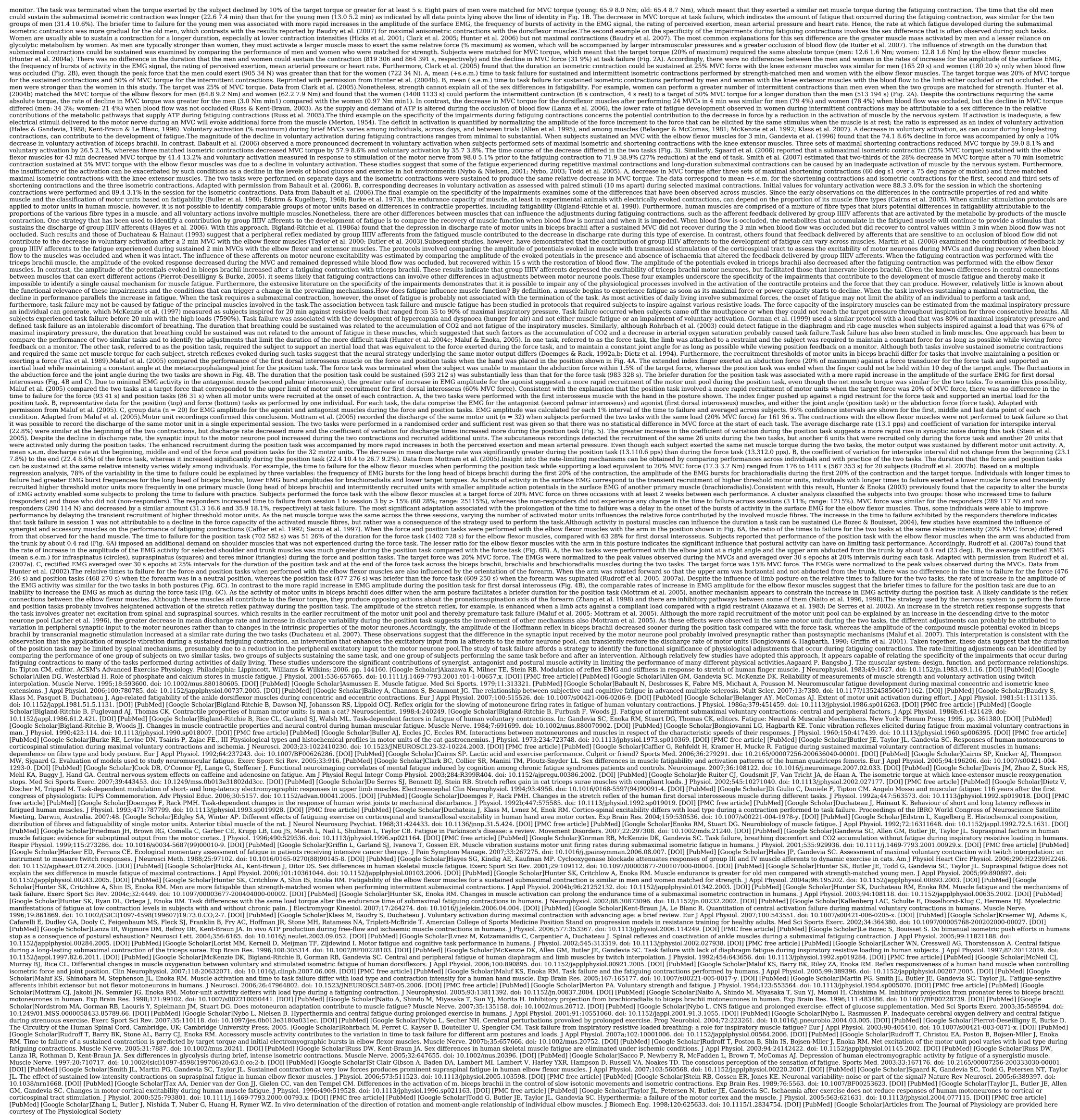
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As a library, NLM provides access to scientific literature. Inclusion in an NLM database does not imply endorsement of, or agreement with, the contents by NLM or the National Institutes of Health. Learn more: PMC Disclaimer | PMC Copyright Notice . 2022 Aug 11;16:893275. doi: 10.3389/fnsys.2022.893275Exercise fatigue is a common
physiological phenomenon in human activities. The occurrence of exercise fatigue can reduce human power output and exercise fatigue assessment.
Great advances have been made in the measurement and interpretation of electromyographic features. With the development of machine learning, the application of sEMG signals in human evaluation has been developed. In this article, we
focused on sEMG signal processing, feature extraction, and classification in exercise fatigue as also introduced. Finally, the development trend of exercise fatigue detection is prospected. Keywords: exercise fatigue, sEMG, machine learning, feature extraction, classification Exercise
fatigue is a physiological phenomenon that originates from human activities and results in decreased physical performance (Nijs et al., 2011). The main manifestation of exercise fatigue which was defined as the failure to maintain the force output, leading to a reduced performance (Asmussen, 1993). Muscle strength declines
progressively during exercise, so fatigue occurs before the task failure (Gandevia, 2011; Kuniszyk-Jozkowiak et al., 2018; Liu et al., 2011; Rodriguez-Rosell et al., 2021; Rodriguez-Rosell et al., 2021; Rodriguez-Rosell et al., 2021; Rodriguez-Rosell et al., 2018; Liu et al., 2019; Hedayatpour et al., 2018; Liu et al., 2021; Rodriguez-Rosell et al., 2021; Rodriguez-Rosell et al., 2018; Liu et al., 2019; Hedayatpour et al., 2018; Liu et al.,
Kim et al., 2018; Meng et al., 2019; Na et al., 2020; Fundaro et al., 2021; Sato et al., 2021; Ji and Huang, 2021; Yu et al., 2021; Sato et al., 2021; Ji and Huang, 2021; Yu et al., 2021; Ji and Huang, 2021
Questionnaires are subjective. Invasive biochemical tests cause discomfort to the subjects. Noninvasive physiological testing with scientific and statistical approaches can provide confidence and certainty. Muscle fatigue is divided into central and peripheral components. Peripheral fatigue is caused by changes in the neuromuscular junction. Central
fatigue originates in the central nervous system (CNS). The production of skeletal muscle force depends on contractile mechanisms, and failure of nervous, ion, vascular, and energy systems can contribute to the development of muscle fatigue (Wan et al., 2017). During sustained contractions, metabolic changes in the muscle affect the propagation of
action potential. These changes result in a progressive reduction of muscle fiber conduction velocity (CV). This is one of the main causes of the changes in amplitude and spectral EMG variables during fatigue. This physiological variable provides a relevant means to describe and quantify the muscle fatigue (Marco et al., 2017). Exercise fatigue can be
detected through surface electromyography (sEMG) (Chang et al., 2012). Constant exercise load results in the rise of EMG activity during fatigue (Chlif et al., 2018). Electrical currents generated by muscle contractions can be monitored in the form of EMG signals and displayed on a computer (Barszap et al., 2016). Bioelectricity is detectable when
muscle contracts (Tang et al., 2020). Electromyographic techniques are used in sports and Konieczny, 2020; Quittmann et al., 2018) or electrodes placed over the skin surface (Zeng et al., 2021).
Compared with invasive EMG, sEMG is more popular among researchers (Khan et al., 2019; Yamagishi et al., 2019; Silva et al., 2020). This review offers an overall summary of the assessment of human exercise fatigue based on sEMG signals and highlights signal processing, feature extraction, and classification. The possibilities for future work on
exercise fatigue with sEMG will also be discussed in this study. The sEMG signal generated by muscle contraction that can be harvested by electrodes. The sEMG signal is a kind of pseudorandom
physiological signal that is very weak. The voltage of the sEMG signal range from 50 V to 100 mV and the frequency is varied from 10 to 500 Hz (Pancholi and Joshi, 2018). The electrode skin impedance which is one of the noises that affects the quality of EMG signals must be as low as possible to obtain effective signals (Sae-Lim et al., 2019).
Pancholi and Joshi (2018) obtained sEMG signals from five different arm muscles using hardware based on ADS1298 IC (Texas Instruments) and ARM cortex M4 series processor with 4,000 Hz sampling frequency. De la Pena et al. (2019) recorded sEMG-related muscle fatigue in sports training using a portable prototype with a 5,000 Hz sampling
rate. Zhao et al. (2020) acquired sEMG data based on a software platform for visualizing sEMG during dynamic contractions at
an acquisition rate of 10,000 Hz. Wang L. et al. (2021) used wearable sampling electrodes that the sampling frequency is 200 Hz to collect sEMG signals in real-time during the driving tasks. Chen et al. (2021b) used the MP160 physiological record analysis system produced by the American company BIOPAC to analyze the fatigue of miners. Exact
electrode positioning is vital for obtaining reliable EMG signals. A study showed high correlations between all electrode site record more informative signals in subjects (Zanca et al., 2014). All trunk muscles were affected by electrode position changes, but the abdominal muscles were more
affected than the back muscles (Huebner et al., 2015). Ghapanchizadeh et al. (2016) found that the optimal signal from the electrode position over the forearm length. The muscle moves away from its uncontracted position directly
under the EMG electrode when contracts. Elsais et al. (2020) used ultrasound to track the relative motion between skin and muscle to quantify the magnitude of the movement between them and inform protocols for surface EMG placement. The raw sEMG data collected will inevitably be mixed with power line interference and motion artifacts (Zheng
and Hu, 2019). Therefore, effective preprocessing is required before feature extraction of these signals (Ahmadizadeh et al., 2020), normalization, and windowing (Fang et al., 2020). Tapia et al. (2017) used independent component analysis (ICA) and empirical mode
decomposition (EMD) to process sEMG signals. (Wu et al., 2017) achieved better accuracy for the diagnosis of muscular fatigue through ensemble empirical mode decomposition (EEMD) by Hilbert transform (HT). Zhang et al. (2019) decomposed sEMG signals by principal component analysis (PCA) into principal components and weight vectors that
improve the validity of parameters. In Avian et al. (2022), Discrete Wavelet Transform (DWT) is used to process the sEMG signal to increase model performance. The increase from baseline represents the onset of muscle activity. Muscle activity onset can be estimated from EMG and ultrasound (Dieterich et al., 2017). Gupta et al. (2014) determined
the onset of medial gastrocnemius muscle activity using visual and automated methods during a stretch-shorten-cycle muscle activity onset detection based primarily on the sample entropy (SampEn) analysis of the surface EMG. Liu et al. (2015) presented an unsupervised EMG
learning framework based on a sequential Gaussian mixture model (GMM) to detect muscle activity onsets. Appropriate signal preprocessing method is helpful to improve the effectiveness of feature extraction. Feature extraction from the sexual preprocessing method is helpful to improve the effectiveness of feature extraction.
frequency domain, and nonlinear parameters are four major types in sEMG-based signal processing (Too et al., 2018b; Yousif et al., 2
sEMG signal is usually regarded as a random signal whose mean value is zero and variance varies with signal intensity. As the calculation of time-domain features is simple and intuitive, it is a widely used feature extraction method of sEMG signals mainly
include the root mean square (RMS) (Cui et al., 2019), integrated EMG (iEMG) (Alam et al., 2019), waveform length (WL), variance of electromyography (VAR) (Whittaker et al., 2019), and mean absolute value (MAV) (Chapman et al., 2019). With the occurrence of muscle fatigue, the time domain features of
sEMG generally show an upward trend over time (Goubault et al., 2022). RMS and iEMG not only reflect the biomechanical properties and muscle energy changes in the exercise process (Silvetti et al., 2017; Wu et al., 2017). Therefore, RMS and iEMG are often used
to indicate muscle activation intensity and human motion state (Triwiyanto et al., 2018). The frequency-domain features are spectrum or power spectrum or po
Researchers believe that frequency domain analysis is more meaningful than time domain analysis in both static and dynamic motion. To quantitatively describe the spectrum and PS features of sEMG signals, the mean frequency (MF) (Hou et al., 2021) and median frequency (MDF) (Park and Park, 2021) are generally used that decrease linearly over
time. The deeper the muscle fatigue, the faster the MF decreases. Both MF and MDF can represent the frequency of measured muscle activity and functional state. MF can also get good results in muscle fatigue detection (Chai et al., 2019). Significant changes in the
PS indicate muscle fatigue, and the PS drifts from high frequency to low frequency. For example, after maximum weight training, the peak value of the sEMG signal will increase and drift to the lower frequency. To make up for the
 information of muscle physiological changes. Traditional sEMG time domain and frequency domain feature analysis method can overcome this limitation. At present, the available time-frequency analysis methods for sEMG signal mainly
 include Short-time Fourier Transform (STFT), Wavelet Transform (WT), Choi William distribution (CWD), and Wigner-Ville distribution (WVD), used for visual observation of signal frequency content evolution over time.
 Instantaneous frequency parameters commonly used are instantaneous mean frequency (IMNF) (Triwiyanto et al., 2017) and instantaneous median frequency (IMNF) (Yousif et al., 2019), which show a downward trend with the deepening of fatigue degree. Average instantaneous MF has higher stability and sensitivity than frequency-domain features
Yousif et al. (2019) applied IMNF and IMDF to assess the muscles fatigue of the male runner during 400 m running with three types of running with three types of running strategies. The semge complexity and entropy decrease linearly with the increase of fatigue degree. The complexity of Lempel-Ziv [C (n)] (Jo et al., 2018) is the speed at which new patterns appear with the
 increase of the length of time series, indicating the degree of randomness of the series, which decreases for most people. Marginal spectrum entropy (MSE) (Jero and Ramakrishnan, 2019) is a useful real-time muscle fatigue assessment
 method with the advantages of fast, reliable assessment of muscle fatique and anti-noise. Compared with approximate entropy and MDF, MSE can be calculated quickly, the data length robustness is better, and muscle fatique can be assessed reliably. It has high stability for different individuals and good noise resistance. SampEn (Cui et al., 2017)
proposed by Richman and Moorman in 2000, measures the probability of the sequence, the higher the complexity of time series. SampEn has a strong anti-noise ability and can reduce data deviation. The higher the entropy. The multi-scale entropy (Fan et al., 2018) of sEMG signals by measuring the complexity of time series.
 decreases as the load increases, which more accurately represents the complexity of the muscle system. Compared with the traditional SampEn, it can more objectively reflect the working status and fatique grade of the muscle. Multi-scale entropy analysis has a small amount of calculation and can adapt to the complexity of dynamic muscle
contraction under time-varying loads. In practical work, normalized average multi-scale entropy can be used as a quantitative index to measure the dynamic fatigue degree of muscles. Recurrence quantification analysis (RQA) (Chen et al., 2018) is used to determine the percentage of line segments (%DET) reflecting the periodicity of signals. The RQA (Chen et al., 2018) is used to determine the percentage of line segments (%DET) reflecting the periodicity of signals.
software is used to calculate and determine the percentage of line segments. Under dynamic and static loads, %DET increases linearly with the occurrence of muscle fatigue in all-out cycling exercises. Cui et al. (2017) used SampEn to investigate the fatiguing features of muscle-tendon units (MTUs)
 within skeletal muscles during static isometric contraction tasks. Hernandez and Camic (2019) investigated the effect of fatigue status and contraction type on the complexity of the sEMG signal, using SampEn and Detrended Fluctuation Analysis (DFA). Kahl and Hofmann (2016) compared the performance of different fatigue detection algorithms
quantifying muscle fatigue based on sEMG signals. Fatigue detection algorithms including spectral moments ratio (SMR), SampEn, fuzzy approximate entropy (fApEn), and RQA (%DET) were calculated. After identifying the extracted features from the sEMG signal, the next important step is classification to detect the fatigue state. With the
 development of machine learning, machine learning algorithms were widely applied to exercise fatigue classification. Classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in this article normally refers to supervised learning where individuals are classification in the supervised learning where it is a supervised learning where the supervised learning where the supervised learning where the supervised 
2017), hidden Markov model (HMM) (Shahmoradi et al., 2021b), linear discriminant analysis (LDA) (Ahmed et al., 2020), and artificial neural network (ANN) (Subasi and Kiymik, 2010). Machine learning algorithms for fatigue classification. Support
 vector machine is a popular machine learning classification method because it is simple, fast, and stable, and shows better accuracy than other methods (Karthick et al., 2018; Wang et 
closely related to the feature extraction method. Dimension reduction plays a crucial role in index extraction, which can reduce the calculation time. Common dimension reduction methods include PCA (Qi et al., 2018a). Khan et al. (2019) used the random forest trained by distributive power frequency of the sEMG signal of
 Network, and Particle Swarm Optimization Support Vector Machine algorithms. CNN-SVM algorithms achieves the highest accuracy rate in muscle fatigue based on the Multidimensional Feature Fusion Network (MFFNet), which is composed of Attention Frequency domain Network (AFNet)
and Attention Time-domain Network (ATNet). The result shows 77.37% higher than other classifiers. Bharathi et al. (2022) developed an automated muscle fatiguing contractions. The extreme learning machine (ELM) model performs well with a 94.09% result
Wang J. H. et al. (2021) proposed a new muscle fatigue recognition model based on the long short-term memory (LSTM) network. Rejith et al. (2016) estimated the elbow kinematics under fatigue of 60.12%. Chen et al. (2021a) studied fatigue of 80.12%.
miners with physiological signals by extreme gradient boosting (XG-Boost). Multi-sensor fusion based on sEMG can collect more dimensions of human activities from multiple dimensions. Thus, it is more comprehensive than fusion methods that use data from a single sensor. Qi et al. (2018) proposed a method for driving fatigue assessment based on
the electroencephalogram (EEG) and EMG. Zhao et al. (2020) proposed a wearable monitoring device by integrating electrocardiogram and electromyogram (ECG/EMG) sensors to acquire data for monitoring fatigue during rehabilitation training. Martinez-Aguilar and Gutierrez (2019) analyzed cortico-muscular and cortico-cardiac coupling to study
the development of muscular fatigue by electromyography (ECG), and electrocardiography (ECG).
 assessment. Fatigue detection based on surface EMG has important application value in sports training, rehabilitation treatment, and movement recognition. This article aimed to provide an overview of sEMG signal processing, feature extraction, and classification in exercise fatigue. In real-time detection, portability of the device, removal of artifacts,
 feature extraction, and classification techniques should be properly investigated. Using appropriate methods can remove noise to improve EMG signal quality. With the increase in the number of EMG channels and features, it is necessary to choose a reasonable dimensionality reduction method. The methods should greatly reduce the computational
complexity of the classifier and preserve maximum information of the signal. Classification still have research significance. A combination of processing methods and pattern recognition techniques may be helpful to increase the classification speed and accuracy. And
the adaptability of good algorithms to fresh samples needs further study. Finally, we propose that the current review can be used as a guide for further improving exercise fatigue assessment based on sEMG for various applications of the human body. JS mainly wrote the manuscript under the guidance of GL and JC. YS, KL, and ZZ participated in the
analysis. All authors contributed to the article and approved the submitted version. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. All claims expressed in this article are solely those of the authors and do not necessarily represent
those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be evaluated in this manuscript was supported by the National Key Research and Development Program
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NLM provides access to scientific literature. Inclusion in an NLM database does not imply endorsement of, or agreement with, the contents by NLM or the National Institutes of Health. Learn more: PMC Disclaimer | PMC Copyright Notice . 2007 Aug 16;586(Pt 1):1123. doi: 10.1113/jphysiol.2007.139477Much is known about the physiological
impairments that can cause muscle fatigue. It is known that fatigue can be caused by many different mechanisms, ranging from the accumulation of metabolites within muscle fibres to the generation of an inadequate motor command in the motor 
that cause fatigue are specific to the task being performed. The development of muscle fatigue is typically quantified as a decline in the maximal contractions can be sustained after the onset of muscle fatigue. There is even evidence that the duration of some sustained tasks is not
limited by fatigue of the principal muscles. Here we review experimental approaches that focus on identifying the mechanisms that limit task failure approach can provide insight into the rate-limiting adjustments
that constrain muscle function during fatiguing contractions. Although it is not difficult to know when one is fatigued, it is entirely another matter to be able to identify the physiological mechanisms responsible for this condition. Despite the accumulation of a substantial literature on the topic since the seminal work of Angelo Mosso in the late 1800s
(Di Giulio et al. 2006), few principles have emerged to characterize the phenomenon of muscle fatique, Although progress has been made in the study of muscle fatique (Nybo & Rasmussen, 2007), we are largely unable to state with certainty why an individual becomes fatiqued under various
conditions. The purpose of this topical review is to examine three issues that constrain a more complete understanding of muscle fatigue and its impact on muscle fatigue and its impact on muscle fatigue and the lack of knowledge on the mechanisms that limit
performance. The discussion will focus on what is muscle fatigue? In contrast to the fatigue encountered in clinical settings (Bailey et al. 2007; Friedman et al. 2007; Hacker & Ferrans, 2007), the term muscle fatigue is used to denote a transient decrease in the
capacity to perform physical actions. The following excerpts characterize the range of effects ascribed to muscle fatique. Intensive activity of muscles causes a decline in performance, known as fatique (Allen & Westerblad, 2001). Performing a motor task for long periods of time induces motor fatique, which is generally defined as a decline in a
person's ability to exert force. (Lorist et al. 2002). CNS administration of caffeine increased treadmill run time to fatigue (Davis et al. 2003). a fatiguing task was performed with the muscles of the left hand until the muscles of the left hand until the muscles of the left hand until the muscles of its amplitude and a
decrease of its characteristic spectral frequencies. (Kallenberg et al. 2007). the sensation of fatigue is the conscious homeostatic control systems (St Clair Gibson et al. 2007). The primary purpose of the study was to use functional magnetic resonance imaging (fMRI) to determine the association between feelings
of mental fatigue and blood oxygen level dependent (BOLD) brain responses during a mentally fatiguing cognitive task. (Cook et al. 2007). Muscle fatigue, it seems, can refer to a motor deficit, a perception or a decline in mental function, it can describe the gradual decrease in the force capacity of muscle or the endpoint of a sustained activity, and it
can be measured as a reduction in muscle force, a change in electromyographic activity or an exhaustion of contractile function. Such broad usage is problematic, however, because fatigue in this context can encompass several phenomena that are each the consequence of different physiological mechanisms, which reduces the likelihood that the
cause of muscle fatigue can be identified. To circumvent this limitation, most investigators invoke a more focused definition of muscle fatigue as an exercise-induced reduction in the ability of muscle to produce force or power whether or not the task can be sustained (Bigland-Ritchie & Woods, 1984; Sgaard et al. 2006). A critical feature of this
definition is the distinction between muscle fatigue and the ability to continue the task. Accordingly, muscle fatigue is a decrease in the maximal force or power that the involved muscles can produce, and it develops gradually soon after the
onset of the sustained physical activity. A common protocol used to quantify the development of muscle fatigue is to interrupt the fatiguing exercise with brief maximal contractions (voluntary or electrically evoked) to estimate the decline in the maximal force capacity (Merton, 1954; Bigland-Ritchie et al. 1986b; Hunter et al. 2004b; Sgaard et al.
2006). Similarly, the amount of muscle fatigue caused by an intervention can be quantified as the decline in the maximal force or power measured immediately after the fatigue occur? The simple answer is that one or
several of the physiological processes that enable the contractile proteins to generate a force become impairment depends on the task being performed. This effect is known as the task dependency of muscle fatigue and is one of the principles to have emerged in this field
over the last 100 years (Asmussen, 1979; Enoka & Stuart, 1992; Bigland-Ritchie et al. 1995). According to this principle, there is no single cause of muscle fatigue and the dominant mechanism is specific to those processes that are stressed during the fatiguing exercise (Cairns et al. 2005). This concept is analogous to the principle of specificity that
characterizes the adaptations evoked by several weeks of physical training (Kraemer et al. 2002; Aagaard & Bangsbo, 2006). Due to the specificity of the impairments that occur during fatiguing contractions, there are no general answers to such questions as are old adults more fatigable than young adults, are women less fatigable than men, can the
nervous system sustain an adequate activation of muscle during fatiguing contractions, and are there differences between muscles? The difficulty in answering such questions becomes obvious when the results obtained in selected studies are compared. First, consider the influence of age on fatigability. Baudry et al. (2007) measured the decline in
torque when young (mean s.d.; 30.5 2.5 years) and old (77.2 1.4 years) men and women performed maximal contractions with the dorsiflexor muscles. The task was to perform five sets of 30 maximal contractions at a rate of one contraction every 3.5 s, and with each contraction comprising a 30 deg range of motion and the
speed controlled by a motor at 50 deg s1. There was a 60 s pause between each set of contractions. The shortening and lengthening contractions were performed on separate days. The young adults were stronger than the old adults as indicated by a greater peak torque during a maximal isometric contraction (38.3 3.1 and 28.6 1.3 Nm, respectively).
Nonetheless, the decline in peak torque during both tasks was greater for the old adults. Figure 1A shows the data for the lengthening contractions in which the final peak torque declined by 27.1% for the young adults. The decrease in peak torque after 150 maximal shortening contractions was 40.9% for the young
adults and 50.2% for the old adults. Furthermore, the decline in peak torque during each set of 30 maximal contractions (Fig. 1A). The fatigue experienced by both groups of subjects was associated with changes in the control of excitation coupling by Ca2+
and, for the old adults only, impairment of neuromuscular propagation. These results indicate therefore that the old adults were more fatigable than the young and lengthening contractions with the dorsiflexor muscles. A, average torque exerted by young and old adults during five sets of 30 maximal
lengthening contractions with the dorsiflexor muscles. Each data point indicates the mean s.e.m. of five successive contractions for 16 subjects in each group. Adapted with permission from Baudry et al. (2007). B, each data point denotes the time to failure for the one young man and one old man who were matched for strength. The task was to
sustain an isometric contraction with the elbow flexor muscles at 20% of maximum for as long as possible. The time to failure was longer for the older man of each pair. Adapted from Hunter et al. (2005) found that old men (71.3 2.9 years) could sustain a
submaximal isometric contraction with the elbow flexor muscles for a longer duration than young men (21.5 4.4 years). The task was to sustain a net muscle torque to a target that was displayed on a
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Emg during fatigue. Can an emg make you tired. Emg too early. Will emg.