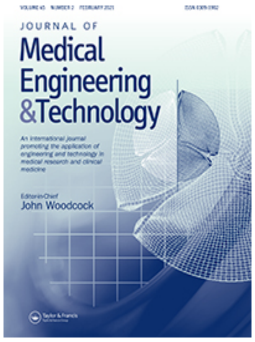

Journal of Medical Engineering & Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ijmt20

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To cite this article: Ejay Nsugbe (2021) Brain-machine and muscle-machine bio-sensing methods for gesture intent acquisition in upper-limb prosthesis control: a review, Journal of Medical Engineering & Technology, 45:2, 115-128, DOI: 10.1080/03091902.2020.1854357

To link to this article: https://doi.org/10.1080/03091902.2020.1854357

Published online: 21 Jan 2021.

JOURNAL OF MEDICAL ENGINEERING & TECHNOLOGY
2021, VOL. 45, NO. 2, 115–128
https://doi.org/10.1080/03091902.2020.1854357

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REVIEW

Brain-machine and muscle-machine bio-sensing methods for gesture intent acquisition in upper-limb prosthesis control: a review

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ABSTRACT

This paper presents a review of a number of bio-sensing methods for gesture intent signal acquisition in control tasks for upper-limb prosthesis. The paper specifically provides a breakdown of the control task in myoelectric prosthesis, and in addition, highlights and describes the importance of the acquisition of a high-quality bio-signal. The paper also describes commonly used invasive and non-invasive brain and muscle machine interfaces such as electroencephalography, electrocorticography, electroneurography, surface electromyography, sonomyography, mechanomyography, near infra-red, force sensitive resistance/pressure, and magnetoencephalography. Each modality is reviewed based on its operating principle and limitations in gesture recognition, followed by respective advantages and disadvantages. Also described within this paper, are multimodal sensing approaches, which involve data fusion of information from various sensing modalities for an enhanced neuromuscular bio-sensing source. Using a semi-systematic review methodology, we are able to derive a novel tabular approach towards contrasting the various strengths and weaknesses of the reviewed bio-sensing methods towards gesture recognition in a prosthesis interface. This would allow for a streamlined method of down selection of an appropriate bio-sensor given specific prosthesis design criteria and requirements. The paper concludes by highlighting a number of research areas that require more work for strides to be made towards improving and enhancing the connection between man and machine as it concerns upper-limb prosthesis. Such areas include classifier augmentation for gesture recognition, filtering techniques for sensor disturbance rejection, feeling of tactile sensations with an artificial limb.

ARTICLE HISTORY
Received 21 June 2020
Revised 10 October 2020
Accepted 15 November 2020

KEYWORDS
Biosensing; cybernetics; man-machine; prosthesis control; upper limb amputee

1. Introduction

There are primarily three main kinds of upper-limb prosthesis: (1) the cosmetic or non-functional prosthesis, (2) harness prosthesis which is worn around the mid-section and actuated mechanically by flexing the dorsal in various ways, and (3) the myoelectric prosthesis (also referred to as the bionic arm), is the most advanced type and works typically with electrodes that sense a neuromuscular signal, alongside a classifier which decodes the intent and selects an appropriate hand gesture [1,2].

Further disseminating the control architecture of the myoelectric limb down into system blocks, movement in a myoelectric limb can be structured as follows: neuromuscular/physiological source signal acquisition; gesture intent decoding and recognition; and activation profile [2]. A depiction of this can be seen in Figure 1 and a contrastive hierarchal diagram of the various established configurations of these blocks can be seen in Fougner et al. [2].

The first part of the system blocks stated above, which is the neuromuscular source signal acquisition, is carried out using bioelectronics sensors and instrumentation. Here, the ability of a myoelectric prosthesis limb to perform the desired hand gesture motion is largely dependent on the ability of the bioelectronics sensor to acquire a quality measure of the neuromuscular signal [4,5].

The second part of the system blocks, which is the gesture intent decoding and recognition process, involves two key phases. The first phase involves the extraction of features from the signal as a means of dimensionality reduction – these features could be standard statistical features such as mean or standard deviation, or in some cases involve auxiliary features such as sample entropy, cepstral and autoregressive coefficient [2,3,6]. The second phase would typically

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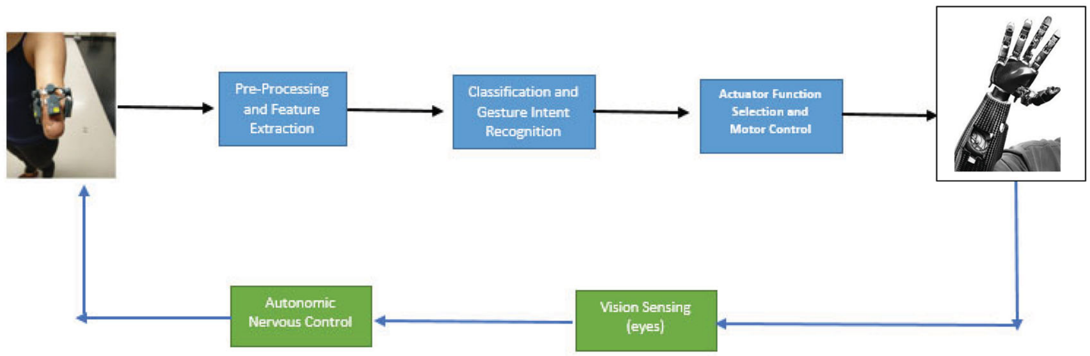

Figure 1. Upper-limb prosthesis control scheme [2,3].

involve feeding the extracted features to a pre-trained artificial intelligence classifier [2,3,6]. There has been a broad range of studies carried out to observe the performance of various classifiers on an acquired gesture intent signal, but the linear discriminant analysis, support vector machine and multi-layer perceptron neural networks have been found to be the favoured classifiers as they possess an optimum trade-off between recognition accuracy and real-time computation performance [7].

The third part of the system blocks, which is the activation profile, typically has common options adopted which include: (1) the proportional control which allows for continuous varying of a control signal that drives the motors and actuators in the myoelectric arm; (2) the on/off control which, unlike the proportional control, does not allow for continuous variation of a signal, but instead facilitates a binary control of the control signal in either an on or off state; (3) the multi-level control which allows for the delivering of multiple instructions in a control signal; (4) the decision ramp function which is a hybrid control strategy that works alongside the multi-level control in order to boost robustness and minimise the likelihood of a misclassification [2].

A semi-systematic review methodology has been used for the review presented in this paper. The aim is to provide an overview on the state of commonly used bio-sensing methods, to provide a structured synthesis of the operating principle and capability for each method, and create a pathway and agenda from which further useful research can be done in this area. Specifically, the contributions of this literature review report are as follows:

- An overview of commonly used invasive and non-invasive biosensing modalities is presented while pinpointing the operating method, using case studies, and analysing the advantages and disadvantages of each sensing modality.
- Using the evaluation strategy mentioned above, a novel contrastive table is introduced which aims to concisely characterise the performance and acquisition property of each discussed bio-sensing modality, while highlighting its key strengths and limitations from a perspective of a prosthesis interface.
- A conclusive overview summarising the extent of technological advancements in the area of bio-sensing for intent recognition is presented, while an exposition detailing areas requiring further research on the basis of the review is also presented – the overview and exposition help provide a streamlined pathway for researchers seeking to innovate in this area.

2. Sensing modalities

For the sake of the review work done in this paper, the various sensing modalities have been grouped as invasive (typically requiring surgical implant), non-invasive, and multi-modal (comprising of more than one sensing modality).

2.1. Invasive sensors

2.1.1. Invasive electromyography (iEMG)

iEMG works with the direct acquisition of neuromuscular signal associated with anatomical contractions directly from the muscle group of interest, for a hand movement classification exercise. Farrell et al. [8] contrasted the performance of iEMG with its surface variant and results showed equivalent classification accuracies for both sensor placements. It was also seen from this study that the features extracted from the signal were more influential for an enhanced classification accuracy as supposed to placement of sensor [8]. The work of Smith et al. [9] showed that iEMG may be better suited to a proportional-based control scheme where continuous contraction of a muscle group is required to drive the prosthesis controllers, particularly for fine motor movements. For torque estimation, work conducted by Kamavuako et al. [10,11] and Farina et al. [12] showed that a larger pick-up surface area is required due to superimposition, and simultaneous firing of motor neurons during certain motions which require the acquisition of global information as supposed to local (iEMG). In addition to being invasive, the main shortcoming of the iEMG stems from its ability to only acquire local neuromuscular signals. This is seen to be unfavoured for pattern recognition control and gesture motions which require a global localisation for the sufficient acquisition of the accompanying signal [9,13].

2.1.2. Electrocorticography (ECoG)

This sensing method works with direct surgical implants in the cerebral portion of the brain for direct measure of electrical activity. Figure 2 shows a grid placement on an exposed brain during an implant procedure [4].

The existing signal gates in the cortex that are responsible for various hand motions can be directly acquired with ECoG sensing and are particularly useful for prosthesis users with distinct motor dysfunctions [15]. This sensing technique has been said to provide quality signals and accurate spatial resolution, and as a result is a highly rated clinical solution that has been seen to produce signals which allow for performing finger motions with classification accuracies spanning in the range of 68–84% [16–18]. Signal processing, electronic hardware and application ethics have been raised as points that need addressing with this sensing modality before it can be commercially available [18].

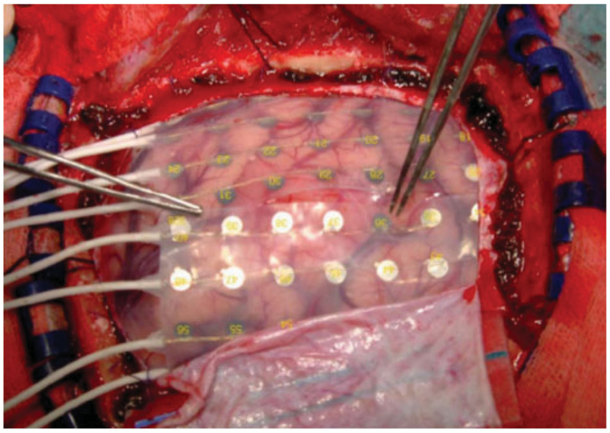

Figure 2. An electrocorticography grid placement procedure during surgery [14].

2.1.3. Electroneurography (ENG)

Electroneurography (ENG) works with the acquisition of signals from the peripheral nervous system using self-opening intra-fascicular neural interfaces (SELINEs) or, in some cases, longitudinal intra-fascicular electrodes (LIFEs). A picture of a thin-film LIFE can be seen in Figure 3 [19].

The potential of ENG can be seen in the work by Micera et al. [20], where it is suggested that the connection to the peripheral nervous system allows for the obtainment of motor information and the long-term possibility of restoring sensory function, thereby resulting in the remarkable prospect of the operation of a prosthesis limb with motor function and sensory sensations. Specifically, through ENG, Rossini et al. [21] utilised the signal output from different nerves to successfully achieve online control for motor outputs and obtained accuracy in the region of 85%, while Micera et al. [19] were able to show that fine digit movement information could be extracted from the resulting ENG signals.

Dhillon and Horch [22] were also able to use LIFEs to link with phantom limb sensations to enable an amputee to select his magnitude for gripping and angular inclinations for joints without using visual feedback. Carpaneto et al. [23] and Rossini et al. [21]

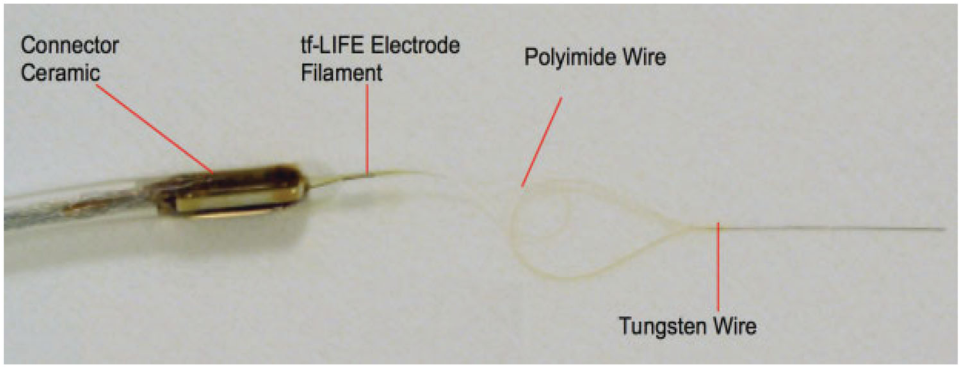

Figure 3. Thin-film LIFE spanning 60 mm [19].

conducted classification exercises and were able to obtain recognition accuracies in the >80% range, and concluded that the results are comparable to that of Electromyography.

Work has also been done by Branner et al. [24] in the design of a microscale intraneural electrode by the name of the Utah Slanted Electrode Array (USEA). In addition to serving as a prosthesis control interface, the applications of the USEA spread towards the restoration of sensory sensations and the alleviation of chronic pain conditions [25–34]. However, the main shortcoming of the USEA implant have been centred around the performance degradation and overall viability, and have prompted research involving the application of adaptive algorithms to help compensate for this [35,36]. Specifically for sensory feedback, Tan et al. [37,38] introduced Cuff electrodes, which are implants that have been seen to restore sensory feedback to subjects with limb loss, where the laboratory based exercises showed subjects embody enhanced object discriminatory capabilities based on the sensations of the objects. It would seem that, at this time, research with the Cuff electrodes is still in its early stages and more work is needed to test the performance of the proposed method on a wider cohort under different scenarios.

2.2. Non-invasive sensors

2.2.1. Electroencephalography (EEG)

Electroencephalography (EEG) is a brain-machine sensing technique which is mainly used for research purposes, and is yet to be widely adopted in commercial prosthesis [39–42]. Despite also having invasive variants, this section is based around the application of the non-invasive variant of EEG. The EEG sensing is viewed as a brain-machine interface (BMI) which works with ionic current change within neurons [4]. EEG is able to closely measure the variations in ionic current fluctuations emanating directly from the brain cells, thereby making it capable of also monitoring evoked potentials from visual signals and mental activities [5].

Agashe and Contreras-Vidal [40] employed EEG sensing for grasp exercises and yielded an accuracy of 76%, whereas Mohamed et al. [41] took advantage of EEG's ability to sense evoked potentials and carried out exercises where participants had to apply imagined actions for task completion and obtained accuracy in the range of 65–71%. Yang et al. [43] adopted a practical approach of down-selection of the 32 EEG channels to applying 6 during prosthesis hand manipulation exercise and achieved an accuracy of 86%.

The shortcomings of EEG, when applied as a prosthesis interfacing tool, are based around low latency and information transfer due to skull thickness, proneness to interferences from background motion, and the relatively long timeframe required to train the user on the application [44,45].

2.2.2. Surface electromyography (sEMG)

Surface Electromyography (sEMG) is a sensing method which acquires the electrical signals associated with the flexion of muscles. In amputees, contraction of the residual muscles around a stump is still capable of producing electrical signals, which serves as the input for prosthetic limbs and has been widely adopted by commercial manufacturers [46].

An optimal number of EMG channels to be used for prosthesis control have been found to vary, and up to 16 EMG channels have been found in certain research-based studies. Commercial manufacturers tend to go with 2 EMG channels on average as an optimal trade-off between real-time computation, prosthesis weight and power consumption; and a large percentage of commercial prosthesis are controlled using EMG sensing [47,48].

The key disadvantages of EMG-based sensing involve the associated complex signal processing methods necessary for the acquired signal. Some of these complexities arise from the inability of some amputees to produce repeatable contractions through which signal is passed, and can also be seen in the sensitivity of EMG to crosstalk (i.e., energy interference from neighbouring muscle groups) [49]. Despite these disadvantages in signal processing requirements, pattern recognition-based control schemes have actually shown signs of improvements in recent years. These improvements have been achieved through algorithms based around the extraction of repeatable features from various muscle-based contractions related to unique arm movement - and importantly, these repeatable features can be used to train recognition classifiers which can differentiate between movements [50–52]. However, a key limitation of this scheme remains the sequential nature of the controller, which restricts continuous proportional-based control [52]. A picture of a wearable sEMG sensor can be seen in Figure 4.

2.2.3. Mechanomyography (MMG)

Mechanomyography (MMG) is a technique which involves the complementary application of both

Figure 4. Wearable sEMG armband [53].

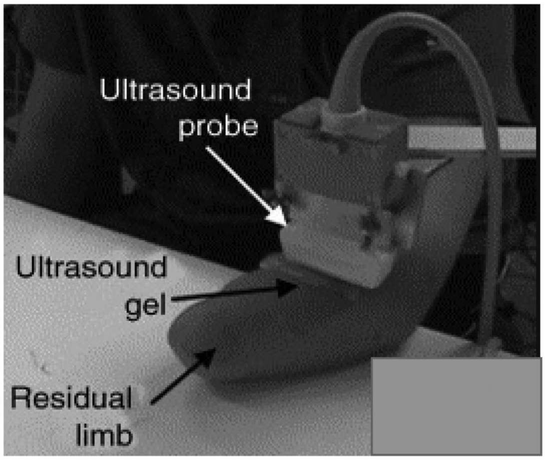

Figure 5. Ultrasound probe and an amputated limb [65].

vibration and low frequency acoustics with accelerometers and microphones, typically in the region of 5–100 Hz, to acquire displacements produced by associated muscular contraction [54–56]. Prior work has seen the application of MMG for tracking levels of muscular fatigue and progression of diseases such as myopathy. More recently, MMG has also been investigated for use in prosthesis control related tasks by Cole et al. [56] and Alves et al. [57].

In a practical comparison exercise by Ni et al. [55], it was noted that a close relationship exists between the sensing principles of MMG and sEMG as both are highly correlated to muscular torque – although MMG has been seen to possess an enhanced detection capability for low muscular contractions relative to sEMG [58]. Furthermore, MMG has the advantage of robustness to skin artefacts and cheaper cost compared with sEMG [59,60].

MMG's shortcomings, however, are related to the fact that both low frequency acoustics and vibrations are highly sensitive to small limb movements which end up contaminating the signal [61]. To overcome this problem, Silva et al. [60] and Posatskiy et al. [62] have researched the design of sensors capable of rejecting dynamic noise and improving the sensor's response to motion artefacts.

2.2.4. Sonomyography

Sonomyography (commonly referred to as ultrasound imaging) is a medical method for the qualitative imaging of deep muscular tissue, and is a strong basis for the diagnosis of musculoskeletal problems [63,64]. It has been said that a direct relationship exists between the features in an ultrasound image and the kinematics of the human upper-limb, thus making it suitable for prosthesis and a number of other assistive devices [54,65,66]. Due to the deep tissue imaging properties and robustness to external electronic interference of ultrasound, there have been strides towards investigating the use of this as an interface in upper-limb prosthesis [67].

Various researchers have conducted studies around ultrasound and prosthesis control. Many of these studies have used the black-white mode (B-mode) imaging option [63,67], notably with Sikdar et al. [68] classifying a number of finger-based flexions with 98% classification accuracy. In another study, Zheng et al. [65] was able to utilise the ultrasound echo feature to estimate wrist-join angles and their respective extent of muscular contraction. With the application of the Horn-Schunk algorithm, Shi et al. [69] were able to identify finger-based flexions, and their results help show that optical flow fields and areas of muscular contractions are broad for a number of finger-based flexions.

Despite the positive results achieved with ultrasound, it is deemed to be unsuitable to be deployed in prosthesis devices due to a combination of ergonomic and cost reasons [70]. An image of an ultrasound probe on an amputated limb can be seen in Figure 5.

2.2.5. Near infrared (NIR)

NIR works in the region of 650–1000 nm, and light can travel through tissue in a non-invasive manner and give an indication of blood diffusion upon muscular contraction due to the optical properties of oxygenated and deoxygenated haemoglobin [71,72]. A typical near infra-red (NIR) sensing involves an emitter and detector configuration whose spacing distance determines how deep an emitted NIR light can travel through biological tissue [71,72].

McIntosh et al. [73] used an ergonomic bracelet to detect and classify a range of 12 gestures which

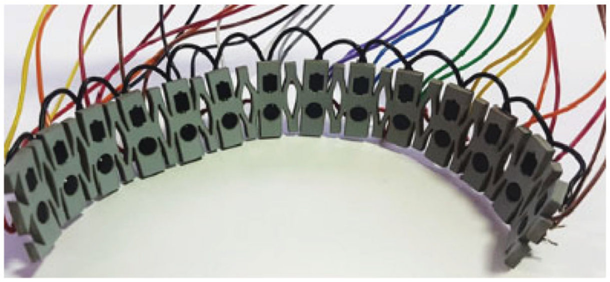

Figure 6. Wearable NIR armband with 14 segments [73].

comprised finger gestures, wrist flexions and hand gestures, with an accuracy of 93%. Other authors have mostly adopted NIR as part of a multimodal sensing platform; this will be discussed futher in Section 2.3. An image of an NIR armband can be seen in Figure 6.

2.2.6. Force sensitive resistance/pressure (FSR)

Pressure sensing, or force sensitive resistance/pressure (FSR), works with the principle of the expansion of a force-sensitive material during muscular flexion. Common materials used include conductive polymers and copper or strain gauges [74–76]. The main strength of this approach is the relative simplicity of the hardware setting, thus allowing for lower power supply demands when compared with other biosensors.

The application of FSR can be found in studies by different authors. For instance, Castellini et al. [77] estimated pressure changes by using a tactile sensor on the forearm of volunteering subjects as the subjects were engaged in finger-based exercises, which showed that finger-based motions could be tracked from the resulting forearm presure. Dementyev et al. [78] and McIntosh et al. [79] have also applied this technique for hand gesture recognition tasks, and both authors obtained >90% on average.

2.2.7. Magnetoencephalography (MEG)

Magnetoencephalography (MEG) is a technique used to measure the magnetic field associated with neuronal electrical activities in the brain. A number of gesture recognition and classification studies have been done using MEG. Although a range of accuracies has been obtained by authors in various studies using MEG, it is said that there is a similarity in the performance capability of both MEG and electroencephalography (EEG) when it comes to distinguishing finger-based gestures [39,80–82]. Sugata et al. [80] used MEG sensing to classify upper-limb motions and obtained accuracy in the region of 66%, while Kauhanen et al. [81] were able to classify finger-based movements from MEG signals and achieved accuracy in the range of 57–94%.

In spite of the capabilities, MEGs tend to be bulky and expensive, and MEG's operating principle makes it susceptible to external magnetic distortions when operating outside of a controlled environment [16,17,83].

2.3. Multi-sensory fusion

The process of a multi-sensory fusion typically involves either a multi-stage classification where there is a sorting phase based on the data received from one of the sensors, followed by the final classification, or an extension of the dimensionality of the feature vector to include signal features from both sensor modules prior to training a classifier.

2.3.1. EMG + inertial measurement units (IMU) & MMG + IMU

Muscular signatures during various arm positions have been seen to vary, and have an influence on the kind of muscular signal produced. Inertial sensors, which contain both gyroscopes and accelerometers, can give an indication of angular positions and orientation. For this reason, they have been combined with sensors such as EMG and MMG to form an auxiliary source of information prior to final classification [84,85].

2.3.2. EMG + NIR

As lactic acid begins to accumulate in the muscle over time, it is known that the magnitude of EMG signals begins to fall. This has been seen to cause misclassification, most notably in cases using a threshold-based classification approach [86–89]. NIR on the other hand, which monitors haemodynamics, has been seen to be robust to muscular fatigue. Thus, EMG + NIR has been the subject of investigation by a number of authors, who have noted an increase in the overall classification accuracy when compared with individual sensing modules [86–89].

Table 1 shows the operating principle of the various sensing modules, alongside their advantages and disadvantages.

3. Control-based improvement of prosthesis devices

With the advancement in sensing technologies, the following are some key challenges that now need

Table 1. The operating principle of the various sensing modules and their advantages and disadvantages.

Placement	Sensing module	Operating principle	Advantage	Disadvantage	Property	Reference
Invasive	Invasive electro–myography	Electric bio–potential generated by a localised sub–muscle group due to neurological activation	– Suitable for proportional control schemes – Good performance when differentiating between finger–based motions – To an extent, avoids the issue of crosstalk due to localised placement	– Not suited for torque estimation exercises – Due to localised placement, it struggles with acquisition	Bio-Electric	[8–13]
	Electro–cortiography	Direct measure of electrical activity in the cerebral cortex within the brain	– Relatively little attenuation in the high spectrum and higher spatial resolution	– Requires invasive implant	Bio-Electric	[4,15–18,90,91]
	Electro–neurography	Involves the implantation of intra–neural nerve stumps to produce motor neuron signals	– Can give an indication of what functional nerve elements are present after amputation	– Fitting the signal acquisition interface requires considerable knowledge of the nervous system, as amputation can sometimes be accompanied by nerve injury	Bio-Electric	[19–38,92,93]
Non-invasive	Electroenceph–alography	Change in voltage from ionic current change within neurons in the brain	– Does not involve exposure to magnetic fields greater than 1 Tesla – Useful for individuals who are unable to make a motor response	– Prone to interference from eye and muscle artefacts, thus a poor signal–to–noise ratio is typically obtained which warrants substantial signal conditioning and processing – Low latency and information transfer rate	Bio-Electric	[4,5,39–45,94–97]
	Surface electro–myography	Electric potential generated by a muscle group during neurological activation	– Non–invasive approach to quantify muscle energy and recruitment pattern	– Limited to monitoring muscle energy and action potential around a localised area of muscle that electrodes have been placed on – Prone to crosstalk i.e. energy interference from neighbouring muscle groups	Bio-Electric	[46–52,98,99]
	Mechano–myography	Represents the low frequency mechanical contraction signals produced by a muscle group, and can be recorded using vibration or acoustics	– Coupling between transducer and limb not necessary – Acquired MMG signals are generally intense, thus less amplification is required	– Prone to interference from environmental noise	Low-frequency acoustics	[54–62,71–89,90–100]
	Sonomyography	Works with the principle of the identification of morphological changes of soft tissues at various depths using ultrasonic imaging	– Ability to detect deep muscle tissue activity – Insensitive to electrical interferences	– Expensive to be incorporated into a prosthetic control system – Probe too large and not ergonomic	Ultrasonic	[4,54,63–70]

(*continued*)

Table 1. Continued.

Placement	Sensing module	Operating principle	Advantage	Disadvantage	Property	Reference
	Near infra–red	Works with the principle of photons emitted by a set of LEDs and absorbed by a muscle tissue while the remainder photons are detected by a detector and can pick up muscle changes due to amount of light reflected (typically in the region of 650–1000 nm)	– Low signal to noise ratio during muscle contraction – Potential for providing spatial and temporal resolution	– Influence of tissue thickness on muscle measurements – Influence and contribution of myoglobin to the measurement uncertainty of the acquired signal	Infra-red Light	[7,71–73,101,102]
	Force sensitive resistance/Pressure	Works with a principle that for a band comprising of a set of copper traces and a conductive polymer, the resistance of the polymer changes with applied pressure –thereby changing the resistance between the copper traces	– Low power consumption – Relatively simple interfacing and signal processing required	– Low accuracy in the classification of finger gestures	Mechanical	[39,74–79]
	Magneto–encephalography	Involves the direct measurement of the associated magnetic fields generated by the electrical activity of the neurons in the brain	– Provides a direct measure of neural electrical activity – Provides high resolution of timing of neuronal activity	– The magnitude of the magnetic signals associated with brain activity are small (10^{-15}T) and challenging to isolate and measure – Vulnerable to magnetic interferences	Electro-Magnetic	[16,17,39,80–83,103–105]
Multi-Modal Fusion	EMG + IMU, MMG + IMU	Fusion of a chosen muscle sensing approach with IMU to assist in dealing with limb orientation and angular variations	– Gesture classification improvement due to added capability to sense limb position and orientation prior to classification	– Pre–process calibration still required, as technique is sensitive to user physiology	Combination	[84,85,106,107]
	EMG + NIR	Combination of muscle fibre recruitment energy and high spatial resolution	– Control signal comprising of haemodynamic and electrophysiological signal sources	– Combination of both sensing modules makes for a slightly bulkier hardware	Combination	[59–61,86–89,108]

emphasis in strides towards control-based improvements of prosthesis devices:

- In order to have a reliable classifier, further work needs to be done to provide a wider range of reflective and varied datasets that can be used to augment the gesture classifier towards recognising signal inputs as it would in an actual situation, and under a range of conditions in everyday life.
- Various means need to be put in place to ensure the acquisition of a bio-signal with a high signal-to-noise ratio. Means to achieve this include designing sensors which have a wider operability; have less susceptibility to external interferences (i.e., power lines); have the ability to filter out and reject undesired motion artefacts as part of the signal condition phase; and also have the ability to address the signal degradation with time problem, specifically in the case of invasive biosensors.
- In certain cases, very little can be done to overcome the natural limitation of a sensing module to its operating principle and the natural way of the human anatomy. In these cases, the prospect of a multi-modal sensor fusion needs to be explored, and where possible, merging the various sensing modules into a single unit as done by Guo et al. [7,108].
- In the majority of upper-limb prostheses, a feedback process does not exist. Instead, a human-induced natural feedback process is carried out using vision sensing as the state observer, and the central nervous system as the controller, which commands the muscular anatomy to adjust appropriately into a desired scheme. Although this results in an effective man-machine collaboration towards task completion, it pales in comparison with the capabilities possessed by the human limb, such as stiffness, proprioception and tactile sensing, to name a few. Therefore, as a means of further personalisation of the prosthesis hand, there is a need for the inclusion of appropriate perception sensors, which would help create a sensory feedback between the human and the artificial limb. Also, the feedback path could include feedback signal transfer means such as nerve stimulation or mechanotactile stimulation.

4. Conclusion

In this paper, a semi-systematic literature review has been conducted where a number of bio-sensing methods for prosthesis interfacing have been analysed based on their operating principles, advantages, and shortcomings. This approach has been used to provide an overview of the key sensing modalities used in upper-limb prosthesis interfacing. Through the overview's methodology, we have been able to develop a tabular-based framework. This framework characterises each reviewed bio-sensing modality based on its operating principles and its physiological property, vis-à-vis its strength and weakness when applied to gesture intent acquisition and prosthesis interfacing. It is intended that this framework would allow for an easier means of down-selection of the various bio-sensing methods under specific design requirements and constraints.

While there are various bio-sensing methods as depicted in this paper, EMG is the most widely used for clinical studies and is the favoured sensing module used in the prosthesis interface by manufacturers. Other muscular contraction-based techniques appear to also be showing steady improvement and would be expected to be complementary to EMG-based interfaces as part of multimodal sensing interfaces, and even begin to compete with EMG-based sensing as alternative standalone prosthesis bio-sensing interfaces.

On the other hand, the invasive bio-sensing modules tend to provide a higher quality signal, but are either highly sensitive to external interferences or degrade with time due to formation of scar tissue around the implant area. More work needs to be done on the stability and overall longevity in real-life use before the invasive techniques can be used widely in prosthesis.

A number of bio-sensing combination and fusion techniques to compensate for the shortcomings of a constituent part of such combinations/fusions, have also been mentioned in this paper. It is predicted that this area, involving combinations and fusions, will continue to expand due to the ergonomic and technical benefits associated with it.

Furthermore, a number of areas which require additional work to improve the connection between an amputee and an associated prosthesis limb, have also been addressed. These areas include gesture classifier augmentation using a wider range of training samples, electronic filters to reject interferences and motion artefacts, multi-modal sensor fusion for an enhanced bio-signal source, and the establishment of a feedback path by embedding perception sensors in the prosthesis arm and receptors in the amputees.

Lastly and importantly, in order to help accelerate the availability and commercialisation of several bio-sensing modalities, this paper advises that researchers carry out key experimental work, which would be representative of the scenarios that users of prosthesis would face in their daily lives. This step will be quite instrumental towards ultimately achieving mass user acceptability.

Acknowledgements

The author would like to thank Dr Eliza Condrea for providing feedback on the manuscript, Mike Fraser for the suggestion to carry out the work done as part of Table 1 and Kerr Editing Services (https://www.kerrediting.com/) for proofreading the manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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