. Akhavian, and A. H. Behzadan, "Ergonomic analysis of construction worker's body postures using wearable mobile sensors," *Applied Ergonomics*, vol. 62, pp. 107–117, 07 2017.

[9] G. LI and P. BUCKLE, "Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods," *Ergonomics*, vol. 42, pp. 674–695, may 1999.

[10] N. Vignais, M. Miezal, G. Bleser, K. Mura, D. Gorecky, and F. Marin, "Innovative system for real-time ergonomic feedback in industrial manufacturing," *Applied Ergonomics*, vol. 44, pp. 566–574, jul 2013.

[11] M. Bortolini, M. Gamberi, F. Pilati, and A. Regattieri, "Automatic assessment of the ergonomic risk for manual manufacturing and assembly activities through optical motion capture technology," *Procedia CIRP*, vol. 72, pp. 81–86, 2018.

[12] W. Marras, F. Fathallah, R. Miller, S. Davis, and G. Mirka, "Accuracy of a three-dimensional lumbar motion monitor for recording dynamic trunk motion characteristics," *International Journal of Industrial Ergonomics*, vol. 9, pp. 75–87, jan 1992.

[13] M. Wunderlich, T. Rüther, D. Essfeld, T. C. Erren, C. Piekarski, and D. Leyk, "A new approach to assess movements and isometric postures of spine and trunk at the workplace," *European Spine Journal*, vol. 20, pp. 1393–1402, aug 2011.

[14] E. Bernmark and C. Wiktorin, "A triaxial accelerometer for measuring arm movements," *Applied Ergonomics*, vol. 33, no. 6, pp. 541 – 547, 2002.

[15] T. Taunyazov, B. Omarali, and A. Shintemirov, "A novel low-cost 4-DOF wireless human arm motion tracker," in *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, vol. 2016-July, pp. 157–162, IEEE, jun 2016.

[16] V. M. Manghisi, A. E. Uva, M. Fiorentino, V. Bevilacqua, G. F. Trotta, and G. Monno, "Real time RULA assessment using Kinect v2 sensor," *Applied Ergonomics*, vol. 65, pp. 481–491, nov 2017.

[17] J. A. Diego-Mas and J. Alcaide-Marzal, "Using Kinect sensor in observational methods for assessing postures at work," *Applied Ergonomics*, vol. 45, pp. 976–985, jul 2014.

[18] T. D. Nguyen, M. Kleinsorge, and J. Kruger, "ErgoAssist: An assistance system to maintain ergonomie guidelines at workplaces," in *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*, pp. 1–4, IEEE, sep 2014.

[19] D. Battini, A. Persona, and F. Sgarbossa, "Innovative real-time system to integrate ergonomic evaluations into warehouse design and management," *Computers & Industrial Engineering*, vol. 77, pp. 1–10, nov 2014.

[20] C. Brents, M. Hischke, R. Reiser, and J. Rosecrance, "Low back biomechanics of keg handling using inertial measurement units," in *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018)* (S. Bagnara, R. Tartaglia, S. Albolino, T. Alexander, and Y. Fujita, eds.), (Cham), pp. 71–81, Springer International Publishing, 2019.

[21] M. Owlia, C. Ng, K. Ledda, M. Kamachi, A. Longfield, and T. Dutta, *Preventing Back Injury in Caregivers Using Real-Time Posture-Based Feedback: Volume III: Musculoskeletal Disorders*, pp. 750–758. 01 2019.

[22] X. Yan, H. Li, A. R. Li, and H. Zhang, "Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention," *Automation in Construction*, vol. 74, pp. 2–11, feb 2017.

[23] E. Valero, A. Sivanathan, F. Bosché, and M. Abdel-Wahab, "Analysis of construction trade worker body motions using a wearable and wireless motion sensor network," *Automation in Construction*, vol. 83, pp. 48–55, nov 2017.

[24] J. Chen, C. Ahn, and S. Han, "Detecting the hazards of lifting and carrying in construction through a coupled 3d sensing and imus sensing system," 06 2014.

[25] A. Ranavolo, T. Varrecchia, S. Iavicoli, A. Marchesi, M. Rinaldi, M. Serrao, S. Conforto, M. Cesarelli, and F. Draicchio, "Surface electromyography for risk assessment in work activities designed using the revised NIOSH lifting equation," *International Journal of Industrial Ergonomics*, vol. 68, pp. 34–45, nov 2018.

[26] W. Umer, H. Li, G. Szeto, and A. Wong, "Identification of biomechanical risk factors for the development of lower-back disorders during manual rebar tying," *Journal of Construction Engineering and Management*, vol. 143, p. 04016080, 07 2016.

[27] M. G. L. Monaco, L. Fiori, A. Marchesi, A. Greco, L. Ghibaudo, S. Spada, F. Caputo, N. Miraglia, A. Silvetti, and F. Draicchio, "Biomechanical overload evaluation in manufacturing: A novel approach with semg and inertial motion capture integration: Volume i: Healthcare ergonomics," pp. 719–726, 01 2019.

[28] J. Manuel, *Desenvolvimento de um Guião de Selecção de Métodos para Análise do Risco de Lesões Músculo-Esqueléticas Relacionadas com o Trabalho (LMERT).* 2015.

[29] "Improving posture classification accuracy for depth sensor-based human activity monitoring in smart environments," *Computer Vision and Image Understanding*, vol. 148, pp. 97 – 110, 2016. Special issue on Assistive Computer Vision and Robotics -.

[30] A. Cuesta-Vargas, A. Galn-Mercant, and J. Williams, "The use of inertial sensors system for human motion analysis," *Physical therapy reviews : PTR*, vol. 15, pp. 462–473, 12 2010.

[31] E. Tee, H. Low, W. Saim, W. Nurshazwani, S. Zakaria, M. Binti, H. Khialdin, M. I Isa, C. Fhong Awad, S. , K. Tee, L. Eugene, I. Hashim, W. Wan Zakaria, S. Binti, S. Mohd Khialdin, H. Isa, M. Awad, and C. Soon, "A study on the ergonomic assessment in the workplace," vol. 1883, 08 2017.

[32] A. Ranavolo, F. Draicchio, T. Varrecchia, A. Silvetti, and S. Iavicoli, "Wearable Monitoring Devices for Biomechanical Risk Assessment at Work: Current Status and Future ChallengesA Systematic Review," *International Journal of Environmental Research and Public Health*, vol. 15, p. 2001, sep 2018.

[33] D. Romero, J. Stahre, T. Wuest, O. Noran, P. Bernus, . Fasth, Fast-Berglund, and D. Gorecky, "Towards an operator 4.0 typology: A human-centric perspective on the fourth industrial revolution technologies," in *CIE46 Proceedings*, pp. 29–31, 10 2016.

[34] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, and A. Ajoudani, "Anticipatory Robot Assistance for the Prevention of Human Static Joint Overloading in HumanRobot Collaboration," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 68–75, 2018.

[35] D. Totah, L. Ojeda, D. D. Johnson, D. Gates, E. Mower Provost, and K. Barton, "Low-back electromyography (emg) data-driven load classification for dynamic lifting tasks," *PLOS ONE*, vol. 13, p. e0192938, 02 2018.

[36] T. Du, X. Ren, and H. Li, "Gesture recognition method based on deep learning," in *2018 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, pp. 782–787, May 2018.

[37] X. T. R. Kong, H. Luo, G. Q. Huang, and X. Yang, "Industrial wearable system: the human-centric empowering technology in Industry 4.0," *Journal of Intelligent Manufacturing*, pp. 1–17, apr 2018.

[38] J. Chen, J. Qiu, and C. Ahn, "Construction worker's awkward posture recognition through supervised motion tensor decomposition," *Automation in Construction*, vol. 77, pp. 67–81, may 2017.