International Journal of Industrial Ergonomics 66 (2018) 1–9

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon

Lifting activity assessment using surface electromyographic features and neural networks

Tiwana Varrecchia [a, *], Cristiano De Marchis [a], Martina Rinaldi [a], Francesco Draicchio [b], Mariano Serrao [c, d], Maurizio Schmid [a], Silvia Conforto [a], Alberto Ranavolo [b]

[a] Department of Engineering, Roma TRE University, Via Vito Volterra 62, 00146, Rome, Italy
[b] Department of Occupational and Environmental Medicine, Epidemiology and Hygiene, INAIL, Via Fontana Candida 1, 00078 Monte Porzio Catone, Rome, Italy
[c] Department of Medico-Surgical Sciences and Biotechnologies, University of Rome Sapienza, Via Faggiana 34, 40100 Latina, Italy
[d] Rehabilitation Centre, Policlinico Italia, Rome, Italy

ARTICLE INFO

Article history:
Received 22 June 2017
Received in revised form
17 January 2018
Accepted 5 February 2018

Keywords:
Work-related low-back disorders
Biomechanical risk
Surface electromyography
Artificial neural networks

ABSTRACT

The surface electromyographic (sEMG) data of 12 trunk muscles of 10 workers during the execution of lifting tasks using three lifting indices (LI) were recorded. The aims of this work were to: 1) identify the most sensitive trunk muscles with respect to changes in lifting conditions based on the selected sEMG features and 2) test whether machine-learning techniques (artificial neural networks) used for mapping time and frequency sEMG features on LI levels can improve the biomechanical risk assessment. The results show that the erector spinae longissimus is the trunk muscle for which every sEMG feature can significantly discriminate each pair of LI. Furthermore, only when using multi-domain features (time and frequency) a more complex artificial neural network can lead to an improved biomechanical risk classification related to lifting tasks.

1. Introduction

Work-related low-back disorders (WLBDs) represent the most common and costly musculoskeletal problems accounting for 26–50% of the total number of reported cases of occupational musculoskeletal disorders (INAIL, 2011; Kim et al., 2010). Furthermore, the scientific literature has shown that WLBDs are a serious threat to occupational and public health, accounting for 13–24% of all workplace injuries and illnesses, 15–25% of the annual number of sick leave days, and 25% of workers' yearly compensation expenses (Kuijer et al., 2014; Garg et al., 2014; Waters et al., 1998).

WLBDs are mainly caused by manual lifting tasks (Le et al., 2017a, 2017b; Waters et al., 2011; Marras et al., 2010; NIOSH, 1981), which occur in the vast majority of workplaces (Becker, 2001). WLBDs can occur when spinal load exceeds tissue tolerance (McGill, 1999; Norman et al., 1998) and can be caused by direct trauma, single exertion ("overexertion"), or multiple exertions. Several other work-related factors including pushing or pulling activities, repetitive tasks, excessive force, uncomfortable and/or sustained postures, prolonged sitting and standing extreme postures, and whole-body vibrations are also associated with the development of WLBDs and impairment (Waters et al., 1994).

To reduce the risk of WLBDs during the lifting of materials, several methods have been developed to identify high-risk jobs that will probably be associated with an elevated risk of low back disorders (LBD) and evaluate the effectiveness of potential ergonomic interventions. Among the methods used by safety and health practitioners to assess two-handed manual lifting demands, the Revised National Institute for Occupational Safety and Health (NIOSH) Lifting Equation (RNLE) (Waters et al., 1994, 1993) is widely used worldwide to prevent or reduce the occurrence of lifting-related LBD and provides an empirical method for computing a manual lifting weight limit. The RNLE consists of one equation for defining the so-called Lifting Index (LI) based on the Recommended Weight Limit (RWL) and the actual weight lifted. The LI has been shown to be a valid indicator of the risk of WLBDs caused by manual

* Corresponding author. Laboratory of Biomedical Engineering BioLab, Department of Engineering, University Roma TRE, Via Vito Volterra 62, 00146, Rome, Italy.
E-mail addresses: tiwana.varrecchia@uniroma3.it (T. Varrecchia), cristiano.demarchis@uniroma3.it (C. De Marchis), martina.rinaldi@uiroma3.it (M. Rinaldi), f.draicchio@inail.it (F. Draicchio), mariano.serrao@uniroma1.it (M. Serrao), maurizio.schmid@uniroma3.it (M. Schmid), silvia.conforto@uniroma3.it (S. Conforto), a.ranavolo@inail.it (A. Ranavolo).
URL: http://biolab.uniroma3.it

https://doi.org/10.1016/j.ergon.2018.02.003
0169-8141/

lifting (Waters et al., 1999, 2011). Indeed, tasks with LI values of 1.0–3.0 are assumed to pose an increased risk for some fraction of the working population, while those with LI values > 3.0 are referred to as highly stressful lifting tasks associated with a high risk of work-related injuries for a large population of workers (Waters et al., 1993). The RNLE, however, also has some weaknesses due to equation and parameter restrictions (Marras et al., 2001; 1999, Dempsey, 2002; Lavender et al., 2009; Elfeituri and Taboun, 2002; Dempsey and Fathallah, 1999; Wang et al., 1998; Nussbaum et al., 1995; Karwowski and Brokaw, 1992).

To overcome these restrictions, we need to move from a semi-quantitative to a quantitative assessment of the risks posed by a lifting task. In this scenario, an instrumental tool (Le et al., 2017a) and many statistical quantitative approaches have been proposed to classify different sub-tasks and predict the biomechanical risk. Among them, some mathematical models allow the prediction of LBD appearance using data obtained from epidemiological studies (Asensio-Cuesta et al., 2010). The most common models used to develop diagnostic tools for LBD prediction are those based on statistical techniques such as logistic regression and generalized additive models or artificial neural networks (ANNs) (Zurada et al., 1997; Chen et al., 2000, 2004). Regarding the latter, the predictive capacity of models based on ANNs is greater than that of models based on statistical methods for the LBD problem. An ANN is a mathematical model that represents a distributed adaptive system built using multiple interconnecting processing elements, just as real neural networks do. In this model, the processing elements (neurons) are distributed in several layers: each neuron receives signals processed and transmitted by neurons in the preceding layer and in turn processes and transmits them to the next layer. ANNs are used in many fields of research (psychology, robotics, biology, computer science) due to their ability to adapt, learn, generalize, organize, or cluster data. Zurada et al. (1997) and Chen et al. (2000, 2004) attempted to use ANNs to predict LBDs by performing many tests with different topological configurations in terms of number of neurons and hidden layers to determine the most appropriate network architecture.

In the ANN approaches proposed by Zurada et al. (1997) and Chen et al. (2000, 2004), the input signals were potentially risky mechanical factors (e.g. lift rate, peak twist velocity average, peak moment, peak sagittal angle, peak lateral velocity maximum) and the aim was the classification (low-risk and high-risk) according to the associated likelihood of causing LBDs.

Previous studies have highlighted the importance of surface electromyography (sEMG) as a technique for improving human movement analysis; sEMG has been shown to provide significant information from time and frequency domain features (Hägg et al., 2000; Kumar and Mital, 1996; Gazzoni, 2010). Several features extracted from the sEMG signal have a neurophysiological correlation, mainly for what concerns the amount of neural drive to muscle, the kind of recruited fibers and the muscle fiber conduction velocity (Farina et al., 2002): for example, the muscle co-activaction index (Ranavolo et al., 2015), the root mean square, the averaged rectified value (Hägg et al., 2000), and the median or mean frequency (Kumar and Mital, 1996), have been successfully and widely used in ergonomics, both in the laboratory and at the workplace.

Based on the previous considerations, here we used the sEMG features as ANN input for predicting LBDs expressed in terms of LI during the execution of controlled lifting tasks.

The sEMG activity from a variety of trunk muscles was recorded with the following aims: 1) to identify the most sensitive trunk muscles with respect to changes in lifting conditions based on the selected sEMG features; and 2) to test whether machine-learning techniques (ANNs) used for mapping time and frequency sEMG features on LI levels can improve the biomechanical risk estimation. Indeed, techniques such as sEMG for risk assessment could be integrated with methods already used for the biomechanical risk assessment, with the aim of quantifying the risk also when the RNLE cannot be applied. In addition, this integrated approach could overcome one of the main limits of RNLE, consisting in jobs misidentification based on risk (Marras et al., 1999).

Furthermore, the possibility to implement the integrated approach on electronic smart devices (smartphones, phablets, tablets and smartwatches) would allow a simplified analysis in the workplace (Ranavolo et al., 2017) as compared to the analysis based on mechanical factors control.

2. Materials and methods

2.1. Participants

Ten male participants (mean age = 32.50 ± 7.63 years, body mass index [BMI] = 25.00 ± 2.57 kg/m^2) were recruited in the study. The participants had no history of musculoskeletal disorders; upper-limb, lower-limb, or trunk surgery; orthopedic or neurological diseases; vestibular system disorders; visual impairments; or back pain. All participants provided informed consent prior to participating in the study, which complied with the Helsinki declaration. No information regarding the expected results was provided to avoid bias.

2.2. Data recordings

An optoelectronic motion analysis system (SMART-DX 6000 System, BTS, Milan, Italy) consisting of eight infrared cameras (sampling frequency, 340 Hz) was used to track the movements of one spherical marker (15-mm diameter) covered with an aluminum powder reflective material placed over the vertex of a load consisting of a plastic crate.

Surface myoelectric signals were acquired at a sampling rate of 1000 Hz using a 16-channel Wi-Fi transmission surface electromyograph (FreeEMG300 System, BTS). After skin preparation, bipolar Ag/AgCl surface electrodes (2-cm diameter; H124SG Kendall ARBO, Tyco Healthcare, Neustadt/Donau, Germany) prepared with electroconductive gel were placed over each muscle (2-cm distance between the centers of the electrodes) according to the European Recommendations for Surface Electromyography (Hermens et al., 2000) and the Atlas of Muscle Innervation Zones (Barbero et al., 2012). Twelve bipolar electrodes were placed bilaterally on the erector spinae longissimus (ESL), erector spinae iliocostalis (ESI), multifidus (M), latissimus dorsi (LD) (Hermens et al., 2000), rectus abdominis superior (RAS), and rectus abdominis middle (RAM) muscles (Barbero et al., 2012). The first four muscles were chosen because of their role as trunk extensors, the last two because of their role as flexors.

Data acquired from the optoelectronic cameras and surface electromyography were synchronized.

2.3. Experimental procedures

A calibration procedure was executed before the first data capture. Spatial accuracy was 0.2 mm. A global reference system was adopted in accordance with the International Society of Biomechanics (Wu et al., 2005). Furthermore, before formal measurements were started, participants underwent a training session to become familiar with the assessment procedures and ensure correct execution of the lifting tasks. Participants also performed two repetitions of a specific exercise (Vera-Garcia et al., 2010) that were needed to record the isometric maximum voluntary contractions (iMVCs) for each of the investigated muscles according to SENIAM