Surface Electromyography in the Field of Human Factors and Ergonomic Muscle Fatigue: A Narrative Review

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Abstract. Recently Work-Related Musculoskeletal Disorders (WMSD) and Fatigue are taking on an important role especially in the progressive increase and tightening of the human-machine interface. Many ergonomists are currently using surface electromyographic (sEMG) signals techniques to investigate and assess muscle fatigue. Therefore, this paper provides a narrative review of current research on sEMG techniques in the field of human factors and ergonomic muscle fatigue.Evaluate and summarize studies related to the use of sEMG in human factors and ergonomics to probe muscle fatigue.Selected articles included publications in journals, books, and conference proceedings between 2012 and 2022 and assessed muscle activity in research using surface EMG techniques, intervention studies in real human subjects, quantitative research methods and evaluation tools, and authoritative study design.The final review included 32 articles and found that surface EMG studies in the field of human factors and ergonomic muscle fatigue mainly included risk assessment of work-related musculoskeletal disorders, workplace layout design assessment, usability assessment, and exoskeleton optimization assessment. Moreover, the current EMG experiments have significant variability in ideal and realistic conditions, and the lack of standardization of data and methods, which limits the development and application of EMG signals in human factors and ergonomic studies.The findings of this study can help ergonomists to understand the current research progress of sEMG techniques in this field in order to better select suitable, reliable, and accurate methods for human factors and ergonomic muscle fatigue assessment.

Keywords:surface electromyography; muscle fatigue; human factors and ergonomics.

1. Introduction

With the development of automation technology and industrial manufacturing, many studies have shown that prolonged exposure to forced postures can cause irritability, distraction, fatigue, and emotional frustration, resulting in errors and poor decision-making [1-3], which in turn can lead to reduced operational performance [4,5]. It can also lead to muscle damage and eventual work-related musculoskeletal disorders (WMSD) [6,7]. Work-related musculoskeletal disorders are injuries to muscles, bones, nerves, and other systems caused by adverse factors in the workplace [8,9]. The prevalence of work-related musculoskeletal disorders in China ranges from 20% to 90%, and the prevalence in individual industries is even as high as 90% or more [10,11]. As a result, it is necessary to investigate the physical effects of equipment, machines, and work environments on people in order to prevent the occurrence of work-related musculoskeletal disorders, reduce their prevalence, improve work efficiency, and reduce safety hazards and accidents [12].

Muscle fatigue research in the field of human factors and ergonomics is a human-centered study of the effects of poor machines and environments on human muscle fatigue. Exploring the collection of physiological data related to human muscle fatigue and analyzing the factors influencing poor human-machine relationships and work environments, thus helping people to improve and enhance the comfort of human-machine environments in order to achieve healthy, safe, and comfortable work environments while improving the efficiency of both people and machines [13]. In various advanced physiological measurement techniques, devices and tools have been applied to investigate human factors and ergonomics issues, such as surface electromyographic (sEMG) signal, electrocardiogram (ECG) signals [14], electroencephalogram (EEG) signals [15], eye tracking [16], motion capture [17], and so on. Among these, sEMG is currently the most applied method in human factors and ergonomics in relation to muscle fatigue studies [18-20]. Surface electromyographic (sEMG) signals [21] are the superimposed effects of superficial muscle motor unit action potential (MUAP) in time and space with electrical activity on the nerve trunk at the skin surface. Researchers have analyzed the amplitude and power spectrum of sEMG signals to determine the level and function of muscle activity. In the 1950s, Knowlton et al. [22] found an increase in the amplitude of sEMG signals during muscle fatigue. Thereafter, Kogi and Hakamada et al. [23] observed a shift in the power spectrum of sEMG signals toward lower frequencies during states of muscle fatigue by monitoring and analysis. Kwatny et al. [24] applied digital signal processing (PDP-6 computer) to explore the properties of the power spectral density of sEMG signals recorded during a fatigue task. They introduced the mean frequency (MPF) of the spectrum to determine the difference between pre-fatigue and fatigue. Besides the MPF, the second popular descriptor of the spectrum is the median frequency (MF), a frequency value that divides the spectrum into two equal halves [25-27]. In recent years, a number of researchers have used various time-frequency signal processing methods [28,29] to investigate changes in the frequency content of sEMG signal data associated with fatigue progression [30-32]. The use of sEMG signals to assess the degree of muscle fatigue has been an issue explored in the field of ergonomics [33-36].

Therefore, the purpose of this paper is to analyze how sEMG signaling techniques can be used to explore muscle fatigue in the field of human factors and ergonomics. The main research objectives are: 1. To present the experimental procedures of sEMG signaling experiments for the study of muscle fatigue in the field of human factors and ergonomics. 2. To evaluate and summarize the studies of sEMG techniques for the investigation of muscle fatigue in human factors and ergonomics. This study will help ergonomists understand the current research progress of sEMG techniques in this field in order to better select appropriate, reliable, and accurate methods for muscle fatigue assessment.

2. Human factors and ergonomic muscle fatigue analysis process based on sEMG signal

The experimental procedure for exploring muscle fatigue using sEMG in human factors and ergonomics consists of the following steps: (1) Acquisition of raw sEMG data during a specific muscle fatigue task. The researcher identifies the muscle under test, the fatigue task, etc., according to the muscle fatigue problem to be explored, and then places electrodes on the designated muscle under test to collect raw sEMG signals from subjects who are performing the fatigue task. (2) Muscle fatigue sEMG pre-processing. Since sEMG is a weak electrical signal that is easily disturbed by external signals, in order to ensure the accuracy of sEMG, the raw sEMG collected under fatigue conditions needs to be preprocessed, such as through dimensionality reduction and denoising. (3) Feature selection and extraction of sEMG muscle fatigue: appropriate feature values are selected as indicators for calculating and evaluating muscle fatigue according to experimental purposes and needs. (4) Muscle fatigue sEMG model construction. Select the right algorithmic model to train the collected muscle fatigue sEMG for data training and model construction to further identify and predict muscle fatigue states. See Figure 1.

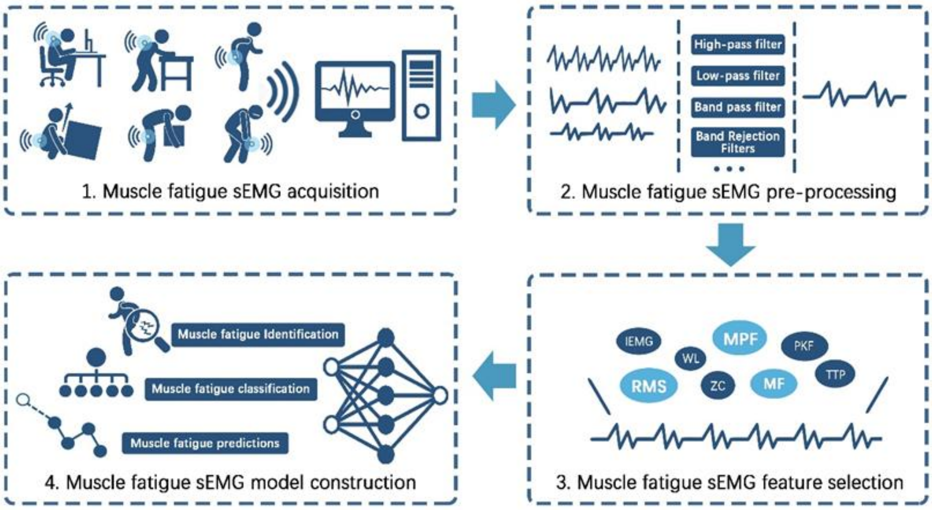

Figure 1. Flow chart of sEMG for muscle fatigue experiments in human factors and ergonomics

3. Methodology

The electronic databases used for this study included:Web of Science, PubMed, Scopus, and ScienceDirect. In these databases we searched for terms and phrases: ("Ergonomics" OR "Human Factors"OR"Human Factors and Ergonomics"OR"Human Factors and Ergonomics design") AND ("sEMG" OR "Surface electromyography" OR "Surface EMG Technology" OR "Surface EMG Signal"OR"Muscle electrical signals") AND ("Fatigue"OR"Muscle fatigue"OR"Muscle injury" OR "Muscle load" OR "Muscle fatigue risk factors" OR "Risk assessment of muscle fatigue" OR) AND ("Work load" OR "Musculoskeletal disorders" OR "Work-related musculoskeletal disorders").Five main eligibility criteria were used for each study, including: (1) Papers published in journals, books, and conference proceedings between 2012 and 2022 are included. (2) The use of sEMG techniques in studies or experiments to assess muscle activity. (3) Real human subjects were used to conduct the intervention study on the subjects. (4) Application of quantitative research methods and evaluation tools. (5) Employing published or authoritative research designs (for example,randomised clinical trial,controlled experiments,and cause-and-effect comparative designs).

4. Results

Finally, 32 articles from 2285 articles screened met all criteria for inclusion in this review.AND we understand that sEMG signals are used in four main areas: human factors and ergonomics muscle fatigue in body burden risk assessment; workstation layout assessment; product usability assessment; and exoskeleton optimization assessment.

4.1 Human Factors and Ergonomics Muscle Fatigue in Body Burden Risk Assessment

Excessive body load and uncomfortable work postures can lead to work-related musculoskeletal disorders, so it is important to assess the body's musculoskeletal load risk during work. Recently, sEMG techniques have been applied to explore and assess the risk factors for muscle fatigue and physical loading in a variety of different occupations. Akesson et al. [37] proposed that excessive head flexion angle and slow upper arm movement speed are the main factors contributing to the risk of upper extremity muscle fatigue and body musculoskeletal load in dental hygienists performing their daily tasks. McGill et al. [38] found carrying a load in one hand resulted in more spine load than splitting the same load between both hands. When carrying double the load in both hands, spine load decreased, suggesting merit in balancing load when designing work. Chopp et al. [39], in evaluating the effect of the posture of the arm above the head on muscle fatigue, found that the greatest muscle fatigue was produced during overhead when the arm was above the head and swung 15° backward. Merino et al. [40] estimated the body musculoskeletal load risk of workers during a banana processing task by directly measuring sEMG data.Guo [41] et al. found that in people performing a manual packing task for 60 minutes, the sEMG median frequencies all decreased. These results suggest that repetitive motion leads to an increased incidence of musculoskeletal disorders in packaging workers.

The sEMG assessment methods are not only used to assess the risk of body musculoskeletal loading in different occupational jobs. Moreover, with the development of electronic technology, many studies are now focused on investigating the effects of electronic devices on musculoskeletal load risk. Ko et al. [42] found using the right hand for one-handed typing produced greater muscle activity and predisposed the fingers to muscle fatigue and injury risk by measuring sEMG data for the upper trapezius (UT), biceps brachii (BB), common finger extensors (EDC), superficial finger flexors (FDS), and short thumb flexors (FPB). Onyebeke et al. [43] suggested that in the condition with a forearm-supported platform, there were fewer occurrences of forced postures of the wrist and smaller levels of activation of shoulder muscles.Alhaag et al. [44] used the response of myoelectric signals on the facial surface to investigate the effects of display type, viewing distance, and viewing time on visual fatigue and concluded that 3D displays produced less visual fatigue stress compared to 2D displays.

4.2 Human factors and ergonomic muscle fatigue in workplace layout assessment

Workplace layout design affects all work areas and also has a significant impact on the daily lives of workers. The sEMG signals can be used to improve workplace comfort by assessing human factors and ergonomic problems of muscle fatigue in the workplace.Early surface electromyography was mostly applied to evaluate the layout of workstations in industrial production. Lee et al. [45] explored the effect of workplace layout on local muscle fatigue through sEMG signals in a simulated repetitive seated hand transfer task.The workplace station height and parts bin placement were also adjusted based on the experimental results to reduce the muscle load on the upper extremity during repetitive handling. Antle et al. [46] conducted an experiment to have subjects perform a repetitive folding box task that assess the effects of using an upright or partially upright posture in a specific workplace on muscle fatigue and injury.After analyzing sEMG signals and blood pressure .

In recent years,More and more people are working on computers which will produce strain on our muscles and ligament tissues, etc., among which the most serious damage to shoulder and neck muscles will occur. Therefore, it is very important to design and evaluate the layout of the office computer workstation. Lin [47] et al. compared the differences in upper extremity posture, upper extremity muscle activity between users using a seated workstation and an upright workstation. The experimental results showed less muscle fatigue in the trapezius shoulder of the standing computer workstationand less muscle fatigue in the left shoulder and right deltoid. Muscle fatigue was higher in the right shoulder of the seated computer workstation. Gao et al. [48] evaluated the effects of lower extremity muscle activity and spinal contraction in office workers using a traditional sit-stand workstation versus a sit-stand alternating office station. This study showed a 15% decrease in muscle activity in the quadriceps and hamstrings of office workers using sit-to-stand workstations and an 11% increase in light activity in workers using sit-to-stand workstations. Botter et al. [49] combined traditional computer workstations with sports to compare the variability in posture, muscle, and physical activity of traditional workstation and dynamic workstations.The results showed that muscle activity (8.1% MVC) was significantly higher in the trapezius muscle at the dynamic workstation. Another study [50] further explored the effects of using different combat-style workstations in a real office environment on lumbar spine and muscle activity, in the hope of improving the human factors and ergonomics of computer workstations.

4.3 Human factors and ergonomic muscle fatigue in product usability assessment

The sEMG signal is also commonly used to assess human factors and ergonomic muscle fatigue problems in equipment and tools to improve the comfort and usability of equipment and tools to improve the efficiency of people's daily work. Firstly, surface electromyography is often used to enhance the comfort of the seat.The objective of study was to identify how sEMG signal relate to self-reported vehicle seating discomfort. The visual measurement data provides informative comments on the comfort design of car seats [51]. Hiemstra-van et al. [52] evaluated the usability of a new active seating system by measuring changes in upper extremity muscle levels of people while performing different tasks.

In addition, some studies have been conducted to improve the performance of products by measuring the surface electromyographic signals of hand muscles. Kang [53] et al. tested five different weight distributions of cordless stick vacuum cleaner handles (top front, top rear, bottom front, bottom rear, and center) to investigate the effect of weight distribution at different positions on upper limb muscle activity.Guo et al. [54] investigated the effect of operation type and handle shape on the operational efficiency of high-speed train drivers by combining sEMG signal experiments. This study showed that a sagittal plane rotational operation type of controller could significantly reduce the upper limb workload.

Due to the popularity of the Internet and smart devices, more and more research is now focused on evaluating the interaction usability of smart devices. In their study, Kim [55] et al. compared the differences in typing effort and muscle activity between a virtual keyboard, a laptop keyboard, and a traditional mechanical keyboard to assess users' typing performance when using different types of keyboards.They [56] also further investigated the effect of virtual keyboard key size on forearm and wrist muscle activity during typing to enhance the efficiency and comfort of virtual keyboard typing. Coppola [57] et al. found the importance of the touchscreen's sliding position .Lee [58] et al. explored the effects of different computer key switch designs on finger muscle activity and showed that dorsal interosseous muscle activity increased by 36.6% and all muscle activity times decreased by 49.1% except for deep finger flexors when using a flexor spring key switch compared to a rubber dome key switch. Kim et al. [59] optimized the interface design of a portable joystick haptic system using sEMG signal sensors in order to enhance the immersion and realism in virtual reality scenarios. Trudeau et al. [60] explored changes in thumb motor performance during one-handed use of a cell phone helping optimize specific thumb interaction actions to improve the user experience during one-handed interaction.

4.4 Human factors and ergonomic muscle fatigue in exoskeleton optimization assessment

Long-term heavy-duty work (manual lifting, heavy handling, transporting goods, pushing and pulling operations, etc.) may cause fatigue of the trunk muscles, which in turn may damage the stability of the spine and cause chronic low back injuries. An exoskeleton is a device that helps to improve the abilities of workers and reduce the physical effort required for their activities. De Looze et al. [61] evaluated the potential impact of various industrial-assisted exoskeletons on the physical load on the body. A 10% – 40% reduction in back muscle activity was reported during dynamic lifting and static holding. Chen et al. [62] evaluated the efficacy of exoskeletons in assisting subjects with weight-lifting tasks by assessing muscle activation while wearing the exoskeleton through sEMG signals. Von Glinski et al. [63] used sEMG signals to determine if sEMG activity in the back muscles was reduced or altered during the use of an active lumbar wearable exoskeleton, HAL (Hybrid Assistive Limb, HAL).In Qu et al. [64] ,sEMG signal experiments were used to assess the effects of a simulated weightlifting task with an industrial passive-assisted exoskeleton on muscle activity, perceived exertion, and usability. The results showed that this exoskeleton significantly reduced muscle activity in lumbar erector spinae, thoracic erector spinae, middle deltoid, and labrum-biceps muscles;Yan et al. [65] proposed a lightweight, wearable passive exoskeleton and evaluated it experimentally using sEMG. The average reduction in muscle activity under exoskeleton conditions was 44.8% - 71.5%. Antwi-Afari et al. [66]evaluated the effects of passive exoskeleton systems on spinal biomechanics and subjective responses of construction workers during manual repetitive lifting tasks by sEMG signals and found that the use of passive exoskeleton systems similarly reduced back discomfort during weightlifting. Luger et al. [67]showed that passive exoskeletons can help workers adjust their body posture during weight-lifting tasks and avoid severe muscle fatigue. Through sEMG signal experiments, Tetteh et al.[68]found that a passive exoskeleton can reduce the biomechanical load on the surgeon during surgery.

The study of optimal assessment of exoskeletal assistance based on sEMG signals has helped to reduce some of the frequent, muscle-loaded physical work that people do at work; reduce the risk of musculoskeletal disorders in heavy and overloaded physical workers, and improve the work capacity of workers. However, there is no standardized method to compare the effectiveness of exoskeletons in a uniform manner, so the utility of exoskeletons in non-ideal situations is yet to be studied in a progressive and extended manner.

5. Discussion

In this paper, we learn about the progress of sEMG techniques in human factors and ergonomics regarding muscle fatigue studies. In these studies, sEMG techniques can help investigate the human factors and ergonomics of muscle fatigue so that tools, equipment, and environments can be adapted to human needs and avoid undesirable factors such as forced postures. However, in fact, most of these muscle fatigue-related studies are currently conducted under simulated ideal laboratory conditions. The evaluations also mostly focus on how to identify more categories under ideal conditions or without interference, by comparing and analyzing different noise processing methods, dimensionality reduction methods, feature and model identification, and other aspects to improve the accuracy and precision of sEMG signal identification. For example, in an ideal laboratory environment, excluding many realistic environmental interference factors, sEMG monitoring devices can achieve more than 95% accuracy in a real-time classifier. However, evaluation under realistic conditions is frequently subject to numerous confounding factors (e.g., electrode offset, individuality differences, muscle fatigue, limb posture, or other comprehensive interference), reducing the accuracy of sEMG signal recognition.

The use of a single model to collect information has the limitation of expressing incomplete information to accurately assess human work posture and muscle fatigue risk factors in the work environment. Therefore, some other auxiliary information needs to be introduced to avoid or correct errors. Multimodal data can combine information from multiple modalities, drawing on the advantages of different modalities to accomplish effective integration of information [69-71]. Multimodality can achieve information complementarity between modalities and enhance feature representation [72]. Many researchers have recently used multimodal data fusion methods for muscle fatigue studies in human factors and ergonomics, fusing sEMG signals with other modal data such as EEG signals [73], and ECG signals as a way to improve recognition rates and system robustness while reducing data uncertainty. For example, Chen et al. [12474] sought to accurately investigate the physiological fatigue and psychological stress of miners working in a high altitude, cold, and low oxygen environment. They conducted experiments in a realistic plateau environment and simultaneously measured multiple physiological indicators, including ECG, sEMG signal, pulse signal, blood pressure, reaction time, and lung capacity. The above information was then fused and factorized using SVM and RF techniques, resulting in the classification and identification of muscle fatigue categories. Xi et al. [75] used a combined EEG and sEMG study to assess the effect of dynamic information from the cortical muscle system on muscle fatigue.Kim et al. proposed a multimodal fusion system based on a transfer learning paradigm for 2D input image features of sEMG signals [76], and the classification accuracy and precision were significantly improved using this multimodal fusion system compared to the traditional unimodal sEMG signal training model.

Therefore, future research should consider multimodal data fusion for human factors and ergonomic assessment.

Furthermore, according to our study, human factors and ergonomic muscle fatigue studies based on sEMG signals have focused more on the assessment of specific fatigue postures under specific muscle fatigue tasks. In general, there is great variability in posture and different choices of assessment metrics when performing different tasks. In addition, individual differences can lead to different assessment results. There are also many similar studies that have explored muscle fatigue using sEMG signal methods and chosen different eigenvalues as assessment criteria; therefore, the results of the assessment vary widely. Besides, there is no uniformity in the stage of muscle fatigue degree classification, and we do not have clear rules and general criteria for what is considered mild fatigue, moderate fatigue, and severe fatigue.

As shown above, different assessment criteria weaken or ignore the generalizability of assessment methods and data. The lack of common data and uniform assessment criteria has prevented the generalization of many data and models, which has limited research and development in the field. Large-scale publicly available datasets serve as an important driving force to accelerate the development of machine learning techniques with deep learning as the core in natural language processing, speech recognition, and image processing and recognition, providing a convenient and effective way for researchers in this field to mine new data and create new methods. However, in the field of sEMG signal-based human-causal and ergonomic muscle fatigue studies, there are few publicly available universal datasets, and only a few publicly available datasets related to sEMG signal gesture recognition exist, such as Ninapro [77] and CapgMyo [78]. Therefore, establishing a common experimental paradigm for human factors and ergonomic muscle fatigue studies based on sEMG signals, identifying uniform evaluation criteria, and constructing publicly available common datasets are current challenges and problems in this field.

6. Conclusions

Based on a brief introduction of the milestones and application results of muscle fatigue research in human factors and ergonomics based on sEMG signals, this paper discusses in detail the main issues in this research area and provides an outlook on future research trends in this field. In general, sEMG techniques have now made breakthroughs in human factors and ergonomics, including muscle fatigue and body load assessment, workplace layout assessment, product usability assessment, and exoskeleton optimization assessment. However, the current human factors and ergonomics studies based on sEMG signals have great variability in ideal and realistic conditions, and there are problems such as inconsistent data and methods that limit the development and application of sEMG signals in human factors and ergonomics studies. Therefore, future research needs to focus on multiple interventions and influences in order to conduct experiments in real-world environments. This would be an important step in the further development of sEMG techniques in the field of human factors and ergonomic muscle fatigue.

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