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Prosthetic hand control: A multidisciplinary review to identify strengths, shortcomings, and the future

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ABSTRACT

Prosthetic hand control has fired the imagination of many researchers and thousands of papers have been published in this field, but the user acceptance has not been strong and there appears to be a significant gap between the published research and its translation. One observation of the literature is that while this requires multidisciplinary research, most articles appear to be topic focused, with lack of literature that connect across the different disciplines. This paper reports a multidisciplinary, candid review which has evaluated literature of four major associated topics: (i) User requirements, (ii) Signal recording, (iii) Signal analysis and (iv) User feedback, with the aim to identify the potential directions for research that will improve the translation of this technology. Special effort was made to collate diverse views and authors.

This review has found that more research for the analysis and evaluation of the user requirements is necessary to ensure that the amputees use these devices extensively. Further research is also required into the development of both, the paradigm and the technology to give feedback to the user from the prosthetic hand device. There is also the need to improve the electrodes and recording techniques to ensure uninterrupted user-control over extended periods of time. One important outcome of this paper is that it has uncovered the differences of performance measures used by different authors because of which it is difficult to compare the results reported in their papers.

Contents

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1. Introduction

The human hand offers dexterity that allows one to perform a wide range of tasks; some requiring fine control while others are coarse actions. We use the hand to push and pull, grip objects, perform precision tasks such as writing, and perform gestures for communication. These are achieved by precisely controlled muscles and dense array of sensors that respond to muscle length, and epidermal sensors for touch, pressure, and temperature.

Loss of the hand due to amputation of the arm is devastating to the person and leads to loss of functionality and social acceptability [1]. The use of prosthetic hand to replace this loss is desirable, with modern prosthetic hands having evolved from the mechanical hooks of yesteryears to sophisticated devices that are electrically powered and offer large numbers of degrees of freedom (DOF). While earlier devices were controlled by coarse mechanical movements, modern devices can provide greater dexterity and have the provisions for complex actions. These have the capability for individual finger flexion and extension, movement of the thumb and rotation of the wrist; are lightweight and covered with a skin-matched covering, appearing like the natural hand. Such devices have been developed for effective functionality, aesthetics, and social interaction with the proviso that the user can give reliable commands.

Modern prosthetic devices can be controlled by users with a wide range of commands. Effective use of these devices, that ensures the safety of the user while also being natural, requires commands for gestures and actions that may be coarse or fine control. These devices require commands for the flexion and extension of individual fingers, thumb and wrist; sensing for touch and grip; and also, generation of estimates of the force. The commands by the user may be based on movement, neural activity or other means. In many applications, commands are mechanically sensed using accelerometers, capacitive techniques, or using proximity sensors worn on the body [2]. These require the user to move their limbs which, however, may not be possible or convenient. Alternatively, neural activity-based commands are focused on the intent of the user and can be more intuitive and natural, especially for people with an amputation [3,4].

Determining the intent of the user based on their neural drive is highly desirable for effective control of the prosthetic hand. It promises to be intuitive and natural without requiring the user to perform awkward or secondary movements. For this reason, the control of most major powered prosthetic hands is based on surface electromyogram (sEMG) which provides information regarding the neural activity to the muscles and has the advantage of being non-invasive. However, sEMG is unspecific and gross recording of the muscle activity, while finger movement, grip patterns, and maintained gestures are a result of complex combinations of contractions of multiple muscles in the forearm. There are significant similarities between the activation of muscles associated with different finger movements or hand grips, and the classification of sEMG to distinguish between these intended actions is challenging [5]. This is even more challenging when the person has been amputated at the forearm because the signal level in the residual muscles is low. Identifying the command becomes less accurate because there are large differences in the amputated arm of different patients such as length of the stump and the residual muscle, due to which there is the uncertainty of the location of end-plates and thus the placement of the electrodes.

Developments in command and control strategies along with the improvement in materials and micro-devices has resulted in several successful prosthetic hand devices that are lightweight, strong, and have multiple degrees of freedom (DOF). However, despite such devices offering near-natural hand functionality, the user satisfaction appears to be low and many users discontinue the powered functionalities in less than 6 months from start of use. To identify the cause of such low long-term usage of these devices, researchers have reported the work for determining the desired device requirements and also in identifying limitations of the current devices from the viewpoint of the users.

Prosthetic hand control requires multidisciplinary research and there are number of diverse groups working actively on this topic. Searching for related topics also reveals that there have been number of recent review articles that have investigated certain specific aspects of this problem. However, we were unable to find any single paper that is multidisciplinary and covers the breadth of the problem. To overcome this shortcoming, this review has investigated the literature to identify the research that has been reported in all the associated topics, which would facilitate and improve the communication between researchers from different disciplines. This candid review has used many of the existing review works along with the relevant research papers with the aim to facilitate future research and translation leading to improved acceptance of powered prosthetic hand devices by people with hand amputations.

1.1. Literature search strategy

This multidisciplinary review has investigated the impactful research papers that describe different aspects of user requirements, methods for controlling powered prosthetic hands and user satisfaction. The search strategy for this was developed to identify representative works reported in engineering and rehabilitation journals, and wherever possible, existing review articles have been used. The aim was to identify the current state of the art, associated shortcomings, and the research opportunities in the field for the future. Publications that were obviously biased towards a single manufacturer were excluded from this review. Papers that did not provide the statistical analysis were generally not included while Theses and sponsored company brochures that are not peer-reviewed were also excluded. Papers reporting original research, short papers, review papers and letters published in peer-reviewed journals were included. The search was restricted to the English language. This paper reports the review of 87 research and 5 review articles, and has reviewed the following topics in relation to the prosthetic hand control:

1 User requirements and expectations
2 Methods for recording the muscle activity
3 Methods and features for the analysis and classification of the signals
4 Sensory feedback for prosthetic hand control.

The references for each of these topics have been tabulated in 4 tables, and discussed under the respective sub-heading.

2. User requirements and expectations

One potential factor that makes it difficult for many potential users to use the powered prosthetic hand can be the cost. These devices cost is in the range of $ 15000-100,000 [6], and with additional cost for its customization for the patient, it may be prohibitive for many people. There are number of research groups that have been developing low-cost prosthetic hands to ensure global affordability of these devices, but majority of these appear to be projects for student training rather than for research or translation [6,7]. Polisiero et al. [8] reported the design and realization of a low-cost, EMG controlled prosthetic hand with an aluminium skeleton and DC motor driven fingers. To ensure that the device was low cost and robust, it was provided with the minimum features and the myoelectric controller was largely binary. The force of grasp was estimated based on the current being drawn by the motor and with no other feedback, the user was expected to keep the hand in their vision for effective use. This work demonstrated a simple yet effective device with readily available components valued at $50. While this proof of concept is very interesting and addresses the issue of cost, it does not, however meet the needs of a prosthetic hand that is natural and intuitive (Table 1).

The need for further research and development for prosthetic hand is highlighted by the lack of acceptance and low satisfaction rates reported by users. Several studies have investigated the issue of acceptance of [7–10] with general agreement that this is still an ongoing problem. There are a several factors which have been identified as contributing to this lack of acceptance. The study by Jang et al. [9] found that many users felt the devices were unreliable and unsuitable for complex tasks and based on the 307 surveyed users of devices from a single manufacturer, they determined a relatively low level (30%) of satisfaction. The users were particularly unsatisfied with the functionality of their devices with most having switched to using the device in its passive mode and largely for cosmetic purposes only. The recommendation of this study was for the device to have greater functionality and reliability for user acceptability.

Similarly, Peerdeman et al. [10] studied the user acceptance of upper limb prosthetic devices and found that this was low. The factors identified as needing attention were (i) lack of feedback, (ii) non-intuitive control, and (iii) user training. Their assessment of the state of the art devices and research direction was that there was a need for improving the reliability of EMG based commands, integration of the controller with sensory feedback and to consider the psychophysical factors. They recommended the need for the device to be tailored for the individual user to provide the appropriate functionality and suitable control methods. A study by Atzori and Muller [11] on myoelectric robotic prosthetic devices concluded that trans-radial amputation has a dramatic effect on the capabilities of the patients but the available devices do not fulfill the user requirements. The users do not appear to be comfortable with and accept these devices because of the unnatural command structure and they proposed the use of pattern-recognition based devices that exhibit intelligence and learns about the user.

A prosthesis design with a more user-focused approach was reported by Cipriani et al. [12]. To tailor the device to the user, they developed a system for identifying the user requirements, device design criteria, and a framework to develop the device for individual trans-radial amputee. This paper highlights the need for user-focused approaches. To that end, the goal of the literature review by Cordella et al. [1] was also to provide design inputs in the prosthetic field and, consequently, increase user satisfaction rates and reduce device abandonment. They showed that loss of one hand can significantly affect the level of autonomy and the capability to perform daily living, working and social activities. It was observed that the current prosthetic solutions contribute in a poor way to overcome these problems due to limitations in the interfaces adapted for controlling the prosthesis and lack of force or tactile feedback. They concluded with a list of requirements for sensory feedback, thumb performance, precision, heat dissipation, operation outside visual field, low noise, device usage (150,000/ cycles year), the flexibility of cover (skin), dexterity - independence of fingers, stable grasp, the strength of flexion and multiple DOF for the wrist.

The paper by Farina et al. [13] observed that there is a significant effort going into the development of simultaneous and proportional control and command techniques for multiple DOF using myoelectric signals from the forearm. They identified that the current devices appear to only improve the functionality of the individual marginally while requiring significant efforts and training. They also recognized that despite 60 years of intensive research in prosthetic hand control, there is no system that is commercially available which satisfies all the needs of the users. It was also noted that none of the systems work in near real-time (<200 ms), have an intuitive user interface, are sufficiently reliable and are robust to changes in ambient conditions and electrode repositioning. They also mentioned that significant research is underway in all these directions.

The work by Chadwell et al [14] observed that the acceptance of powered prosthetic limb was still a problem. They observed that there was a need for well-established and accepted measure to evaluate the systems and recommended the use of 4 subjective measures for this purpose: task completion, task duration, quality of movement and gaze behavior. While these are useful measures, these appear to be open to bias, and their implementation is not clear.

2.1. Response time

A key factor in the acceptance of prosthetic hand devices is that the delay between giving the desired command and the response of the device should be very small. Scheme et al. [15] studied the underlying cause of the mismatch between the research outputs and clinical acceptance of myoelectric control for multi-functional prosthetic hand devices. Their review indicated that a delay greater than 300 ms was not accepted by the user for proportional controllers.

Table 1
User requirements and expectations.

References	Purpose of the study	Description of the tasks	Number of able-bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Polisiero et al. [8]	Explore the design and realization of a low-cost, electromyographically controlled hand prosthesis for amputees living in developing countries.	Opening and closing the hand	Not Provided	Not Provided	RMS, MAV, STD, MDV	Prototype of the Hand	Grasp force vs Voltage	Restricted to certain movement. Emphasis on motor properties
Jang et al. [9]	Assess prosthetic use by upper extremity amputees, and their difficulties with prostheses in activities of daily living and occupations.	Daily living activities	NA	307	A survey questionnaire included general demographic characteristic, side and level of amputation, type of prosthesis and its use, and difficulties in the activities of daily living, employment and driving	There were no statistically significant correlations between satisfactions with prosthesis, amputation level or type of prosthesis.	The most common type of prosthesis was the cosmetic hand type (80.2%)	Critical literature survey of the use of prosthetic hand.
Peerdman et al. [10]	This study has described the process of determining user requirements and then shown the application of these to evaluate the state of the art in myoelectric forearm prosthesis research.	User defined activities	NA	NA		Reviewed the state of the art of research in the main prosthetic subsystems (EMG sensing, control, and feedback) showed that modern research prototypes only partly fulfill the requirements.	EMG-sensing should align with patients, improving simultaneous control of wrist movements and grasps, deriving optimal parameters for force and position feedback, and considering the psychophysical aspects of feedback, such as intensity, perception and spatial acuity.	The review study has evaluated the requirements and proposed methods for improved forearm prosthesis.
Atzori and Muller [11]	This study provides an overview of the advancements in prosthesis for both commercial and scientific domains. It has outlined the current and future possibilities in this field and the potential partnership between market and scientific research.	Prosthetic hands and control systems.	NA	NA	Review	Commercial products that are based on pattern recognition to recognise the movements have recently been released. However the most common control systems are still usually unnatural and require user training and must be learned through extensive training.	Pattern recognition, proportional control and TMR are the current promising techniques	This study has reported the market assessment of the prosthesis products and its requirements.
Cordella et al. [1]	This study has reviewed the list of requirements for upper limb prostheses based on the performed analysis on user needs.	NA	NA	NA	Review	To better compare the results obtained in the studies performed by different research groups, the introduction of a common evaluation scale regarding prosthetic usefulness, such as Likert scale, should be considered.	An in-depth analysis of bilateral prosthesis user needs and priorities was carried out.	This work has reviewed the literature on the needs of upper limb prosthetic users

Table 1 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able-bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Farina et al. [13]	A review article to identify issues regarding EMG amplitude and neural drive with focus on amplitude cancellation.	Review and simulation	Review and simulation	N/A	Review of EMG amplitude cancellation investigated along with simulation.	The review paper has also reported simulation to highlight the issues regarding amplitude cancellation, and motor unit size.	The paper is raising awareness of the non-linearity of the relationship between neural drive. Also, for the purpose of	This paper has shown that the relationship between EMG and neural drive is not simple and they have raised concerns of the use of EMG for identifying force and actions.
Chadwell et al. [14]	To design the protocol to assess electromyographic (EMG) skill of the user and predictability of the prosthesis response as significant parts of the control chain, and to relate these to functionality and everyday usage.	Protocol development	Two amputees	N/A	Pilot study	Protocol for the assessment of user skill in controlling EMG signals ("EMG skill") and "unpredictability" in the acquisition of these signals. These are assessed against overall user "functionality" and "everyday usage" of the myoelectric prosthesis.	Pilot work and initial analysis of the results suggest that this protocol will be able to successfully identify differences in the "EMG skill" level of participants and characterize the "unpredictability" at the electrode interface.	The study has reported the protocol based on the user skills.
Kent et al. [18]	This study investigated the clinical need for increased dexterity of prosthetic hands, and presented a clinically viable solution to this problem for an anthropomorphic artificial hand.	Rotational tasks – screw and unscrew objects	10	5	EMG signals were mapped to the developed synergy to control four joints of the dexterous artificial hand simultaneously.	With the able-bodied subjects, the developed synergy controller reduced task completion time by 177% on average. The limb absent subjects completed the task faster on average than with their own prostheses by 46%.	There was a statistically significant improvement in task completion time with the synergy controller for amputees.	This study has reported a viable solution for people with an upper limb absence to use a more dexterous artificial hand to screw or unscrew objects.
Yang et al. [20]	This paper reports the use of EMG from the forearm to identify 4 thumb actions, along with the 12 finger movements.	A supervised system that uses number of machine learning methods to classify the EMG.	4	0	4 machine learning methods along with RMS of the signal, with manual selection of threshold to identify background activity	Accuracy of identification of the finger and thumb actions.	Large inter-subject variation. Electrode location unsuitable for most amputee patients.	The authors themselves have admitted that forearm is not the appropriate place to identify thumb actions.
Li et al. [23]	Developed a protocol to assess the real-time myoelectric control device.	Investigated the time of start, and completion of the commands, and accuracy.	0	5	Machine learning, and virtual prosthetic hand were used. Experiments were conducted with 10 channels, and channel reduction methods were used.	Motion selection time, completion time, accuracy and completion rate.	They concluded that the accuracy is dependent on total number of actions. Significant difference between amputee hand and able hand. The onset delay for both was about 0.2 s and 1.2 for completion.	This work highlights the need for having fewer electrodes, and need for delay in identification of the commands. They have also shown that there is significant difference between able and amputee hand.

Several studies have investigated the impact of this need for reduced delay on the accuracy of the prosthetic control. Farrell et al. [16] studied the delay in the analysis of EMG against the classification accuracy and reported that a trade-off exists between accuracy of the multifunctional prosthesis control and the time of operation. Increasing the delay may improve the accuracy but degraded the performance by decreasing the responsiveness of the prosthesis to the user command. They experimentally identified the optimum window for EMG analysis and found that for able-bodied subjects, the best experience was in the range of 100 to 125 ms, with linear degradation in performance with increasing delay. Similarly, Smith et al. [17] investigated the relationship between window length, user performance, and classification error. They experimented with delays ranging from 50 to 500 ms and found that for larger delays, the user performance and error reduced. Thus, it was shown that there is the need for optimization to maximize user performance while at the same time reducing errors. They recommended the use of time window in the range of 150–250 ms, but this could change with factors such as increased computational capacity.

2.2. Device functionality

Crucial to the use of a prosthetic device is the ability to perform everyday tasks. Observations by Cordella et al. [1] recommended the need for an increased number of grip options, where the patients can realize grasping and manipulation to perform functions that are important for daily living. They also recommended the need for the integrated tactile sensors for the prosthesis to provide the user feedback of touch, slippage, pressure and temperature. Another important recommendation from this work was the need for inbuilt intelligence for the device such that the user does not require continuous visual contact with the device which will free them for performing other tasks such which require their visual attention, and thus perform naturally and intuitively.

One particularly significant set of functions that are often involved in tasks performed in everyday life are the rotational functions. Kent et al. [18,19] investigated the potential for a multifunctional prosthetic hand to perform routine rotational functions such as screwing or unscrewing objects. They found that the current prosthetic hand devices were limited in the way the user could perform daily activities such as unscrewing the cap of the jar and suggested that more research and development was required for a hand that allowed the user the natural movement of screwing/ unscrewing a jar top or something similar.

The analysis by Yang et al. [20] of user requirements has shown that the thumb plays a significant role in the dexterity of the human hand but has been largely ignored in the development of the prosthetic hand and its control. They also observed that the destruction of the thumb movement associated muscles in forearm amputation makes using EMG to identify thumb commands highly erroneous. They concluded that alternate methods are required to give people with hand amputation the ability to control thumb actions of the prosthetic hand.

2.3. How many degrees of freedom (DOF)?

Most authors suggest that users prefer a prosthetic hand device that offers a larger number of DOF. While that may be true in isolation, the review article by Zecca et al. [21] shows that this is only one of the factors because increasing the DOF comes at the cost of other user concerns. Their review article of myoelectric control for prosthetic hands concluded that while there are a number of options for controlling the multifunctional prosthetic hand, the realistic number of DOF for reliable control was very low and significant improvements for both, command and control were required. One approach to the control of prosthetic devices is to have a user specific control technique.

In 2009, Castellini et al. [22] recognized that despite the advancements in mechatronics and materials which have led to the availability of powered prosthetic hand devices that are highly dexterous, one shortcoming was the difficulty for the user in controlling these prosthetic hand. They proposed a user specific control technique which first identifies the most suitable grip parameters for the individual and is then trained to identify the command from the myoelectric recording from the trans-radial stump of the person. Such methods would identify the effective DOF for the user, thereby reducing the error while satisfying the requirements for the individual.

In work by Li et al. [23], another user-specific system was developed. Its aim was to identify the most suitable hand/ wrist movements and desired force for the specific user. The need for such a system was identified when comparing the recognition of wrist and hand-movement commands from EMG of the able hand and the stump of the amputated arm. The results showed that while the EMG of the able hand was suitable for classifying 10 actions, the DOF for the amputated hand was significantly lower and with poor accuracy. In order to address this, they developed a machine learning/ artificial intelligence-based and user-specific system.

While user specific control systems go some way to alleviate limitations surrounding the number of DOF, determining limits on the number of DOF to achieve the desired performance may also prove an important step in the design of prosthetic devices. The study by Castro et al. [24] recognized the need for a large number of DOF for the prosthetic device to be able to offer greater flexibility to the user but concluded that it is necessary to limit the number of DOF for accurate classification of sEMG. They attempted to maximize the sensitivity and specificity by generating a series of confusion matrices and determined that for the system to be both sensitive and specific, it was essential to determine the minimum number of actions and DOF.

3. Methods for recording muscle activity

Managing the quality of the electromyogram signal is an essential for reliable and accurate control of myoelectric prosthetic hand. The associated literature review was found to belong to five classes: (a) Signal recording, (b) Signal modelling, (c) Surface electrodes, (iv) Number of Electrodes and High-Density EMG (HD-EMG) and (v) Implantable electrodes. These have been described below (Table 2).

3.1. Signal recording

The quality of the recording of the muscle activity is a necessary consideration if accurate control of the prosthetic hand is to be achieved. Clancy et al. [25] investigated the reliability of using the amplitude of EMG and concluded that it is essential to reduce the noise at the source by proper skin preparation, use of active electrodes and placing the electrodes at suitable locations. This procedure is essential because otherwise the noise and cross-talk can make the signal quality poor. They noted that despite the best efforts of experimenters to control the experimental conditions, noise still gets recorded along with the signal and this must be managed with the help of signal filtering. They recommended the use of adaptive filtering to overcome the inter-experimental differences in signal properties.

An investigation into different methods to reduce line-noise (50 or 60 Hz) by Mewett et al. [26] concluded that while commonly used techniques such as notch-filtering or methods such as spectral interpolation were suitable for reducing noise, all of these techniques altered the signal properties, and the filtering process was

Table 2
Methods for recording muscle activity.

References	Purpose of the study	Methods	Data/Signal used in this study	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Clancy et al. [30]	To review data acquisition and signal processing issues relative to producing an amplitude estimate of surface EMG	1.To identify the sources of EMG measurement noise and techniques for diminishing its influence 2. to estimate the amplitude of the noise-reduced sEMG	NA	1.Electrode motion artefact 2. Electrode noise 3. Cable motion artefact 4.Whitening 5. Demodulation and re-linearization 6. Smoothing	Reviews various methods and techniques implemented to reduce the nosie and accurately estimate the amplitude	1. Active electrodes, almost eliminate cable motion artefact. 2. esearch into improving the amplitude estimate via EMG signal whitening and multiple channel combination has been highlighted.	This study has reviewed various issues and techniques implemented to measure and eliminate noise. This review also highlights the techniques to estimate the amplitude of EMG which are important while recording muscle activity.
Mewett et al. [30]	To propose a new method to remove the power line interference from the EMG signals	1. Spectral Interpolation 2. Notch Filter	A set of 500 simulated surface EMG signals was created to test the performance.	Both the positive and negative frequency components of the interference are interpolated, to obtain a real-valued signal.	ANOVA analysis for significance test.	Neither spectrum interpolation nor a notch filter is an ideal method, as both attenuate power line interference instead of removing it.	These methods can therefore distort signals containing little or no interference.
Merletti et al. [30]	To present the state of the art of technology and instrumentation for detection and conditioning of sEMG signal.	Presented various techniques, methods, designs and analysis for detection and processing of sEMG signal	Simulated and raw EMG signals are reported	Sampling, configuration of detection system, electrodes and contacts, high density electrodes, spatial filtering	Simulation and acquisition of the raw EMG signals by using various geometry and configuration of electrodes	High-density sEMG electrode grids and multichannel amplifiers provides spatial information in addition to the temporal information content of the sEMG signal. the effects of the subcutaneous tissue layers and of the detection volume on the recorded sEMG signal.	This review provides the technological advancement during 2009 in the electrode configuration and the design of the instrumentation for the acquisition of the EMG signal.
Farina et al. [30]	To propose a model for fast and accurate simulation of the surface EMG.	The influence of thickness of the subcutaneous tissue layers, fiber inclination, fiber depth, electrode size and shape, spatial filter transfer function, interelectrode distance, length of the fibers on surface, single-fiber action-potential amplitude, frequency content, and estimated conduction velocity are investigated	Simulated signal based on the single muscle fiber action potential	The EMG variables - the peak-to-peak amplitude, MNF, and the estimated CV of the single-fiber potentials are computed for validation	The effects on surface EMG potentials of electrode shape and size, spatial filter transfer function, IED, fiber inclination, fat thickness, and IAP generation and extinction have been studied using the proposed model.	The results show the changes in the SEMG potentials with respect to electrode positioning, detection system design and the correct interpretation of the EMG signal.	The thickness of the tissues separating the sources and the recording electrodes is assumed constant along the fibers. The issue of crosstalk has not been addressed.

Table 2 (*Continued*)

References	Purpose of the study	Methods	Data/Signal used in this study	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Wheeler et al. [32]	To design and implement a differential, time-invariant, surface electromyogram (sEMG) model	The model uses realistic physiological parameter values to simulate both electrical sEMG and muscle force output signals	Simulated and raw EMG signals are reported. Raw EMG signals were recorded 10 healthy volunteers	The model considers the entire muscle with multiple MUs. The MU size, initial temporal offset, and the muscle fiber conduction velocity have been considered to have normal distribution with mean and standard deviation values based on experimental results.	The RMS of sEMG and the force output of the both experimental and simulated data were computed.	Rate of change of RMS with force (MVC). And the accuracy of linear fit for rate of change of RMS was correlated	The model has implemented the real-world simulation parameters to generate both sEMG and force signals from the biceps brachii at varying contraction levels. The effect of various parameters such as orientation of fiber and the electrode location has not been discussed.
Siddiqi et al. [32]	To develop and test a model that simulates surface electromyogram (sEMG) signal of m. Tibialis Anterior.	The model incorporates a novel firing rate equation with a customized recruitment threshold distribution.	Raw EMG signals from 8 healthy volunteers. Simulated EMG signal form the model	Root Mean Square (RMS) and Median Frequency (MDF) of the experimental and simulated EMG signals were calculated.	A one factor Analysis of Covariance (ANOCOVA) was performed for comparison of the linear regression slopes of the normalized EMG RMS and median frequency between experimental and simulated signals at a significance level a = 0.05.	ANOCOVA statistical results show that there is no significance between the slopes of normalized RMS and MDF of the experimental and simulated EMG.	A new model for TA with customized recruitment threshold distribution was reported. The change in the location of the electrode has not been discussed.
Jiang et al. [33]	A novel signal processing algorithm for the surface electromyogram was proposed to extract simultaneous and proportional control information for multiple DOFs.	A Degree of freedom related nonnegative matrix factorization (NMF) algorithm was used to extract the neural control information from the surface EMG	Raw EMG signal from 12 healthy subjects and simulated signals from the model.	The model assumes that there exists control information at the spinal level and further quantifies the control information as a set of time varying force functions, with a dimension equal to the number of DOFs of the limb movement.	The performance of the proposed force function estimation method, multivariate R^2 indices were used.	The experiment results showed that the proposed DOF-wise NMF algorithm has the capability to estimate the forces produced at multiple DOFs during dynamic contractions by using the multichannel surface EMG.	This study demonstrated the feasibility of obtaining simultaneous and proportional control signals at multiple DOFs for a prosthesis. Only DOFs are used to estimate the force and other factors have not been discussed.
Hermens et al. [34]	Develop recommendations on EMG sensors, sensor placement procedures, signal processing and modelling.	Review of studies reported on the EMG sensors, sensor placement procedures, signal processing and modelling.	Signals from healthy participants and simulated signals were reported.	Various signal analysis techniques and modelling were reported	NA	Recommendations were provided on the development of EMG sensors, sensor placement procedures, signal processing and modelling for uniform research of EMG.	The advent of High-density EMG has made these recommendations to be revisited.

Table 2 (*Continued*)

References	Purpose of the study	Methods	Data/Signal used in this study	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Comert and Hyttinen [36]	To investigate the design of the structure supporting the electrode for reducing the motion artifact by stabilizing the skin deformations around the electrode.	four textile electrodes with different support structure designs: 1. a soft padding larger than the electrode area, 2. a soft padding larger than the electrode area with a novel skin deformation restricting design, 3.a soft padding the same size as the electrode area, and 4. a rigid support the same size as the electrode.	Raw EMG signals recorded from 5 subjects	The impedance changes caused by electrode motion, the biopotential changes caused by electrode motion, and the ECG affected by this motion artifact, three simultaneous measurements were performed using the electrode subject to motion in all three measurements leads	The RMS values were used to investigate the effect of movement magnitude on the motion artifact for the different electrode designs. The power spectrum densities (PSD) of the data were calculated and compared with the PSD of the preprogrammed motion to assess the similarity between the applied motion, the impedance, and the motion artifact.	The effect of the structure design is observed both in the measured surface potential as motion artifact and the change in the skin–electrode impedance, both of which follow the applied motion pattern. The results show that a support structure that restricts epidermis deformation in response to motion.	This study has shown that a physical electrode structure design which supports the skin in dealing with the motion artifact.
Young et al. [38]	To investigate the optimal inter-electrode distance, channel configuration, and electromyography feature sets for myoelectric pattern recognition in the presence of electrode shift.	Training data were recorded at three different interelectrode distances: the distal electrode was placed either 2, 3, or 4 cm from the proximal.	Seven different wrist and hand motion classes were tested	EMG signals recorded from Seven non-amputee subjects.	Electrode configuration using four channels at all three shift locations (0, 1, and 2 cm) with a 2 cm interelectrode distance	The results for the different interelectrode distances indicated that failure rates and completion times were nearly the same for each interelectrode distance with no shift. In the presence of electrode shift, with inter-electrode distance of 4 cm compared to 2 cm, failure rates were 20% lower and completion times were more than 2 s faster.	This study has found that larger interelectrode distances and a combination of longitudinal and transverse channels reduced system sensitivity to electrode shift. Only time domain and autoregressive features were discussed.
De Luca et al. [39]	To investigate the influence of inter-electrode spacing on the degree of crosstalk contamination in surface electromyographic (sEMG) signals in the tibialis anterior generated by the triceps surae using bar and disk electrode arrays.	The degree of crosstalk contamination was assessed for voluntary constant-force isometric contractions and for dynamic contractions during walking.	Single-differential signals were acquired with inter-electrode spacing ranging from 5 mm to 40 mm. Double differential signals were acquired at 10 mm spacing using the bar electrode array.	Crosstalk contamination at the target muscle was expressed as the ratio of the detected crosstalk signal to that of the target muscle signal.	During walking, the crosstalk contamination on the tibialis anterior muscle reached levels of 23% for a commonly used 22 mm spacing single-differential disk sensor, 17% for a 10 mm spacing single-differential bar sensor, and 8% for a 10 mm double-differential bar sensor.	The study reported that the Crosstalk contamination and inter-electrode spacing is a serious concern in gait studies when the sEMG signal is collected with single differential sensors.	The contamination can distort the required muscle signal and can lead to misinterpretation of its activation timing and magnitude.

Table 2 (*Continued*)

References	Purpose of the study	Methods	Data/Signal used in this study	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Staudenmann et al. [42]	To determine the relative importance of several electrode sensor configurations for optimizing muscle force estimation using HD-EMG grid.	This study studied the factors such as the size of a single electrode, the IED, the sensor's spatial distribution	11 healthy subjects performed isometric right arm extensions at 20%, 50%, 80% of (%MVC) and three different elbow angles (60, 90 and 130)	Normalization of force to the mean over the force plateau and EMG to the mean of the EMG over the force plateau region. The quality of the EMG based estimation of muscle force was quantified with the root mean square difference between normalized force and EMG	Electrodes of the actual size in the grid (1.2 mm diameter) were compared to conventional electrode sizes simulated by averaging the signals from 5 neighboring electrodes over the monopolar basic signal set with various IEDs.	The bipolar basic set showed a clearly less homogeneous EMG pattern over the grid. The results reported show that the recording surface, is dominantly responsible for the improvement in EMG based force estimation. The elbow angle showed a strong and systematic effect on force estimation over all configuration properties.	The study has reported the changes in the estimation of the force due to the various electrode sensor configurations using HD-EMG
Huang et al. [43]	To investigate a reduced number of electrodes and the placement required to extract enough neural control information for accurate identification of user movement intents.	An electrode selection algorithm for the HD EMG recordings, which sub optimally selects a reduced number of electrodes required to preserve enough neural control information for accurate classification of user movement intents.	Four Amputee underwent Targeted muscle reinnervation procedure	An electrode selection algorithm based on the sequential forward searching (SFS) method was developed to select a limited number of electrodes that contain most of neural control information for reliable classification.	The comparison of 16-movement classification accuracy using electrodes placed according to Suboptimal, Clinical, and Geometrical Configurations is reported.	The results from this study show that 12 or less EMG electrodes placed over TMR and other residual muscles can be used to record neuromuscular control information for the amputated limb, including the control of finger movements.	This study has reported the tools for the clinical implementation of a multifunctional prosthetic control strategy that combines TMR and EMG pattern recognition.
Martinez-Valdes et al. [44]	To assess the intra- and inter-session reliability of estimates of motor unit behavior and muscle fiber properties derived from high-density surface electromyography (HDEMG).	The discharge timings of motor units of the vastus lateralis and medialis muscles were automatically identified from HDEMG by a decomposition algorithm.	Ten healthy subjects performed submaximal isometric knee extensions during three recording sessions (separate days) at 10%, 30%, 50% and 70% of their maximum voluntary effort.	The number of detected motor units, their discharge rates, the coefficient of variation of their inter-spike intervals, the action potential conduction velocity and peak-to-peak amplitude were characterized.	Reliability was assessed for each motor unit characteristics by intra-class correlation coefficient.	Reliability within and between sessions was found for all motor unit characteristics at all force levels (ICCs > 0.8).	The study has reported that the Motor unit features can be assessed non-invasively and reliably within and across sessions over a wide range of force levels.
Weir et al. [47]	To develop a multichannel electromyography sensor system capable of receiving and processing signals from up to 32 implanted myoelectric sensors (IMES).	An IMES system consisting of a telemetry controller, integrated magnetic drive with RF receiving antenna coil, and an IMES implant was designed.	acute in vivo experiments, and chronic in vivo experiments were performed.	An in vitro experiment was demonstrated to show the functioning of magnetic and RF link when an IMES was placed in muscle tissue, a precursor to implanting IMES in cats.	One second of each reflex event containing both pre- and post-onset EMG data was processed. Comparison of the recorded IMES signal to the recorded Noraxon signal in individual muscle(s) was accomplished by cross correlation and examining the magnitude-squared coherence between the two signals.	The acquired EMG from the chronic in vivo experiments shows a maximum cross correlation of 0.09. Magnitude-squared coherence between the two measured signals does not exceed 0.40, and for most of the recording spectrum, coherence is lower than 0.10	This study has reported the development of IMES system capable of measuring focal intramuscular EMG comparable in both the time and frequency domain to commercially available clinical EMG systems.

not lossless. One interpretation of this work is that it is essential to reduce line noise during recording rather than to depend on the processing of the signal later, which cautions the dependence on filtering for signal quality. However, despite all the progress in circuit design, Galiana-Merino et al. [27] observed that line noise is still a major problem in the quality of sEMG, and may be due to several reasons including electrode placement and skin conditions. They reported a new method based on stationary wavelet transforms and tested it on real signal recordings and showed that it reduced some of the artefacts. One of the observation of this work was that it highlights issues regarding the quality of signals due to changing conditions. In this context, it may also be worth considering other factors such as changes due to sweat, drying of the gel, or change in the contact pressure between the skin and the electrode, which can play a significant role in the signal quality but are not fully within control during the recording of the data.

Another aspect that is routinely encountered while recording sEMG are the mechanical perturbations. De Luca et al. [28] reported a study where they established the relationship between movement artifacts and the filter properties required to filter these signals. While this study was performed in the context of kinematics and biomechanical experiments, this is an important issue for myoelectric controlled prosthetic devices which are used for extended periods while the user is actively moving and performing tasks.

Merletti et al. [29] reviewed the relevant papers for detection and filtering of sEMG, and reported many of the limitations of sEMG including the electrodes and line-noise. This work covers several issues related to the signal recording and conditioning and shows some of the benefits of the various signal conditioning techniques. Subsequently, they have also demonstrated the successful use of signal modelling and simulation to demonstrate the potential of high density EMG (HD-EMG). However, one important factor which is absent of research that measures the change of signal properties over time. It is evident that studies have not reported the stability of long-term recordings. While it is well accepted that there will be changes in the signal due to electrode to skin contact and ambient conditions, and external disturbances, these have commonly been ignored.

3.2. Signal modelling

As shown by Farina et al. [30] in their study, there are large inter-subject and inter-experimental variations in the sEMG signal properties which makes its interpretation very imprecise. They recommended that to investigate the limitations of recording the signal and identify suitable methods for analysis, it is essential to model the signal generation in a way which accurately represents the anatomical and physiological process. For this purpose, they developed a model of the generation of sEMG by describing the underlying physiology and anatomy. Wheeler et al. [31] observed that the model by Farina et al., while a significant advancement of the earlier work, did not consider two important factors: fiber type and multiple sizes of the motor units. They modified the model and also demonstrated that the non-linear relationship between force and muscle activity is important and should be considered when investigating the variability in the strength of muscle contractions. Sidiqi et al. [32] reported a model which incorporated changes to deal with limitations in the model by Wheeler et al. because that was based on a fixed electrode configuration and suitable only for muscle fibers that are parallel to the surface. By incorporating these changes they were able to show a strong correlation between the simulated and experimental recordings for low level and high-level contraction. These models have also attempted to identify changes due to factors such as ageing and disease.

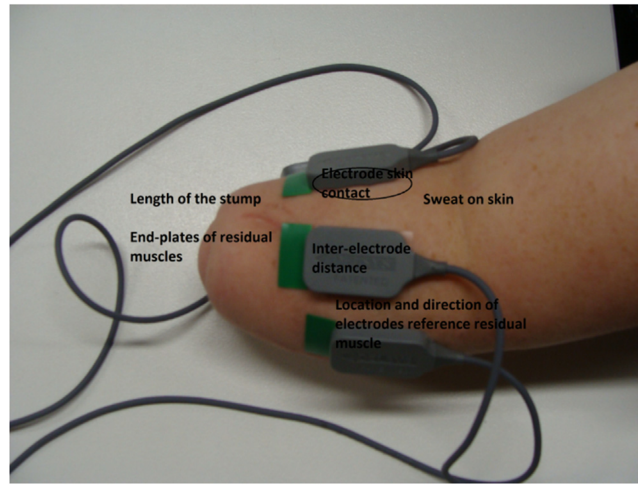

Fig. 1. The number of parameters that can influence the EMG recording.

As well as using modelling to understand any limitations of the recording technique, it can also be used to aid the understanding synergy between muscles and how muscles work together. Jiang et al. [33] used a generative model for surface EMG which assumes that muscles share spinal neural drives. These shared drives correspond to the intended activations of different DOF of natural movements and are embedded within the surface EMG. A direct application of the proposed method would be providing simultaneous and proportional control of multifunction myoelectric prostheses. Thus, it can be concluded that there are models that are based on the anatomical and physiological information and the outcomes of which describe the real-life recordings for able bodied people. These models had also investigated changes in the neuromuscular parameters associated with ageing and disease, which suggests that these could be used irrespective of the age. However, the models were implemented for able-bodied people only and effect of amputations was not investigated. The effective use of these models for helping prosthetic hand control will require knowledge of how this recording of the muscle activity will change due to amputation, and the length of the residual muscle, which however does not appear to be well understood.

3.3. Surface electrodes

Electrodes play a very important role in the quality of sEMG, and electrode type and placement can influence the myoeletric signal recording. To discuss these issues, a generic figure of the electrode placement is presented in Fig. 1. Number of parameters regarding the electrodes that can significantly influence the EMG recording have been mentioned in this figure.

The European concerted action for Surface EMG for Non-Invasive Assessment of Muscles (SENIAM) has provided recommendations for EMG electrode types and electrode placement procedures. The review of Hermens et al. [34] on the development of these recommendations indicates surface electrodes made using Ag/ AgCl appear to be the most widely used for recording sEMG, though other materials such as gold, tin, and stainless steel have also been considered. They also found that with a few exceptions, most myoelectric controlled prosthetic hand devices used bipolar electrode configurations. Their work also showed that the majority of the electrodes were circular disc-shaped with a diameter of 8–10 mm, and inter-electrode distance of 20 mm, though these parameters were not always defined. However, the shortcoming they identified is that SENIAM has been developed for able bodied people and there is no standard for amputee patients.

One cause of changes to the signal property is the shape, size and placement of the electrodes. Details of electrode shapes and inter-electrode distance (IED) was shown to be a significant problem for EMG recording by Alemu et al. [35]. They investigated the effect of IED on the EMG recording for able-bodied people and found that there were significant differences in the spectrum and magnitude of the signal for different IED. They recommended that for reproducibility of sEMG experiments, the IED and electrode size should be clearly mentioned, and comparison of different experimental results should have matched IED. There are no similar studies that have investigated the effect of these factors for amputated limbs, but this highlights the necessity for planning the electrode selection and placement to reduce variability.

Another significant effect on the recording of biomedical signals is due to variation in the pressure from the electrode to skin surface. While this had previously been recognized anecdotally, the paper of Comert and Hyttinen [36] experimentally confirmed this. This work recommended the use of padding and the need for development of a framework but fell short of suggesting techniques for high-quality signal recordings to overcome the variability of the pressure over extended periods. There is no literature that has recommended a technique to manage signal differences due to electrode –skin pressure variations. To ensure that myoelectric prosthetic hand control is suitable for being used for several hours, and the user is able to self-place the electrodes, it is essential that research is conducted to overcome this limitation.

One of the bottlenecks in the use of multifunctional powered prosthetic hands with myoelectric user interfaces is the need for experts to identify the electrode location for the individual user. This is attributable to the significant anatomical inter-subject variations. Rainoldi et al. [37] studied the inter-subject difference in the location of the innervation zone to identify the extent of this problem and they found that there was a need for the development of the electrode placement protocols for reduced variability.

To determine the best placement of electrodes and for identifying the optimum IED, Young et al. [38] focused on determining a configuration that was less sensitive to factors such as electrode shift during replacement. Their work recommended the use of multiple electrodes along with a complex analysis technique to overcome the shortcomings due to the electrode shift over repeated placements. They found that increasing IED from 2 to 4 cm improved the system performance in terms of classification error, though that is questionable based on some other reports [32,36]. Additionally, they investigated the electrode configuration and recommended that electrodes should be oriented both longitudinally and perpendicularly with respect to muscle fibers to reduce the impact of electrode shift. This study demonstrated the efficacy of such electrode placement for able-bodied subjects, but it is not clear how it would translate to the trans-radial amputee patients.

A study with similar aims to those of Young et al. [38] was conducted by De Luca et al. [39] for the lower limb muscles where they studied the effect of electrode shape, size and inter-electrode distance on the signal quality. Their work suggested that 10 mm IED was the most suitable and they also concluded that there was no significant difference due to the electrode shape being a bar or a disc. Recent work by Waris et al. [40] found that there was degradation of command identification with time. They also reported that other factors that contributed to the accuracy were the electrode selection and their placement. There were significant changes to conductivity and shift artefacts with time resulting in the change in signal properties. Thus, it can be concluded that issues such as electrode shape, placement and distance between electrodes plays an important role in the recording of sEMG, but there are yet no definitive answers.

From the literature and Fig. 1, it can be seen that while attention has been paid to some of the factors that influence sEMG, there are several issues that have not yet been considered. There appears to have been little work done regarding overcoming the electrode-skin contact variability over time, nor has significant effort been made to develop an easy to use protocol to identify the relative position of the residual muscles and their end-plates for suitable electrode placement. This section has shown that more research is required for the development of electrodes, method of their placement and determining suitable location, especially for amputee patients.

3.4. Number of electrodes and high-density EMG (HD-EMG)

In order to determine the correct user command based on the sEMG recorded from the forearm requires an estimation of the relative force being generated by different muscles around the joints. sEMG is an estimate of the activity of the muscle, and recordings from different muscles is typically required for identifying the user command. However, the traditional method of sEMG uses a pair of bipolar differential electrodes, and the estimate of the muscle activity is based on assumptions such as relative location of endplates [41]. Number of researchers have attempted to use larger number of electrodes to improve the performance.

Tenore et al. [4] developed a system to identify the flexion of individual fingers which was using 32-electrodes, significantly larger number of electrodes than had been used by earlier works. They were able to demonstrate the use of the configuration for identifying the individual finger movement of able bodied participants but reported only for one trans-radial amputee patient. Reviewing the work, it is also not evident how this electrode configuration would function for most of the people with hand amputation because of the length of the stump is different for each amputation. It is also not evident how this can be self-managed and placed by the user because of its inherent complexity.

HD-EMG is the recording of the electrical activity using a dense array of electrodes placed on the surface of the muscle for high-spatial resolution of muscle activity and this has many advantages such as not requiring precise location of the end-plates of the muscle. Staudenmann et al. [42] studied HD-EMG for the purposes of force estimation from EMG and found that HD-EMG improved the estimation of the force by 30% when compared with bipolar EMG recording. This indicates that this electrode configuration has the potential to be used for myoelectric user interfaces.

To investigate the use of HD-EMG for the purposes of identifying the user intent, Huang et al. [43] performed feature selection on HD-EMG recordings. They found that there were significant redundancies and with only 12 electrodes, the user command was accurately identified 90% of the times. They developed a framework and protocol which can be employed by the user to place the electrodes without the need for clinical support. This is an important step because self-placement of the electrodes is an essential aspect to support the independence of the users.

One of the early users of HD-EMG were Merletti et al. [41] who in 2008 proposed the use of this technology for identifying individual motor unit action potentials, and later in 2009 [29], they reviewed the state of the art of the technology of detection and conditioning systems. In their review paper, they investigated the electrode configuration, impedance, noise, transfer function, electrode geometry, and location on the recording electrodes. Their work and subsequent review covers a range of applications, and this is relevant to prosthetic hand control because it highlights the limitations of the bipolar EMG and the potential of using HD-EMG for measuring the muscle activity.

Martinez-Valdes et al. [44] studied the reliability of using HD-EMG for estimating motor unit action potentials for applications such as accurate recognition of myoelectric based user commands. Their work showed that the system provided sufficient accuracy over a wide range of muscle activity, ranging from 10% to 70% MVC. While the use of HD-EMG has been proposed by many researchers, this paper appears to be the first that assessed its reliability for the measurement and estimation of motor unit properties. HD-EMG derived measures of motor unit behavior were found to provide reliable results across and within sessions. The use of motor unit decomposition was the proposed analysis method and found to be accurate over force levels ranging from 10% to 70% of the maximum force.

One common difficulty encountered in the design of a myoelectric control scheme for the prosthetic hand is to select the number of electrodes to be used. Number of researchers such as Tenore et al [4] and Staudenmann et al. [42] have suggested that higher number of electrodes give better results, however there is the cost and complexity factor that goes with the increase in the number of electrodes. In the review of Scheme et al. [15], they recommended the use of four appropriately placed bipolar electrodes to discriminate between the required hand actions. Muceli et al. [45] analyzed the theoretical basis for dimensionality reduction in HD-EMG signals from forearm muscles. They recorded HD-EMG from the forearm muscles of 6 individuals and determined that 6 channels or greater resulted in similar outputs for simultaneous multi-degree of freedom prosthesis control.

There is a definite appeal of the use of HD-EMG for identifying the intent of the user command. It also may have the potential for identifying the best location of bipolar electrodes if that is the preferred option. While there are some obvious concerns such as the complexity of the data and cost of the device, however, it does not require assumptions such as the location of end-plates which is a limitation suffered by the traditional bipolar electrodes. The higher resolution would also overcome poor specificity of bipolar EMG recording. However, HD-EMG has not yet become main-stream which may be due to the cost of the equipment and complexity of the experiments. Future research may help reduce the cost and develop the protocols for the widespread use of this technology which may overcome some of the limitations associated with conventional myoelectric based prosthetic control.

3.5. Implantable electrodes

Surface electrodes for recording muscle activity have the advantage of being non-invasive and low-cost. However, these come with shortcomings due to noise, movement artifacts and factors such as pressure and sweat which can make them unreliable and result in poor specificity. Along with the variability of the recordings over time, one of the difficulties associated with the use of myoelectric recordings to control a multifunction prosthetic hand is the cross-talk and poor selectivity. With the growth of implantable electronics and wireless communications, implanted electrodes have been proposed as an alternative solution. These devices are placed inside the muscle with wireless connections to external equipment. Dhillon et al. [46] showed the use of implanted electrodes located inside the arm of the patients. They were able to record the muscle activity from these electrodes and identify the user commands while simultaneously stimulating these electrodes to give the user the phantom sensation of touch and force for closing the control loop of the prosthetic hand device.

Weir et al. [47] developed and tested an array of electrodes that were implanted in the muscle and wirelessly recorded the muscle activity. To overcome the problem for cross-talk and poor selectivity, they developed a multichannel 32 implanted myoelectric sensors (IMES) system. The researchers had used a transcutaneous magnetic link to provide power and access the signals from the implanted electrodes with the implants being designed for long-term use with no servicing requirements. They showed that the system was stable for more than 4 months and recommended this method for recording muscle activity as the quality was not affected by the ambient conditions or movement artifacts. This system appears to promise good signal quality from the region where the electrode is located.

The appeal of implanted sensors for myoelectric control is that the signal is free of cross-talk. However, what these studies do not provide is a method to record the overall activity of the muscle which could be a serious limitation when the muscle activity is at low levels and only few motor units may be active. For the effective use of these electrodes, there must be a method which covers a number of motor units and not limited to very few. It is not evident how many electrodes will be required to cover the different motor-units needed to allow control of the prosthetic hand for complex actions requiring multiple levels of the force of contraction. The other difficulty is that due to the invasive nature of the procedure, there are very few groups who can conduct the experiments into the efficacy of these electrodes. Hence, further research is required that will enable implanting of these electrodes with a minimally invasive procedure.

4. Methods and Features for the Analysis of sEMG

Control of the myoelectric prosthetic hand requires that the user command is accurately and efficiently obtained from the recorded EMG signal. Numerous strategies using sEMG have been proposed implementing different features of the signal and techniques to classify these and determine the command. The review by Parker et al. [48] identified two main streams of classification of the signal: pattern recognition and direct mapping. While control of the prosthetic hand may be achieved using direct mapping of the electrode channel to a specific function, such a paradigm will not support switching between two functions but only between the given state and the neutral point which makes it unnatural and not intuitive. On the other hand, pattern matching approaches classify multi-dimensional recordings to multi-functional actions and map it to the corresponding DOF. They also identified independent component analysis (ICA) as an interesting approach with potential to be effective for prosthetic control (Table 3).

One review by Oskei and Hu [49] studied the different signal features and analysis methods, and also compared the steady state and dynamics of the gestures. Their work investigated the different signal processing algorithms and the methods for classification such as machine learning techniques. This well documented and focused has surveyed EMG analysis and reported a technical comparison between the different approaches.

Chowdhary et al. [49] undertook a review of papers related to the application of EMG for prosthetic hand control and identified wavelet-based filtering as most suitable for noise reduction. They also recommended histogram analysis coupled with support vector machines (SVM) as suitable methods for classification of the signals. This paper provides an easy to access review of papers in this topic and the summary of individual works, but it does not provide a comparison of the outcomes between the different filtering methods, such as wavelets and bandpass filters. A thorough review of the start of state-of-the-art sEMG classification techniques for the purposes of myoelectric control was performed by Hakonen et al. [50]. This review paper investigated the effects of the inter-electrode distance, the shape of electrodes, the potential of HD-EMG, and the electrode placement with respect to the innervation zone, and classification options in terms of the ability to classify the data. They have recommended the use of bipolar electrodes, identified that a sampling rate of 500 Hz was sufficient, and a window size of less than 200 ms did not compromise the accuracy. This is a very useful observation because it can reduce the computational complexity significantly. Another important aspect of

Table 3
Methods and features for the analysis of sEMG.

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Parker et al. [48]	Give an overview of the status of signal processing for prosthetic control.	N/A	N/A	N/A	Overview of myoelectric signal processing based on the keynote lecture given at the International Society of Electrophysiology and Kinesiology Congress. Identifies the myoelectric signal processing challenge & provides a historical perspective before moving on to the current state-of-the-art & future directions and expectations.	N/A	• Current commercially available one channel, two or three state systems are well developed and reasonable reliable. • Multifunction prostheses exist but still require effective control strategies. • Acceptable performance needs to be in terms of both classification and active daily living assessment.	N/A	Despite the improvements there are still many myoelectric signal processing challenges in order to be able to provide prosthetics with simultaneous, independent & proportional control for multiple degrees of freedom.
Chowdhary et al. [49]	Compare methods for analyzing EMG signals.	N/A	N/A	N/A	A review of signal processing & classification techniques for sEMG. Focus is on two main areas: the pre-processing & different methods for processing & classifying sEMG. Covering noise sources, EMG signal processing, EMG features & classification.	N/A	• Optimal results are obtained by employing wavelet transforms & higher order spectra in the processing of EMG signals. • SVM classifier with AM-FM histogram features give the best classification accuracy. • Extra features improve classification results but PCA & LDA are recommended for very large numbers of features.	N/A	• To extract important information regarding the nervous system a combination of processing methods & pattern recognition techniques are recommended.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Hakonen et al. [50]	Review digital signal processing for myoelectric interfaces.	N/A	N/A	N/A	Review of myoelectric digital signal processing including: the acquisition system identifying recommendations for sEMG electrodes, filtering and sampling rate, and preprocessing algorithms for classification. Decoding myoelectric information looks at segmentation, features, and myoelectric control strategy. The challenges and future trends identified are the number of control commands, simultaneous and proportional control, variation in limb posture, variation in contraction force, and interface integrity with time. Finally, the applications cover assistive technology, rehabilitative technology, input devices and silent speech recognition.	N/A	• Between 4 & 6 bipolar electrodes recommended for hand & forearm posture recognition. • It is not always necessary to target electrodes onto single muscles. • Accurate classification is possible with sampling rates down to 500 Hz. • Classification may be improved using preprocessing algorithms (ICA, cPCA). • Segments should ideally be around 200 ms but can be reduced using majority voting. • A combination of time & frequency domain features takes advantage of better classification accuracy of time domain but lower sensitivity to noise of frequency domain.	N/A	• For control of multiple degrees of freedom pattern recognition-based methods are recommended. • Dynamic portions of EMG signals are important for myoelectric control and must be included in the learning process. • The optimal feature set will depend on the classification task as well as the measurement system. • The best, worse and average case delays can be estimated as functions of window length, processing time, window overlap.
Zardoshti-Kermani et al. [51]	Evaluate features for mapping EMG onto a low dimensional feature space in order to discriminate between classes of movements.	Different levels of contraction of the biceps & triceps.	0	1	8 EMG features: integral of absolute value (IAV), zero crossing (ZC), variance (VAR), first autoregressive (AR) coefficient, v-order operator, log operator, Willison amplitude (WAMP), and EMG histogram (HIST) are implemented and the separability of the movements in the feature space evaluated.	• Class separability: percentage of trials misclassified & Davies-Bouldin cluster separation measure. • Robustness: class separability for different levels of additive white noise. • Computational complexity – time taken to compute features.	• EMG HIST feature has the best overall performance in low noise. • 1 AR coefficient is sufficient in low noise – more coefficients are required as the noise increases. • ZC and WAMP degrade with noise • Window sizes of only 100 ms are required.	The methodology investigates the robustness of the features to noise. Further investigation is required to compare for different subjects and different sessions.	• The proposed EMG HIST feature is effective, easy to implement & fast to compute • Many effects such as subject variation, training and fatigue require carefully designed experiments.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Boostani and Moradi [52]	Identify the best features for motion classification and control of artificial hand.	Imagined movements of amputated hand & wrist.	0	10	Recordings were taken from 8 channels for 15 different movements each repeated 20 times. 19 time, frequency and time-frequency domain features were extracted from the recordings and the different feature spaces evaluated.	• Scattering criterion. • Davies-Bouldin criterion. • Sensitivity of feature space to noise. • Calculation time.	• Wavelet packet transform provided the best results in terms of separability and sensitivity but had a much higher computation time. • The best overall results were obtained from the energy of wavelet coefficients in nine scales and cepstrum coefficients.	The results presented cover a wide array of different features and movements tested with a larger number of amputee subjects than many other studies. To produce a more natural control transitions not only steady state need to be considered.	• Quantitative analysis of feature quality is required. • A high quality feature space had maximum class separability, robustness, and low complexity. • Time-frequency domain features offer some of the highest quality features.
Arjunan and Kumar [53]	Demonstrate the use of fractal features for classification of sustained isometric contractions.	Flexion of fingers and/or wrist.	5	0	4 channels of EMG were recorded for 4 different flexions of the fingers & wrist. All flexions were held for several seconds & repeated 12 times. The experiments were repeated twice on different days. 6 features were extracted from the sEMG – root mean square (RMS), mean absolute values (MAV), VAR, waveform length (WL), fractal dimension (FD) & maximum fractal length (MFL). Features were classified using an artificial neural network.	• Significance testing. • Classification accuracy.	• MFL identified as the most significant of the features, for single & multiple channels • Comparing the combinations of FD with another feature the pairing with MFL is the most significant. • For multichannel classification the MFL provided the best accuracy • For single channel classification using FD the combination of MFL provided the best accuracy.	The proposed fractal features provide better results than the established features but were not compared against more state-of-the-art features.	• Fractal features are not sensitive to inter-experimental variations & do not require exact positioning of electrodes. • Fractal features of sEMG are suitable for single channel classification.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Phinyomark et al. [55]	Compare the robustness of EMG features for long term use.	10 different upper limb motions.	1	0	EMG data was collected form 4 electrode positions on the top, bottom, medial & lateral sides of the forearm. 10 upper limb motions were analyzed from 121 trials recorded over 21 days. 50 features were implemented based on time domain, frequency domain & both linear & nonlinear analysis. Classification was performed using LDA.	Classification accuracy with different training sets.	• For classification of trials where either the classifier was trained using all of the preceding trials or the 5 preceding 5 highest classification accuracy was achieved with MFL & sample entropy (SampEn). • MFL had a slightly higher accuracy for all preceding data whereas SampEn had for the preceding 5 trials • Using only the first 5 trials from the first day as training data the accuracy of MFL was lower whereas SampEn remained above 90%. • For classification using multiple feature sets the highest accuracies were obtained for combinations including SampEn & cepstral coefficients.	The results test a comprehensive set of features for continuous classification. However, no indication is given as to where the misclassification occurs which would be of use to the reader.	• SampEn provides a stable feature which gives consistently high classification as time between training & testing increases. • Only a limited training set is required as using all data vs only the preceding 5 trials did not improve classification.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
AbdelMaseeh et al. [56]	Identify multi-channel EMG activation trajectories for hand movement classification.	40 different hand movements.	40	0	Multichannel EMG is filtered, rectified, smoothed & normalized. A channel is assumed to be active if the activity is significantly different from the background activity & a movement is assumed to occur when several channels are simultaneously active for a continuous period of time. The trajectory of this movement is then identified and multidimensional dynamic time warping (DTW) is then used as a distance measure between the trajectory & each of the labeled trajectories. The trajectory is then given the label of the movement with the closest labeled trajectory.	• Classification accuracy. • Confusion matrix. • Movement error rate.	• Using the DTW classification an accuracy of on average 89% for offline classification and 87% for online classification was achieved across all 40 subjects & 40 movements. • 9 movements were classified above 95% for offline & 12 above 90% for online. • Confusion occurs for movements that are similar to the true movement e.g. different types of grasps. • Movement error rates for online classification averaged 0.09 with 11 subjects below 0.05. • Subsets of 21 movements for each of the subjects obtain 100% offline classification accuracy.	The use of the trajectories allows the movement to be considered as single instance from all of the EMG channels simultaneously. The flexibility of the DTW means trajectories do not need to have the same durations or amplitudes. However, as indicated by the authors one of the primary limitations of such an approach is the need for the entire movement to be completed before the trajectory can be identified & classified.	• Simple movements of the hand & wrist were easier to distinguish than more complicated grasping & functional movements. • To obtain a real-life control system the number of movements detected by the classifier should be tuned for each subject individually.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Sanger [63]	Demonstrate the use of a Bayesian filter to give an estimate of EMG which has low variability & fast transitions.	Elbow flexion with different force levels.	5	0	Recordings were taken from the biceps & triceps during elbow flexion against isometric constraint. A nonlinear recursive filter based on Bayesian estimation is implemented using 3 different measurement models: Poisson, half-Gaussian, & exponential. Performance of the proposed algorithms were compared against 2 standard linear algorithms – a low-pass filter with order 1000 & cutoff frequencies of 0.1, 1, or 5 Hz & and optimal linear estimator of torque given the EMG signals – with torque being used as an indicator of muscle activation level.	• Root mean square error (RMSE) for estimated torque. • Signal-to-noise ratio (SNR). • Correlation coefficient (r^2) between measured & estimated torque.	• A Poisson model is not a good fit to the EMG data but either an exponential or half-Gaussian are appropriate estimators. • A Bayesian algorithm assuming an exponential or half-Gaussian performs significantly better than other models in terms of SNR, RMSE and r^2. • A linear 1 Hz low-pass filter performs similarly to the Bayesian model in all but SNR where the Bayesian model vastly outperforms the linear model.	The proposed Bayesian algorithm performs well in the given conditions and was shown to be efficient to implement and relatively insensitive to the parameters of the algorithm. The authors identify several future directions for the work. A comparison against other nonlinear filters as well as linear filters would be useful.	• The Bayesian algorithm is flexible and can be used with different statistical models of the EMG distribution. • A Bayesian model has rapid responses to EMG onset and offset preceding changes in torque. • Further exploration of different models to different isometric & nonisometric conditions is required.

Table 3 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment	Outcomes
Han and Jo [67]	Investigate the use of a probabilistic model using latent neural states (LNS) to infer EMG profiles.	Wrist movements and hand opening and closing.	7	0	4 channels of EMG were recorded from the forearm while the subject performed 9 different motions. A supervised hierarchical Bayesian model was used to represent the sEMG. Once the model has been learnt it is then used to classify future data. sEMG profiles are modeled over time as a sequence of data units with trials from multiple channels forming a collection of a sequence of units. Trials are represented by random mixtures over latent intentions where each LNS is characterized by a Gaussian distribution. Classification is based on the most likely classes assuming a trail is associated with a sequence of intentions.	• Classification accuracy. • Similarity of LNS. • Hierarchical cluster analysis of LNS.	• In high activation level classification accuracy was above 90% for all but one subject. • In low activation level classification accuracy reduced no matter the number of LNS. • Classification accuracy of combined activation levels was lower than the single level accuracies. • Online classification providing a classification every 50 ms mainly misclassified at movement transitions. • On average 84% classification accuracy could be obtained when the data was classified using a model trained with the data from the other subjects.	The ability of the model to use the different LNSs to adapt to the control strategies of different subjects makes this approach potentially useful, one caveat is the possibly high computation time. The authors comment on high computational complexity after 50 LNSs, at the same time the EM algorithm can be computationally expensive.	• The proposed method does not require feature selection & provides a model that is natural & reflects muscular activation patterns. • There is the potential for using this approach to aid understanding of the muscular control patterns.
Sensinger et al. [69]	Compare adaptation paradigms for EMG pattern recognition over repeated trials.	Forearm & wrist movements, grasp patterns – 3 for amputees & 5 for able-bodied.	7	4	Several different supervised and unsupervised adaptation paradigms were implemented with a linear discriminant classifier to provide outputs every 30 ms.	Classifier error over time.	• All supervised and most unsupervised adapting classifiers reduced error over time. • The largest improvement in error was obtained using supervised adaptation.	To create practical controllers, adaptation paradigms coupled with ongoing classification are useful, however supervised adaptation requiring correct class label is not always viable.	• Suggested future requirements are a better mathematical & therapeutic framework regarding what constitutes robustness and optimal performance.

this paper is that they have tabulated the list of EMG features and some relevant properties while also suggesting some techniques for filtering the signal. As with the review of [48], the authors have identified pattern recognition and direct classification as the two main control approaches. However, while direct classification, non-pattern recognition methods for identifying myoelectric command may be possible for coarser actions such as elbow or lower limb movement, its suitability for prosthetic hand control has not been demonstrated. This may be because of the complexity of the actions and the associated anatomy.

The review of the literature associated with the methods and features for the analysis of sEMG was grouped in three groups: (a) Feature extraction and selection, (b) Classification, (c) Adaptive and Customised Pattern Recognition, and (d) Identifying muscle synergies.

4.1. Feature extraction and selection

Suitable feature set to represent the sEMG signal is important for identifying the associated action, and different approaches have been used to determine the optimum features to represent the signal. In investigating the features of above elbow amputees the review of work by Zardoshti- Kermani et al. [51] provides insight and describes the growth in this field, which however is important only from a historical perspective. While their work investigated the residual biceps, their negation of most of the features is useful because it demonstrates the limitations of using sEMG as a control signal. It should be noted that the use of biceps for controlling the elbow has lower complexity when compared with the control of the multi-functional, dexterous prosthetic hand and thus the same solution may not be applicable. But despite this the detailed evaluation of the features in this work provides the understanding and the framework which can be useful for future researchers.

Boostani et al. [52] on the other hand considered the features of sEMG recorded from trans-radial amputee patients for the command control of a prosthetic hand. They reported results from 10 patients using 8 channels of sEMG with 15 hand-action commands. The evaluation consisted of 19 features with the outcomes based on cluster analysis. They also considered the computational complexity and noise resilience of the features. This detailed analysis was a very useful exercise in the evaluation of the different features for the specific application based approach. The results show that there is a significant difference between the results using different features and it also shows that while we may reduce the error and complexity by appropriate choice of the feature, they reported that there is still potential for significant error. Based on the user requirement assessment reported earlier, this may have a significant impact on the user and the efficacy of the device.

An alternative to the types of features of sEMG commonly reported in the literature is in the works reported by Arjunan et al. [53] who investigated the fractal features of sEMG. They compared number of features and proposed the use of maximum fractal length (MFL) along with fractal dimension (FD) to be suitable for classification of low-level muscle contraction. They have also reported in [54] that FD is dependent on the muscle properties rather than the strength of contraction and the combined use of FD with MFL is indicative of both, the property of the active muscles and its strength of contraction. While this is a promising approach, with an average accuracy of 90% for only able-bodied subjects with 4 DOF, its suitability for being used as it is for prosthetic hand control has not been established.

One study that compared different features to identify the best set of features for classification of sEMG was by Phinyomark et al. [55] who tested 50 different features, including FD, to identify the user commands for 11 movement options. With the help of linear discriminant analysis (LDA), they were able to achieve 99% accuracy when using a set of 4 features: cepstrum coefficients, sample entropy, root mean square (RMS) and waveform length. While such results appear to be very promising, there is difficulty evaluating this study because they have only used the data from one able-bodied subject.

Abdel- Maseeh et al. [56] proposed a different approach to describe the sEMG features and selection process. They recognized that to control a dexterous prosthesis requires multifunction control with the number of the controlled functions exceeding the number of EMG channels and defined the problem as a “multi-class classification of multidimensional sequence”. The multi-muscle activity was described using time-warping and used to identify the potential trajectory of the action. A distance-based approach was then used to determine the most probable trajectory and classified based on the stored labels. This novel approach was tested on the public database, NinaPro (Non-invasive Adaptive Hand Prosthetics) which contains data recorded from both able-bodied and amputee people. The results presented for the able-bodied participants are very promising but it is difficult to evaluate this because without considering amputee participants can lead to erroneous conclusions. Recent work by Waris et al. [40] found that there was a significant difference between the classification of able-bodied and amputees. They found that the length of the stump was an important factor in the classification results which questions all the works where only able-bodied have been reported.

Myoelectric signals have also been used to provide control of other assistive devices which may have the potential for being used for prosthetic hand control. Sun et al. [57] investigated different feature set for the purpose of myoelectric signals to control a wheelchair in real-time. The results of 97% accuracy are promising using the protocol that required binary commands from the myoelectric activity. However, it should be noted that the control of a wheelchair gave the participants of their experiments real-time feedback which could be an important factor that improves their ability to control the chair. Binary commands are not considered to be natural for prosthetic hand control.

Many of the approaches for the identification of sEMG features have been based on the use of recordings from able-bodied subjects. Further, feature selection has often been based purely on the classification accuracy, and the experiments appear to have been conducted for a short period of time. Thus, there are two difficulties in the evaluation of many of these studies: participants and performance measure. The first is that results based on able-bodied participants cannot be compared with amputee participants. The second is that describing the performance based only on accuracy can be erroneous. Therefore, it would be useful to jointly analyze the underlying physiology, signal analysis and detailed understanding of the classification. This is particularly important if we want to extend the knowledge from able-bodied participants and apply these for amputee patients. It is also critical to determine how these features change with the signal properties over a long duration of time.

4.2. Signal classification

Choice of the classifier has been considered to be important for accurate classification of sEMG for prosthetic hand control and methods such as LDA, SVM and neural networks having been reported [58,59]. However, the review of Hakonen et al. [50] reported that the selection of the classifier with appropriately selected features showed relatively limited improvement and they also observed that the most commonly used and recommended classifier for sEMG was the LDA classifier. They found that there are several factors such as feature selection and recording method which have an impact on the accuracy of the classification regardless of the classifier used.

The dependence of the classification of sEMG on thresholds was recognized to be very important by Momen et al. [58]. Another observation of their study was that myoelectric control system that was designed with able-bodied participants was not suitable for amputee patients and development of systems off-line may not lead to systems which are suitable for real-time implementation. They also highlighted that having a list of very specific hand-actions during training may not be comfortable for all users and could result in poor satisfaction. They proposed a new method where the individual patient specific device was trained for the user specified hand actions while the machine checked the repeatability and discernibility during training. However, they found that even with this user customized approach, many of the users were dissatisfied with the device.

One of the major difficulties related to the classification of sEMG has been identified to be cross-talk where EMG of one muscle mixes with that of a proximal muscle. With the significant anatomical overlap of the muscles controlling the hand actions and simultaneous contraction of multiple muscles, the sEMG signal recorded from all location had cross-talk and corresponded to the summation of activity of multiple muscles. One method to overcome this problem is the use of blind-source separation [60]. However, Naik et al. [61] found that multiple repetitions of ICA resulted in significantly different results which were not evidenced by earlier papers due to the reporting style; reporting only the accuracy but not the sensitivity and specificity. They proposed an alternate method to separate these signals using Multi-Run ICA which is a combination of the mixing matrix and network weights to classify the sEMG recordings. This approach has the potential to overcome the ambiguity problems but requires further investigation of factors such as the computational complexity.

Studies by Arjunan et al. [59] identified imbalance in the data leading to incorrect classification when using classifiers such as LDA, SVM and Neural networks and proposed the use of Twin-SVM to overcome this problem. Twin-SVM has the advantage of having two hyper-planes which does not require the assumption that the training dataset is balanced. Another study by the same authors [62] used S-transform and tested it with multiple channels recorded from amputee patients to identify commands for functional grips. One of the strengths of this technique is that it does not require the classifier to label every data window but only when it recognizes the change of the state. However, while the results showed significant improvements, these were only tested off-line and their potential for real-time applications was not discussed.

Determining the initiation of the activity is essential for positive user experience. However, due to the inherent noise in sEMG, this is not a trivial task. Some of the methods to determine the start of the user command demodulate the recordings to obtain the envelope. These techniques incorporate low pass filtering which was found by Sanger [63] to be a limiting factor because it introduces an inherent delay. He proposed an alternative with the use of a recursive filter using Bayesian estimation approach to identify the background activity from the command associated signal. The work had an improved accuracy for the estimation of the force of contraction, and with a faster response than linear filters.

Another approach of the analysis of the recordings to determine the start of the command gesture was by Huang et al [64] which uses the Gaussian mixture model (GMM). However, this approach assumes Gaussianity of the signal which may be inexact. To overcome this limitation, Bayesian statistical approach to identify the start of the command was proposed with the advantage over GMM that it does not have to assume Gaussianity. The assumption of the signal property may be a problem because it has been shown that the probability distribution of sEMG at low levels of contraction is non-Gaussian [65] and may be better represented by the exponential model proposed in [63].

Several other probabilistic methods have been proposed with the potential for continuous representation of the state of the sEMG. For instance, Chan et al. [66] proposed the use of hidden Markov models to identify the state transition probability. Their argument for recommending this was the lower computational complexity of this approach making it suitable for real-time operations. The system was tested on able-bodied subjects and the accuracy was reported to be around 90%. The approach employed by Han and Jo [67] proposed a hierarchical Bayesian model to classify sEMG with the probability model for the movement strategies learned by assuming that the motion strategies can be modeled and estimated from the sEMG. This has the advantage of not requiring feature selection prior to the analysis. They tested the proposed technique using two active bipolar electrodes placed on carefully selected locations to identify eight complex hand actions and they also investigated the inter-subject variability. The results highlighted significant differences in the performance of the same actions by different participants and the need to identify individual-specific characteristics.

Another important requirement for the control of the prosthetic hand is the stability of both the recording and the classification system over prolonged periods because these devices require continuous usage over several hours. While majority of the work reported in literature has been based on laboratory based, short-time recordings, Yang et al. [20] conducted their experiments for a few hours rather than the standard laboratory-based short-time recording. They developed a two-channel sEMG recording, real-time analysis, and prosthetic hand control system which they tested on eleven trans-radial amputee subjects. They studied finger movement and grip commands and also conducted the clinical evaluation of the control of multi-function prosthetic hand device. The strength of this paper is that it is one of the few that conducted the experiments over longer duration than most other works. They found that within the period of 2–3 h, the signal classification became unstable due to factors such presence of sweat, ambient conditions of temperature and humidity, change to skin impedance and connectivity between the skin and the electrodes and recommended the need for adaptive techniques.

The review of the literature highlights that comparing the works of different authors and results of different classification strategies is difficult because of the different measures and approaches used for reporting the results. Many studies have only reported the accuracy, making it impossible to determine the total misclassifications and only some of the more recent papers have reported the confusion matrix or sensitivity and specificity. Another concern is that majority of the studies have only worked with able-bodied participants, and the significant differences that may arise between amputee subjects has been ignored. Lastly, most studies have worked with very few participants and it is difficult to evaluate the statistical strength of these studies. The repeatability of the experiments has generally not been tested which makes it difficult to establish the usability of the techniques by patients.

4.3. Adaptive pattern recognition

Typically, multi-functional prosthetic hands are controlled such that each command considers a single DOF achieved in a simple binary way. Hahne at al. [68] have shown that with the use of advances in machine learning approaches for myoelectric prosthetic hand control and online training and testing of myoelectric controllers for individual users improves the adaptiveness of the device and user acceptability. Such methods for training and adapting the system may be either supervised or unsupervised and Sensinger et al. [69] evaluated many supervised and unsupervised training paradigms. They observed that the supervised methods outperformed unsupervised ones significantly. They related inter-experimental variability of the signal with the resultant classification and also reported that when user constraints are reduced, the error increased. Thus, when using machine learning for individualized prosthetic hand devices, supervised training and constraints over user commands are the limiting factors to the final outcome.

When investigating inter-experimental variability, Liu [70] proposed an adaptive technique which improved the repeatability of the experiments. They used a combination of autoregressive and time domain features and classified these using an unsupervised classifier. The experiments were conducted on able-bodied volunteers for 3 independent hand-actions (contraction/extension) and 1 rest condition, and the results indicate approximately 10% misclassification. This work shows the importance of testing the repeatability of the experiments without which the results may lead to incorrect conclusions.

It has been recognized that one of the challenges in the use of the myoelectric control is the non-stationary nature of the signal. The signal properties change due to a number of factors that are often not within the control of the user, some of these being: electrode shift, ambient conditions, electrode pressure and skin-electrode interface. Vidovic et al. [71] recognized that these changes cause covariate shift and proposed a supervised adaptive method to reduce the error due to this shift. The proposed approach adopted a trained classifier using a small calibration set which was tested with both, able-bodied people and amputee patients. They demonstrated significant improvement in the accuracy and user satisfaction but the method required substantial supervision.

Zhai et al. [72] proposed an adaptive classification method based for a self-calibrating classifier using convolutional neural networks. This study reported the confusion matrix and from the results, it is evident that this method of reporting the results is necessary because reporting only the accuracy could have been misleading. Unfortunately, however, many researchers only provide the accuracy which may not give the entire picture; high accuracy need not reflect low misclassification. Thus, it is essential that for appropriate comparison, it should provide information regarding misclassifications to prevent incorrect interpretation of the outcomes. While an adaptive classification method is highly desirable with continuous changing signal properties, this paper shows that this can lead to high level of misclassification and raises the fundamental question: 'Is myoelectric a suitable modality for being used for controlling the powered prosthetic hand?'

The recent work by Waris et al. [40] has investigated the effect of duration of the experiment on classification of movements for controlling the prosthetic hand. Their work found that the classification errors increased with time, and this also questions the suitability of this modality for controlling the prosthetic hand. Unless there is a method for retraining the system on an hourly basis, the error would be unacceptable for this application. They also found that the accuracy is dependent on the length of the residual stump which would suggest that it is essential for each device to be custom trained and tested for the user.

4.4. Identifying muscle synergies

The use of factorization algorithms to decompose sEMG data from multiple channels based on the theory of muscle synergies has been proposed as a method for identifying the user commands. The synergy framework relates the relatively higher dimensional muscle activation patterns to lower dimensional task level commands with the principle being that larger numbers of DOF can be controlled from the lower dimensional space due to presence of synergies. The review of Santello et al. [73] considered the question whether the use of muscle synergies can be used to simplify the controller for prosthetic hands by translating intent into actions. They identified studies which appear to have successfully exploited the use of synergies to control prostheses but observed that this had not been confirmed. They found that conclusive evidence would require large amounts of sEMG signals with good SNR – which is a challenge with amputee subjects. They also highlighted that the issue was further complicated because subject's sEMG was known to change with time and that extracting synergies and passing them to a machine learning algorithm could potentially lead to loss of information and therefore the accuracy.

Many of the approaches for synergy-extraction are based upon nonnegative matrix factorization (NMF). In [33] a signal processing algorithm for sEMG was proposed to extract simultaneous and proportional control information for multiple DOF. A DOF-wise NMF was developed to estimate neural control information from the multichannel surface EMG. It was shown, both by simulation using the modelling approach described earlier, and experimentally, that the proposed algorithm could extract the multi-dimensional control information. A similar approach was taken by Muceli et al. [45] whereby they showed that the NMF approach using HD-EMG was robust to both, numbers of electrodes and electrode shift. They also showed that this method could be used to simultaneously activate two DOF, and suggested that this could be a viable approach for extraction control signals for multi-DOF prosthesis control.

Comparison of NMF approaches for simultaneous proportional control with a supervised artificial neural network and linear regression was performed by Farina et al. [13]. They showed that despite very different offline accuracy when estimating kinematics from EMG using different methods, for an online task completion test, the completion times and trajectories to hit the target were similar which indicates that there is little benefit in fine-tuning of these methods. They also highlighted a limitation of most myoelectric control schemes for prosthetic devices are their reliance on the indirect estimation of the neural activity from sEMG. These indirect methods are based on many factors that are outside the control of the user and hence unsuitable for reliable and robust detection of the user intent. The alternative proposed by them was to use direct methods to estimate the neural activity from the signal using decomposition techniques. While the authors highlighted the potential of using direct methods, they acknowledged the significant challenges in the development of this in near future.

5. Sensory feedback for prosthetic hand control

The control of hands by able-bodied people is partly reflexive and this does not require them to visually monitor their hands while performing most of their hand-action. The skeletal muscles have spindle (stretch) receptors which elicits the stretch-reflex and provides feedback regarding the stretch of the muscle. The hand is rich with tactile sensors that allow the individual to have fine touch sensation and the joints sense the angles. Our hand control is closed-loop system, where the muscle control adapts to the environmental situations and even mitigates factors such as fatigue. Childress [74] as early as 1980 realized that effective control of the prosthetic hand needed to be closed-loop and required sensory feedback. They realized that sensory feedback is a prerequisite within the prosthetic hand control loop for stable and intuitive manipulation of the prostheses and to significantly improve the functionality of the prosthetic hand. When there is the absence of sensory feedback, it necessitates the user to use visual feedback and this has been found to cause a high mental burden on the amputees [75]. This stress gets reduced even with simple approaches such as by adding auditory cues which reduced the cognitive effort and it resulted in the reduction in the dependency on visual feedback (Table 4).

Table 4
Sensory Feedback for Prosthetic Hand Control.

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Childress [74]	Significance of sensory feedback in closed-loop control of prosthetic hands	Non-invasive sensory feedback including visual, incidental and artificial mechanical vibration etc.	Not applicable (NA)	NA	NA	NA	artificial sensory feedback, artificial reflex and control interface feedback can be integrated for closed-loop control	The incidental feedback was still dominant, but other artificial sensory feedback is very necessary.
Gonzalez et al. [75]	To assess cognitive effort when manipulating a robot hand with and without the usage of a sensory substitution system based on auditory feedback	Based on psycho-physiological measurement, auditory feedback only control, visual feedback only control, and audiovisual feedback control were compared.	10 male subjects	NA	Immediately after each test, the subject had to answer the NASA TLX questionnaire, and the subject's EEG, ECG, electro-dermal activity (EDA), and respiration rate were measured during the test	NASA TLX questionnaire	The use of an auditory display as a sensory feedback system reduces the attentional demand needed to complete the task, rather than the cognitive effort.	The NASA TLX, the EEG's Alpha and Beta band, and the Heart Rate could be used to further evaluate sensory feedback systems in prosthetic application.
Clippinger et al. [76]	To restore artificial sensation based on electrical stimulation of medial nerves by implanted electrodes	Psychophysical experiments were conducted to evaluate the artificial sensation using a novel miniaturized electronic system	NA	9 amputees	The frequency increased from 0 to 100 or 200 Hz	Subjective description	Different kinds of sensation including fist clenching, finger sensation, paresthesia, etc. was produced.	Artificial sensory restoration has been carried out tens of years ago. But it is still not applicable as a commercialized product.
Antfolk et al. [78]	To present a non-invasive simple sensory feedback system based on mediated by air in a closed loop system.	The authors investigated the capacity of the system to mediate detection of touch, discrimination between different levels of pressure and, on the amputees also, the ability to locate touch.	20 healthy nonamputees	Twelve trans-radial amputees	The Mann-Whitney test in SPSS was performed for analyses.	Subjective description based on psychophysical experiments	A median touch threshold of 80 and 60 g in amputees and non-amputees, respectively, and 90% and 80% correct answers, respectively, in discrimination between 2 levels of pressure. The amputees located 3 touch sites correctly in 96% of trials.	This simple sensory feedback system has the potential to restore sensory feedback in hand amputees, but it can easily affected by the limb movement
Raspopovic et al. [81]	To restore touch sensation in a person with hand amputation using transversal intrafascicular multichannel electrodes (TIMEs)	By stimulating the median and ulnar nerve fascicles using transversal multichannel intrafascicular electrodes, the participant was asked to modulate the grasping force of the prosthesis with no visual or auditory feedback.	NA	1	Phantom finger mapping, and real-time fine force control	Force level discrimination	Three different force levels were distinguished and consistently used by the subject. It was also demonstrated that a high complexity of perception can be obtained, allowing the subject to identify the stiffness and shape of three different objects.	Theoretically, TIME electrode can be used for high resolution of phantom finger sensation. While, the implantation time is still short at present.

Table 4 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Dosen et al. [84]	To present an integrated, compact, multichannel solution comprising an array electrode and a programmable stimulator for somatosensory feedback	Two coding schemes (15 levels), spatial and mixed (spatial and frequency) modulation, were tested in able-bodied subjects, psychometrically and in force control with routine grasping and force tracking using real and simulated prosthesis.	8 able-bodied subjects	NA	Tukey's honestly significant difference criterion (HSD) was used for the pairwise comp.	percent success rate in Psychometric tests	Mixed and spatial coding, although substantially different in psychometric tests, resulted in a similar performance during both force control tasks. Furthermore, the ideal, visual feedback was not better than the tactile feedback in routine grasping.	Non-invasive electrotactile sensory feedback can be potentially used for wide clinical applications.
Svensson et al [85]	To review the different kinds of sensory feedback approaches	Give details of non-invasive and invasive types of artificial tactile feedback.	NA	NA	NA	Benefits and limitation	Invoking embodiment has shown to be of importance for the control of prosthesis and acceptance by the prosthetic wearers. It is a challenge to provide conscious feedback to cover the lost sensibility of a hand, not be overwhelming and confusing for the user, and to integrate technology within the constraint of a wearable prosthesis	NA
Tan et al. [86]	To provide long-term artificial tactile sensation to upper-limb amputees	By using multichannel Cuff or FINE electrode, the subjects were asked to describe the phantom-finger areas and characterize the relationships between stimulus parameters with the sensation intensity and the size of perception area.	NA	2	ANOVA statistical testing analysis	Subjective description based on psychophysical experiments. Also the functional testing of the closed-loop control was conducted.	Tactile perceptions were described as natural tapping, constant pressure, light moving touch, and vibration. Changing average stimulation intensity controlled the size of the percept area; changing stimulation frequency controlled sensation strength. Artificial touch sensation improved the subjects' ability to control grasping strength of the prosthesis and enabled them to better manipulate delicate objects.	Extra-neural electrodes including Cuff or FINE electrodes have the high potential for wide clinical applications to produce the sensory feedback.

Table 4 (*Continued*)

References	Purpose of the study	Description of the tasks	Number of able- bodied participants	Number of amputee participants	Description of the analysis	Outcome measure	Results and conclusions	Critical assessment
Otiz-Catalan [87]	To present an osseointegrated human-machine gateway for long-term sensory feedback and motor control of artificial limbs	The subject performed daily living and professional activities using a myoelectric hand controlled using implanted electrodes via the OHMG.	NA	1	NA	Daily movement time	It was demonstrated in one subject, for more than 1 year, that implanted electrodes provided a more precise and reliable control than surface electrodes, regardless of limb position and environmental conditions, and with less effort.	Sensory feedback of the lost hand can be further developed.
Kuiken et al. [88]	To develop new electromyogram control signals and nerve transfers to skin, to provide a pathway for cutaneous sensory feedback to the missing hand.	The targeted reinnervation surgery was conducted on a woman with a left arm amputation at the humeral neck. After full recovery the patient was fi t with a new prosthesis using the additional targeted muscle reinnervation sites.	NA	1	NA	Functional testing was done and sensation in the reinnervated skin was quantified.	The control was intuitive and functional testing showed substantial improvement on mean scores in the blocks and box tests.	Suitable for high-level amputation.
Tabot et al. [89]	To test the feasibility of restoring somatosensory feedback through intracortical mirostimulation in nonhuman primates.	To intuitively convey sensory information that is critical for object manipulation including information about contact location, pressure, and timing through intracortical microstimulation of primary somatosensory cortex.	NA	Three Rhesus macaques	Location, pressure, and timing were analyzed	Discrimination correct rate	Animals can perform a tactile discrimination task equally well whether mechanical stimuli are delivered to their native fingers or to a prosthetic one. Timing of contact events can be signaled through phasic intracortical microstimulation at the onset and offset of object contact.	Stimulus encoding for ICMS would be more difficult to accomplish native phantom finger sensation.
Flesher et al. [90]	To quantify the perceptual quality of the stimuli through intracortical microstimulation using Utah electrode array	Sensory modalities and the perceptual intensities were quantified.	NA	One tetraplegic patient	Detection threshold, perceived intensity, just-noticeable difference, etc.	Correct rate in psychophysical experiments	Many of these percepts exhibit naturalistic characteristics (including feelings of pressure) can be evoked at low stimulation amplitudes, and remain stable for months. Further, modulating the stimulus amplitude grades the perceptual intensity of the stimuli.	Stimulus encoding for ICMS would be more difficult to accomplish native phantom finger sensation, and the interruption of adjacent probes would be obvious.

Many of the able-bodied muscle control functions are reflexive and we generally pay little attention when we are griping something or performing other routine actions. We do not need to be 'conscious' of the touch or pressure and the process appears to be autonomous with little voluntary involvement. This is also desired when we are using an artificial (prosthetic) hand such that the sensor data can be used to automatically optimize an appropriate grasping force [76]. If the feedback from sensors is provided to the user, this would inform the user regarding the response of the prosthetic hand to their commands without requiring regular visual feedback. Such feedback could give them a natural response to their commands thereby allowing them to dynamically modify this if required. It would also prevent accidents and injury due to incorrect estimation of the force. This can also be used to incorporate an artificial reflex-based control which makes the control of the prosthetic device reflexive and less reliant on continuous user commands. For the success of the sensory feedback, the three important topics that have been identified are; (i) Methods for sensing, (ii) Sensory feedback and (iii) Artificial reflex feedback and these are discussed below.

5.1. Sensing Modalities

Light touch, sustained pressure, and slippage are the most important forms of sensing required for the prosthetic-hand user to realize closed-loop control. One of the early efforts used multiple tactile sensors for static pressure, vibration or shear force which were mechanically fixed to the fingers of the prosthetic hand [77]. The corresponding electrical signals generated by the sensors can be delivered to the amputated subjects. Since then, there has been significant progress with the availability of light-weight, low-cost and reliable sensors that are small enough to be mounted on prosthetic devices. With the advancement of wireless technology, it is now feasible to place number of sensors without the need for wires. However, there are a number of challenges that exist which have to be overcome before sensory feedback can be provided routinely in commercial prosthetic devices.

Antfolk et al. [78] investigated the sensitivity and accuracy of users for identifying force levels based on tactile feedback. They determined that the accuracy of the users to estimate the touch was in the range of 90%. Other works and review article by the same authors [79,80] reported the difference between matched and unmatched modality for the user to respond to the sensor information. This is important because in many cases it may not be feasible to provide matched modality feedback to the users.

Another question that needs to be considered when designing sensors for the detection of touch and force is the extent of mechanical mismatch between the sensors and biological skin tissue. There is also the compliance of the object which may cause a distortion of the sensor output. Raspopovic et al. [81] investigated the response of the patients to the use of tactile sensors and found that the results were promising. The technology has also been developed using stretchable silicon nanoribbon strain sensors with thickness and stretchability like the skin [82]. However, the density of the sensors, recording, and analysis of the signal and feedback to the users are questions that still require research.

5.2. Sensory feedback

There has been significant progress in the development and miniaturization of sensors which can be placed on the prosthetic hand and similar devices. One challenge that must be addressed is to provide the feedback; the delivery of the sensory information to the user. It is Antfolk highly desirable that the feedback is intuitive, so that the user can cognize the information and respond. It is also important that the user recognizes situations such as emergencies. The implementation of the feedback which would provide the greatest ease for the user would be performed non-invasively. Mechanotactile, electro-tactile and auditory feedback are some of the non-invasive methods that have been considered for providing this feedback. However, these have limitations and invasive methods where the nerves are directly stimulated are also being evaluated. In this context, literature was reviewed with the aim of highlighting some of the current techniques and the emerging methods, and have been grouped in three: (i) Mechanotactile feedback, (ii) Direct nerve stimulation and (iii) Artificial reflex feedback, and a brief description of these is given below:

5.2.1. Mechanotactile feedback

Mechanotactile feedback is conventionally considered to be non-invasive and modality-matched tactile feedback, i.e., the exerted pressure, on the residual stump skin is closely associated with the force resulting from the prosthetic hand sensors. Antfolk et al. [78] also adopted air-mediated pressure by connecting silicone bulbs on the prosthetic hand with pads on the amputation stump to produce tactile feedback for the subjects. The corresponding two-level pressure discrimination rate was 90%. Moreover, phantom-finger territories existed near the stump skin for most of the forearm amputees [83]. Appropriate pressure on these regions would produce the somatotopically-matched experience of the lost fingers, and the corresponding mental burden may be reduced [84].

An alternative approach is through vibrotactile feedback, which is achieved in a non-invasive manner through light-weight vibrotactile actuators normal to the skin and has been applied with the commercial myoelectric prostheses such as Otto Bock, and i-Limb hands etc. [79]. It has been shown that short-term vibration feedback can improve the object grasping and release performance for the trans-radial amputees [85].

5.2.2. Direct nerve stimulation

With the development of neural interface technology, peripheral-nerve electrical stimulation has advanced. Dhillon et al. [46] first demonstrated the possibility to implant longitudinal intrafascicular fine electrodes into the medial nerve fascicles within the amputated stump and showed that the sensations were recognized by the user. Raspopovic et al. [81] tested the efficacy of implanted transversal multichannel intrafascicular electrodes placed directly on the medial and ulnar nerves. They were able to demonstrate that this enabled real-time grasping-force modulation without visual or auditory feedback.

Further improvements were reported by Tan et al. [86] and Ortiz-Catalan et al. [87] who showed that electrical stimulation through cuff electrodes surrounding the peripheral nerves produced the tactile sensation of lost fingers. The novelty of their work was that this was monitored for one year and found it to be stable over that period. An alternative to direct stimulation of the nerve was proposed by Kuiken et al [88] using targeted sensory nerve reinnervation strategy. In this method, the median and ulnar nerves were cut and reinnervated to the distal end of other sensory nerves below the chest skin to obtain the sensation. These works have concluded that direct stimulation of the nerves is realizable and facilitates a real-time natural control of prosthetic hands. However, these require the availability of surgeons to perform the procedure and user training, thereby limiting the users due to the surgical risk and cost factor. Further, while this has been demonstrated for the shoulder amputee, this has not yet been tested for the prosthetic hand control which is expected to be more complicated.

5.2.3. Somatosensory cortical electrical stimulation

Somatosensory cortical electrical stimulation has been considered as another option to restore the tactile feedback to the amputee. Experiments have been conducted on non-human primates which showed that percepts projected to the local skin were sensed, and tactile discrimination was observed [89]. Flesher et al. [90] demonstrated that individual finger embodiment can be achieved by direct intracortical microstimulation using a silicon-substrate multichannel Utah electrode array for a long-term spinal-cord-injury subject. However, this is still at early stages and significant efforts are required to realize this prior to human experiments.

5.3. Artificial reflex feedback

There have been earlier attempts to integrate sensor recording with the control of prosthetic devices [93]. Chappell and Elliott [91] reported the use of tactile and temperature sensors with the Southampton Hand and reported that the users were able to modulate their neural control based on this feedback. They also proposed to use the output of these sensors to control the prosthetic hand, thereby providing a closed-loop reflexive control of the device. This will result in the prosthetic hand control scheme having inherent intelligence and less dependence on continuous monitoring by the user. Similar concepts have also been tested in some of the commercial devices, but this area of research is in the early stages and research needs to be conducted and determine the efficacy of this paradigm.

6. Discussion

Control of upper limb powered prosthetic devices continues to fascinate researchers and there are many active research groups that are publishing on related topics. While some of the papers appear to report small projects by undergraduate students, there are many papers that are evidently from large groups with significant facilities. There is also evidence of translation of the research and there are a few companies that have successfully commercialized powered prosthetic hand device. Similar research has also been reported for human-computer interface devices with applications ranging from games to defense. However, it is difficult to place an exact number on the number of research groups that are working on developing interface devices, methods to determine the user commands, and providing the user with feedback.

This review has observed the trends in the research related to prosthetic hand control over the past 20 years. Within the scope of this literature review, the research outcomes can be described in 4 categories: (i) requirements analysis, (ii) signal recording, (iii) signal processing and classification, and (iv) sensory feedback. These are discussed below.

6.1. Requirements analysis and expectations

The successful acceptance of an assistive device is dependent on the analysis of the requirement of the user. There are a few papers that have addressed the issue of user expectations, though limited longitudinal monitoring of the user requirements have been reported. There appear to be seeming contradictions that while users desire a highly dexterous powered prosthetic hand that is lightweight and strong, they do not seem to use such devices when one is made available to them. This highlights the difference between the user expectations and the actual experience. Therefore, it is essential to conduct multi-center objective studies to investigate the user requirements for amputees in different circumstances. It is also essential to investigate the user requirements based on demographic factors such as age, gender, financial situation, and profession.

Factors such as the acceptable delay have been measured and appear to have now been successfully incorporated by the designers of real-time control techniques. Other user requirements that have been studied and incorporated in the devices are the weight, strength and independent movement of the fingers and the thumb. However, an important factor that seems to have been largely ignored is the quantization of acceptable misclassification with most papers reporting the system in terms of the accuracy of the system. There appears to be a significant gap in this area because majority of the papers have not reported measures of misclassifications, or sensitivity and specificity.

One factor that may contribute to user dissatisfaction, but which has not been significantly explored, is the expectation of the duration and circumstances of uninterrupted use of the hand. Most of the papers that have reported the development of the hardware and software to identify the user commands have not reported the duration of the experiments or ambient conditions and we suspect that these were conducted over only a short duration and in controlled laboratory conditions. Another major weakness has been that the works have been developed based on able-bodied participants and many patient specific details have not been considered [92] while there is also the need for standardization of the evaluating and reporting procedure.

6.2. Recording of muscle activity

A review of the literature shows that there is evidence of an agreement between most researchers that the electrical activity recorded from the muscle or peripheral nerve is the most appropriate means of controlling the powered prosthetic hand, though a small number of researchers have considered brain activity recordings as an alternative. The muscle activity has been recorded from the surface or using implanted electrodes, while the nerve signals have been recorded using implanted electrodes. In reviewing the literature, it is evident that majority of researchers have reported the use of surface electromyogram (sEMG) which has also been the primary modality used in commercial products.

Surface electromyogram is the recording of the electrical signals generated with muscle activity and is indicative of the neuromuscular activity. It has the advantage that it is easy to record using simple surface electrodes with inexpensive hardware and without clinical support, and thus very popular in the biomedical engineering laboratories working on prosthetic hand devices. Thus the majority of the work published related to the control of prosthetic hand appears to be sEMG based. It is also not surprising that most papers report experiments conducted with the help of able-bodied participants in laboratory conditions. While this is a very reasonable start, as noted in the publication by Vujaklija et al. [92], there is the need for the evolution of this research to more realistic user-conditions.

There are very few research publications that have considered details such as effect of ambient conditions, length of the stump, the duration of recordings and repeatability. Most of the studies have not evaluated the change in the signal over time, nor the repeatability of the recordings when the users place the electrodes themselves. We were unable to find any study that has studied the effect of combinations of factors such as sweat, ambient conditions of temperature and humidity, and pressure on the electrode. In our opinion, this is a major shortcoming that has reduced the translation of the technology and uptake of the device by the end-users. There is a need to develop electrodes that are suitable for being used for the entire day without requiring user attention.

One weakness of myoelectric control for prosthetic devices highlighted in the literature is the coarse nature of the recording leading to poor specificity. Another issue is that the success of sEMG in identifying complex hand actions requires careful placement of multiple electrodes. To overcome these shortcomings, some research groups have proposed the use of high-density electrodes. While this appears to be promising, there are several drawbacks that need to be addressed such as the complexity of the equipment, protocol for placement of the electrodes and complexity of the algorithms for the analysis of the data.

Researchers have also identified shortcomings such as motion artifacts, and variability in the electrode-skin impedance. To overcome these shortcomings, the efficacy of using intramuscular recordings using implanted electrodes has been demonstrated for nearly 4 months. This is evidently promising and overcomes the problems related to motion artifacts and poor specificity. However, the surgical procedure will be justified only if the changes over extended period of time are investigated. It is also important to study the precision of the command due to the electrode which may be in contact with very few fibers. The other main shortcoming that has not been addressed and needs significant research is the method for placement of the electrodes and determining suitable locations.

6.3. Signal processing and classification

There is extensive literature devoted to the processing and feature extraction of sEMG for identifying hand actions to control prosthetic or other similar devices. It appears to be an extremely crowded area and researchers have proposed a very wide range of features. The approaches used for selection of the suitable features and associated parameters range from heuristic to mathematical model-based selection. The features that have been reported include the use of coarse features that are measures of the strength of the signal, complexity related features, and a measure of the density of motor unit action potential after decomposition of the signal. While some of these are easy to implement, others are computationally complex.

Significant efforts have been reported for determining the most suitable method to classify the signal based on the selected features to identify the user command. The classification methods range from single feature statistical approaches to high dimension machine learning and genetic algorithm-based classifiers. Systems have also been developed that allow training targeted for individual users, and easy retraining to counter differences due to electrode shift.

From the literature, it appears that issues such as accurate identification of the commands within the desired time-delay have been achieved. However, there is a significant difference in the style of reporting the system performance and there is a necessity to have a uniform measure. It is unfortunate that many authors continue to publish the results based on accuracy which is unsuitable for such applications. There is also a difficulty in comparing the applicability of different methods because many of these report offline analysis for able-bodied subjects. The other primary difficulty when comparing methods is the selection of desired hand-actions, different researchers have selected different actions making a comparison of their methods impractical. There is a need to develop a standardized protocol to evaluate the various proposed signal analysis and classification techniques. We propose that the reporting should include the confusion matrix so that the reader can better understand the results. It is also important that the authors should provide justify the number of participants and number of repetitions that demonstrate the strength of their conclusions.

6.4. Sensory feedback for prosthetic hand control

There is evidence of agreement between researchers that improvement in prosthetic hand control requires effective sensory feedback to the user. With the availability of wireless technology, inexpensive micro-mechano-electric sensors, and more lately nano-technology, many researchers have developed devices for sensing touch, pressure, and temperature. However, the bottleneck appears to be in the interface for the feedback to the user; how to provide the information to the user so they can interpret it intuitively, accurately, and reliably.

Researchers have proposed several options for giving feedback to the users such as mechanotactile, electrotactile and direct simulation of the nerves. The review of the literature suggests that this work is in the early stages and there are numerous questions that must be explored. For the appropriate development and selection of the sensors, it is important to determine the realistic user expectation for its parameters such as duration of continuous use, sensitivity, and resolution. Research for providing feedback appears to be in the early stages and it is important to determine the parameters that influence the user response, interpretation of the information, potential data coding and the resolution for the different modalities. It is also important to determine the long-term effect of using the feedback device, i.e. how does the sensitivity change over time?

6.4.1. Summary of discussion

The following points summarize the reported research outcomes and some of the issues which still need to be addressed to achieve better acceptance of the multi-function powered prosthetic hand by the amputee user:

1 Significant effort needs to be made in the analysis of the user requirements and for development of protocols required for objective testing of different devices. There are large differences in the reporting of the results- while some only report average accuracy, more recent works are now reporting misclassification.
2 There is a need to develop a protocol with which the manufacture can communicate the realistic deliverables of the device to the user for effective uptake of the technology.
3 The electronics and materials for the powered prosthetic hand appear to be matured. The weight, strength of the hand and power and speed of the actions are suitable for the operations but the speed of the system to recognise the commands needs further development.
4 There does not appear to be significant research and development work into the development of electrodes that are suitable for long-duration continuous recordings under changing ambient conditions.
5 There are a large number of high-quality publications that describe various signal analysis and classification methods of electromyogram recordings and the work indicates technical maturity.
6 Significant research is required to understand the user requirements for sensory feedback to the users.

7. Conclusion

This literature review has revealed that prosthetic hand control is a very actively researched and current topic. While there are many aspects that appear to have matured, there are others that still require significant effort. The review has shown that there is poor understanding of the user expectations and more research is required in this field. It is important that the user expectations should be carefully analyzed in the context of the devices and situations. It is essential that the realistic device capabilities are conveyed to the users. It is also evidenced that there is wide variability in the style of reporting of the research outcomes which makes it challenging to compare different works and establish the true performance of the reported technique.

Another area of potential research is the development of electromyogram electrodes and methods for stable recordings over extended periods of time and under different ambient conditions.

This is essential for both, surface, and implanted electrodes. While surface electrodes require the device to be functional for a few hours, it is important for the implanted electrodes to be suitable for longer periods. There is also the need for further research in the sensor feedback to the user. The work required ranges from analysis of the user requirements, and methods to give feedback to the user. There appears to be lack of sufficient information regarding the appropriate choice of feedback modalities, the possible sensitivity and any changes over time.

Finally, there is need to develop a comprehensive business plan for sustainability of the research and translation in this field. Currently, it appears that there is large number of researchers participating in this research activity but the commercial potential is not well studied. For the sustainability of research and translation in this field, it is essential that this needs to be better understood. It should also be noted that research into the development of, or the control of, prosthetic hands has had many serendipitous outcomes such as exciting young researchers to engage with biomedical engineering projects. It also appears to attract the attention of governments and has resulted in many robotic and human computer interface developments.

Declaration of Competing Interest

None.

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