Biopotential Signal Monitoring Systems in Rehabilitation

Subjects: Rehabilitation
Contributor: Patrizia Vizza

Rehabilitation consists of an iterative process involving assessments and specialized training, which unfortunately are often limited by healthcare centres' restricted resources. To overcome this limitation, wearable technology should be an important, potential and valid solution to objectively assess and monitor patients inside and/or outside clinical environments. The information extracted by the use of this technology should provide a more detailed evaluation of the impairment, also allowing the identification of rehabilitation therapies.

Keywords: biomedical signal ; monitoring system ; rehabilitation ; signal processing

1. Introduction

Biomedical wearable sensors allow the measurement of physiologic parameters in a continuous, real-time and non-invasive way, including a wide range of advances in electrocardiogram (ECG), electromyogram (EMG) and electroencephalogram (EEG)-based sensing platforms [1][2][3]. These platforms and their related sensors have different diagnostic and monitoring applications [4][5]. For example, physiological monitoring could support both diagnosis and ongoing treatment for many diseases involving movement disorders [6]. Furthermore, home-based motion sensing could assist the subject in rehabilitation path and falls prevention, helping him/her improve his/her independence and lifestyle [7]. Moreover, sensors acquire and analyze biomedical signals to monitoring the effectiveness of home-based rehabilitation therapies, for example, in stroke survivors, in patients undergoing surgery, in subjects involved in accidents or to evaluating the use of mobility assistive devices in older adults [8][9][10]. Moreover, the monitoring of physiological signals and parameters could also be a good support in many clinical and non-clinical applications, e.g., in sporting activities to evaluate performance and physical condition of athletes [1][11], in postural control to correct stability, or in a physiotherapy context after injury [12][13]. Generally, the measurement of physical activity parameters aids in guiding many types of applications; e.g., (i) monitoring physical activity during rehabilitation or in a physical therapy setting; (ii) evaluating the success of an intervention and tracking physical activity post-surgery; (iii) evaluating patient mobility; (iv) all (risk) detection; and (v) monitoring physical activity in patients with chronic diseases and disabilities involving movement disorders. Most recently, the coronavirus disease 2019 (COVID-19) pandemic has affected access to standard rehabilitation services, highlighting the need to define new rehabilitation perspectives as telemedicine [14][15]. During this period, the rehabilitation concept considerably changed: the need for home medical assistance for a new idea of rehabilitation phase in older people both with and without COVID-19, in patients affected by neuro-motor disease, in subjects with limited movements after injury or accident and athletes is becoming essential to help these people in maintaining their daily activities. In this context, tele-rehabilitation became an effective and well-accepted method of providing outpatient and community rehabilitation services to support family and caregivers in the assessment of the home environment, patient monitoring and outpatient therapies [16][17][18]. In emergencies such as the COVID 19 pandemic, access to health services is restricted due to the risk of infections and limitations of health resources [14][19]. For this reason, telemedicine services have proved extremely useful by providing home monitoring and rehabilitation solutions and thus minimizing the risk of infection. Survivors of COVID-19-associated pneumonia may experience a long-term reduction in functional capacity and muscle strength. Telerehabilitation (TR) programs could be effective for patients after COVID-19 [14]. However, few studies have assessed whether telerehabilitation for COVID-19 patients is an effective tool. In [20][21], telerehabilitation programs consist of home exercises for aerobic reconditioning, muscle strengthening, and healthy lifestyle education. The physiotherapist (PT) contacts the patient via video call via a dedicated platform to monitor progress. Moreover, physicians can add chest physiotherapy exercises for lung expansion and strengthening of the respiratory muscles. In these programs, a pulse oximeter as a monitoring device is also used.

Many healthcare devices for rehabilitation provide biosignals, such as blood pressure, blood glucose levels, EEGs, ECGs and EMGs [22]. The main bioelectrical signals are generated by the heart, the brain and the muscles, producing ECGs, EEGs and EMGs, respectively. ECG, EEG and EMG signals are characterized by low amplitude (generally, expressed in mV—millivolts) and low operating frequencies, from frequency Hz to some kHz range [23]. The acquisition, analysis and interpretation of these signals are fully reported in the literature [24][25][26][27][28][29][30][31]. Physical activity is often associated with the cardiovascular and muscular systems. Therefore, electrical signal variations cause ECG and EMG during athletic activities, and they are essential and commonly adopted parameters for healthcare management and rehabilitation protocols. In particular, EMG signal is the typical clinical recording method used to diagnose and monitor neuromuscular behaviours. Surface EMG (sEMG) allows extraction of information on muscle activation during a movement or effort, identifying impairment and functional alteration useful in clinical evaluation [32][33]. This information can be presented in different forms (e.g., amplitude, timing, morphology, muscle fibre conduction velocity or muscle coordination). They are relevant in many fields, from orthopaedics and neurorehabilitation to movement analysis in exercise and sport or aging [34][35]. This review aims to focus on EMG signal acquisition devices, also combined with other biosignals ECG and EEG, in rehabilitation pathways, especially for telemedicine applications. This contribution is proposed as a review by addressing questions such as (i) what are the most recent contributions in literature? (ii) what are the commonly used medical devices? (iii) how do these contributions and medical devices support physiological monitoring in rehabilitation? and (iv) what are the future directions and opportunities for EMG signal acquisition and analysis in a rehabiliation context? Many reviews are presented in the literature regarding biosignal acquisition devices for rehabilitation applications, but to the best of our knowledge, EMG signal has been considered only in specific context for single review. This review is thus a general but detailed comprehensive overview of EMG monitoring systems aiming to resume and to discuss the different and important solutions of EMG applications in different rehabilitation contexts.

2. Wearable Devices for Rehabilitation

Generally, these systems present heavy drawbacks regarding the limitation in acquiring and sending data at high rates, the low energy efficiency and the restricted portability due to their large size and weight. To overcome these limitations and make these systems more efficient, wearable devices are becoming essential in daily and clinical practice to allow continuous monitoring of human activity in terms of changes in biological signals. The increasing trends of wearable devices and the multimodal acquisition of different biosignals are crucial for advancing disease-diagnosis and treatment. Wearable devices perform activity monitoring through two main processes: (i) data acquisition and preprocessing; (ii) transmission, analysis and classification of acquired data. Signal preprocessing, for example, includes amplification and filtering stage; signal analysis, instead, involves averaging or extraction of relevant features to be used as training data for classifier [36].

In literature, many contributions are available concerning the design and the implementation of wearable sensors aiming to define platforms of multimodal acquisition and recognition of different biosignals, such as electroencephalography, electromyography and electrocardiography, for continuous and automatic monitoring of human health status, improving diagnosis, follow-up and therapeutic strategies of several disorders. Wearable devices usually involve smart sensors to detect and monitor a set of physiological parameters aiming to support their continuous monitoring for diagnostic, therapeutic and control purposes [37]. The great demand of the aging population for healthcare management needs the use of these wearable medical devices to monitor personal health information in real-time to prevent diseases and emergency health risks. Today, many wearable healthcare devices provide biosignals, such as EEGs, ECGs, EMGs, blood pressure or blood glucose levels. Electrical signal variations cause ECG and EMG during muscular activities, and they are important and commonly adopted parameters for healthcare management and rehabilitation protocols.

Liu et al. in [38] propose a portable and wireless acquisition system to acquire physiological signals. The system mainly consists of a portable device, a graphic user interface (GUI) and an application program for displaying the signals on a computer or a smart device. This device is characterized by eight measuring channels, a powerful microcontroller unit, a lithium battery, Bluetooth 3.0 data transmission and a built-in 2 GB flash memory. The results show that as this system can measure signals in real-time, supporting physicians and researchers can perform experiments collecting physiological signals of interest.

A summary of these contributions about wearable monitoring systems chosen among the papers in the literature published in the last 5 years is made in **Table 1** .

Table 1. Summary of selected wearable monitoring system included in this review.

Authors	Signals	Channels	Platform Characteristics	Features
Tran et al., 2021	Bio-potentials	4 channels	Four-channel neural recording analog front-end composed by a low-noise amplifier (LNA), a programmable gain amplifier (PGA) and buffers; 4-to-1 multiplexer (MUX) and analog-to-digital converter (ADC)	Programmable gain from 45 dB to 63 dB, input-referred noise of 3.16 μVRMS within the 10 kHz bandwidth, noise efficiency factor of 2.04, power efficiency factor of 4.16, power consumption of 2.82 μW per channel powered from 1 V supply voltage
Yin et al., 2021	Bio-potentials, impedance respiration	Single 1 channel	Oversampling and fast digital lock-in technology, ADS1294R, STM32F103RET6 for signal processing	Improve the common-mode rejection ratio (CMRR) and the signal-to-noise ratio (SNR) of the signal
Zhao et al., 2020	ECG/EMG	N.A.	Low-energy Bluetooth module	Wearable monitoring device, software platform for data analysis
Biagetti et al., 2020	Bio-potentials	3 channels	Six electrodes, 24 bits of resolution and a sampling rate up to 3.2 kHz for each channel, Bluetooth Low Energy wireless link	Wireless sensor, real-time acquisition, maximization of the available bandwidth, reliability of the transmission
Nakamura et al., 2020	ECG/EMG	N.A.	Analog front-end (AFE)	Capacitive measurements
Liu et al., 2019	Bio-potentials	8 channels	Powerful microcontroller unit, lithium battery, Bluetooth 3.0 data transmission and built-in 2 GB flash memory	Portable device with a graphic user interface (GUI) and an application program for displaying the signals on a computer or a smart device
Park et al., 2018	Bio-potentials	128 channels	Energy-efficient integrated circuit architecture of a Δ-modulated ΔΣ AFE with multi-shank neural probes connected to individual AFEs	The Δ-ΔΣ AFE is characterized by a consume of each single-channel AFE of 3.05 μW from 0.5 and 1.0 V supplies in an area of 0.05 mm^2 with 63.8 dB signal-to-noise-and-distortion ratio and 3.02 noise efficiency factor
Raheem et al., 2018	Bio-potentials	2 channels	Programmable gain amplifier (PGA) and 10-bitΣΔ (SDM-ADC)	High impedance, power consumption of 11 mW, programmable gains from 52.6 dB to 72 dB and input referred noise of 3.5 μV in the amplifier bandwidth
Mazzetta et al., 2018	EMG	Differential 1 channel	32 bit ARM® Cortex®-M4, microSD, Bluetooth 4.0, 592 mWh battery, micro-USB connector, 30 × 30 × 15 mm dimensions, weight of 10 g	Power consumption, compactness and energy autonomy, wireless and comfortably wearable
Biagetti et al., 2018	sEMG	N.A.	Ultralight wireless sensing nodes, base station for data transmission through a 2.4 GHz radio link, communication protocol designed on top of the IEEE 802.15.4 physical layer	Low-cost wearable wireless system, user interface software for viewing, recording and analyzing data
Kast et al., 2017	Bio-potentials	Bipolar 64 channels	Up to eight front-end acquisition modules with synchronization module, a separated universal serial bus data-link to the computer and an ADS1299	Raw data are analyzed and stored on a personal computer or a single-board computer
Sarker et al., 2017	ECG/EMG	8 channels	24 bit resolution/channel and 500 samples/s, IoT-based system	Compact and wearable portable bio-signal acquisition device, real-time data wireless transmission, low energy consumption
Li et al., 2017	ECG/EMG	N.A.	150 mAh rechargeable Li-ion battery, packaged into a 39 × 32 × 17 mm 3D printed small box, total weight of 24.0 g, power management circuit, dual power supply for operational amplifiers	Wearable wireless non-contact system, ultra-high input impedance, feasibility of long-term biopotential monitoring

Authors	Signals	Channels	Platform Characteristics	Features
Senepati et al., 2017	ECG/EMG	N.A.	Band pass and band stop FIR filters, Successive Approximation Register (SAR) DAC, Spartan-3E FPGA and 0.18 µm CMOS TSMC technology	Area of 33,005 μm^2 area, power consumption of 0.382 mW, suppressing of baselines wander and power line interference noise (50/60 Hz)
Bhamra et al., 2017	ECG/EMG	N.A.	ASIC technology in a 0.18 µm CMOS process, high-pass and low-pass cutoff frequencies being 0.5–300 Hz and 150 Hz–10 kHz, antialiasing filter, successive approximation register (SAR) analog-to-digital converter (ADC), power management	Wireless, programmable gain from 38 to 72 dB, AFE and ADC dissipation of 5.74 µW and 306 nW, measured input-referred noise of 2.98 µVrms, noise efficiency factor of 2.6, power efficiency factor of 9.46, area of the AFE of 0.0228 mm^2
Kim et al., 2016	Bio-potentials, PPG, BIA	N.A.	CMOS technology, low-power and multimodal analog front-end (AFE)	Wearable health monitoring, low dimension and power consumption
Mahmud et al., 2016	ECG	N.A.	Fully integrated analog front-end (AFE), temperature sensor, accelerometer, Bluetooth Low Energy (BLE) module	Multiparameter real time monitoring, small dimensions, Android application, alerts
Piccinini et al., 2016	ECG/EMG	N.A.	ADS1294 Medical Analog Front End, CC3200 microcontroller, two Li-ion charged batteries	Portable solution, size physical reduction, robustness in wireless transmission, reliability in data acquisition and processing
Lee et al., 2016	ECG/EMG	N.A.	Mixed-signal processor system-on-chip (SoC), Bluetooth Low Energy (BLE) chip, 200 mAh battery	Wireless transmission, power efficiency, 12 h of continuous recording
Augustyniak et al., 2016	Bio-potentials	Single-ended 5 channels	Programmable AFE ADAS1000, 24-bit resolution analog-to-digital converter with programmable data rate up to 128 kHz	Wired and wireless body sensor networks, configurable gain for channel

3. Commercial Wearable Devices

Wearable portable systems aim to daily acquire and processes different health data, providing early detection of pathological signs and improving the treatment and the continuous monitoring of disease. Many commercial EMG and ECG sensors are available, and they are designed and created to satisfy different specifications. In this section, the review proposes a description of the common commercial biosignal acquisition systems for physiological monitoring. These systems have been chosen to be the most used devices in health practice presenting similar characteristics to be compared.

Biometrics Ltd offers different data acquisition systems to collect analog and digital data from various sensors and are available in wireless, portable and laboratory configurations. Wireless systems furnish total freedom of movement without being constrained by wires [39]. They are available in 2-, 4-, 8- and 16-channel configurations to acquire EMG signals by using surface, small and lightweight sensors, allowing muscle activity readings to be smooth and robust with a range of up to 30 m from its receiver. The main features of these types of sensors are (i) a bandwidth from 10 Hz to 250 Hz through to 10 Hz to 5000 Hz and (ii) a sensitivity for the peak to peak measurements ranging from +/− 60 mV to +/− 6000 mV [40]. Portable systems are comprehensive packages of sensors and instrumentation for static and dynamic measurements in a clinical setting, a research centre, or at any remote location such as an office, workplace or home. Biometrics offers three different versions of EMG sensors: (i) surface EMG sensors, (ii) wireless surface EMG sensors and (iii) surface EMG amplifier.

Biosignalsplux represents an advanced wireless toolkit to collect and analyze reliable and high-definition biosignal data [41]. It offers a set of cabled and wearable sensors. The biosignalsplux electromyography (EMG) sensor is a high-performance bipolar sensor with low noise for seamless muscle data acquisition. This sensor is designed to monitor muscular activity, and the bipolar configuration is ideal for uncompromised low-noise data acquisition. The raw data output provides medical-grade data enabling it to be used for advanced and highly accurate biomedical biomechanics and sports research. Its main features are (i) bipolar differential measurement, (ii) pre-conditioned analog output, (iii) high signal-to-noise ratio and (iv) medical-grade raw data output. It is also ready-to-use, and it is miniaturized. The wireless single-channel EMG device for real-time muscle sensing is muscleBAND. It is an integrated single-channel EMG sensor with a triaxial accelerometer and magnetometer for real-time acquisition of muscle activity and motion data with an integrated dual Bluetooth module. This sensor allows data acquisitions with up to 16-bit resolution at up to 1000 Hz sampling rate, with the internal battery providing enough power for continuous data streaming.

Delsys proposes complete wireless EMG-based solutions for monitoring human movement in research, clinical and educational settings [42]. These solutions are composed of (i) research, mobile and lite systems, (ii) EMG sensors, (iii) mobile software and (iv) software for devices integration. The most used EMG sensor is Trigno Avanti Sensor, which can capture muscle activity and movement data accurately. It is designed to work with all Trigno systems, and it is characterized by (i) patented technology, (ii) improved RF performance, (iii) cable-free design, (iv) selectable EMG bandwidth settings and (v) on-board signal processing. It also allows differential EMG input acquisition in a very small dimension and weight. Trigno Research+ is a high-performing device designed to make EMG signal detection reliable and easy, offering a full set of physiological and biomechanical monitoring tools to simplify complex research and provide the highest quality data. Proprietary RF protocol guarantees synchronization between all sensors and allows data transmission from Trigno wireless sensors to a Trigno base station. **Table 2** reports the main characteristics of the selected wearable monitoring systems.

Table 2. Main characteristics of the commercial wearable monitoring systems.

Features	Biometric	Shimmer	Biosemi	BTS Bioengineering	Biosignal Plux	BITalino	Delsys
Type of sensor	Wireless EMG Sensor	Shimmer3 EMG Unit	ActiveTwo	FreeEMG 1000 H_2O	Electro-myography Sensor	Electro-myography Sensor	Trigno Avanti Sensor
Size (mm × mm × mm)	42 × 24 × 14	65 × 32 × 12	120 × 150 × 190	Probes: 41.5 × 24.8 × 14	28 × 70 × 12	12 × 27	27 × 37 × 13
Weight	17 g	31 g	1.1 kg	13 g—battery included	25 g	N.A.	14 g
# channels	1	2	8 up to 256	1	1	1	1 differential input
Input impedance	>100 Mohms	N.A.	>100 M @ 50 Hz		>100 GOhm	10/7.5 GOhm/pF	
Input range	+/−6 mV	Approx. 800 mV @ gain = 6	+262 mV to −262 mV	N.A.	Up to 10 mV	±1.64 mV @ VCC = 3.3 V	11 mV/22 mV rti
Gain	+/−60 mV to +/−6000 mV	1,2,3,4,6,8,12 (software configurable)	N.A.	N.A.	1000	1009	11 mV/22 mV rti
CMRR	>96 dB (typically 110 dB) @ 60 Hz	N.A.	>90 dB @ 50 Hz	N.A.	100 dB	86 dB	<−80 dB
Consumption	N.A.	N.A.	4 Watt @ 280 channels	N.A.	1 mA	0.17 mA	N.A.
Bandwith	0–250, 470, 950, 5000 Hz	8.4 kHz	Up to DC—3200 Hz @ −3 dB	N.A.	25–500 Hz	25–482 Hz	10–850 Hz 20–450 Hz
Data transmission	Wireless	Bluetooth Radio – RN-42	Fiber optic	Wireless IEEE 802.15.4	Bluetooth Low Energy	N.A.	2.400-2.483 GHz ISM Band, Proprietary RF Protocol - BLE V4.2
Resolution	N.A.	24 bit	24 bit	16 bit	12 bit	N.A.	16 bit
Sample rate	N.A.	125, 250, 500, 1000, 2000, 4000, 8000 SPS	2048 Hz–4096 Hz–8192 Hz–16,384 Hz	N.A.	N.A.	N.A.	4370 sa/sec

Features	Biometric	Shimmer	Biosemi	BTS Bioengineering	Biosignal Plux	BITalino	Delsys
Battery type and life	**Rechargeable Li-ion Polymer, Up to 8 h**	**450 mAh rechargeable Li-ion battery**	**Battery power with >10 h @ 144 channels, >72 h @ 16 channels**	**Battery Li-Po, Up to 6 h**	**N.A.**	**Battery Li-Po 700 mAh**	**Rechargeable Li-Po Battery Up to 8 h**

References

1. Seshadri, D.R.; Li, R.T.; Voos, J.E.; Rowbottom, J.R.; Alfes, C.M.; Zorman, C.A.; Drummond, C.K. Wearable sensors for monitoring the physiological and biochemical profile of the athlete. NPJ Digit. Med. 2019, 2, 1–16.
2. Palumbo, A.; Calabrese, B.; Ielpo, N.; Demeco, A.; Ammendolia, A.; Corchiola, D. Cloud-based biomedical system for remote monitoring of ALS patients. In Proceedings of the 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Seoul, Korea, 16–19 December 2020; pp. 1469–1476.
3. Qureshi, F.; Krishnan, S. Wearable hardware design for the internet of medical things (IoMT). Sensors 2018, 18, 3812.
4. Postolache, O.A.; Mukhopadhyay, S.C.; Jayasundera, K.P.; Swain, A.K. Sensors for Everyday Life: Healthcare Settings (Smart Sensors, Measurement and Instrumentation, 22); Springer International Publishing: Cham, Switzerland, 2017.
5. Palumbo, A.; Vizza, P.; Veltri, P.; Gambardella, A.; Pucci, F.; Sturniolo, M. Design of an electronic device for brain computer interface applications. In Proceedings of the IEEE International Workshop on Medical Measurements and Applications (MEMEA), Cetraro, Italy, 29–30 May 2009; pp. 99–103.
6. Vizza, P.; Tradigo, G. On the analysis of biomedical signals for disease classification. ACM SIGBioinform. Rec. 2019, 8, 7–10.
7. Patel, S.; Park, H.; Bonato, P.; Chan, L.; Rodgers, M. A review of wearable sensors and systems with application in rehabilitation. J. Neuroeng. Rehabil. 2012, 9, 21.
8. Vizza, P.; Tradigo, G.; Curcio, A.; Indolfi, C.; Veltri, P. Intracavitary signal analysis for atrial fibrillation prediction. In Proceedings of the IEEE International Conference on Bioinformatics and Biomedicine Workshops, Philadelphia, PA, USA, 4–7 October 2012; pp. 814–815.
9. Cong, P. Circuit Design Considerations for Implantable Devices; River Publishers: Gistrup, Denmark, 2018; p. 9788793519862.
10. Panja, A.; Fernandes, R.; Jondhale, S.; D'souza, P.; Uma, L.; Thale, S. A novel configurable signal acquisition system for multiple bio-signal measurements: Assistive technology for home rehabilitation. In Proceedings of the IEEE International Conference on Technological Advancements in Power and Energy (TAP Energy), Kollam, India, 21–23 December 2017; pp. 1–6.
11. Li, R.T.; Kling, S.R.; Salata, M.J.; Cupp, S.A.; Sheehan, J.; Voos, J.E. Wearable performance devices in sports medicine. Sport. Health 2016, 8, 74–78.
12. Steele, C. Applications of EMG in Clinical and Sports Medicine; IntechOpen: Rijeka, Croatia, 2012.
13. Nascimento, L.M.S.D.; Bonfati, L.V.; Freitas, M.L.B.; Mendes Junior, J.J.A.; Siqueira, H.V.; Stevan, S.L., Jr. Sensors and Systems for Physical Rehabilitation and Health Monitoring-A Review. Sensors 2020, 20, 4063.
14. Negrini, S.; Kiekens, C.; Bernetti, A.; Capecci, M.; Ceravolo, M.G.; Lavezzi, S.; Zampolini, M.; Boldrini, P. Telemedicine from research to practice during the pandemic. "Instant paper from the field" on rehabilitation answers to the COVID-19 emergency. Eur. J. Phys. Rehabil. Med. 2020, 56, 327–330.
15. Varela-Aldás, J.; Buele, J.; Ramos Lorente, P.; García-Magariño, I.; Palacios-Navarro, G. A Virtual Reality-Based Cognitive TeleRehabilitation System for Use in the COVID-19 Pandemic. Sustainability 2021, 13, 2183.
16. Smith, E.E.; Mountain, A.; Hill, M.D.; Wein, T.H.; Blacquiere, D.; Casaubon, L.K.; Linkewich, E.; Foley, N.; Gubitz, G.; Simard, A.; et al. Canadian stroke best practice guidance during the COVID-19 pandemic. Can. J. Neurol. Sci. 2020, 47, 474–478.
17. Salawu, A.; Green, A.; Crooks, M.G.; Brixey, N.; Ross, D.H.; Sivan, M. A proposal for multidisciplinary tele-rehabilitation in the assessment and rehabilitation of COVID-19 survivors. Int. J. Environ. Res. Public Health 2020, 17, 4890.
18. Werneke, M.W.; Deutscher, D.; Grigsby, D.; Tucker, C.A.; Mioduski, J.E.; Hayes, D. Telerehabilitation during the COVID-19 Pandemic in Outpatient Rehabilitation Settings: A Descriptive Study. Phys. Ther. 2021, 101, pzab110.

19. Tanaka, M.J.; Oh, L.S.; Martin, S.D.; Berkson, E.M. Telemedicine in the era of COVID-19: The virtual orthopaedic examination. J. Bone Jt. Surgery. Am. Vol. 2020.

20. Andrenelli, E.; Negrini, F.; de Sire, A.; Arienti, C.; Patrini, M.; Negrini, S.; Ceravolo, M.G. International Multiprofessional Steering Committee of Cochrane Rehabilitation REH-COVER action. Systematic rapid living review on rehabilitation needs due to COVID-19: Update to May 31, 2020. Eur. J. Phys. Rehabil. Med. 2020, 56, 508–514.

21. Bickton, F.M.; Chisati, E.; Rylance, J.; Morton, B. An Improvised Pulmonary Telerehabilitation Program for Postacute COVID-19 Patients Would Be Feasible and Acceptable in a Low-Resource Setting. Am. J. Phys. Med. Rehabil. 2021, 100, 209–212.

22. Kim, J.; Campbell, A.S.; de Ávila, B.E.F.; Wang, J. Wearable biosensors for healthcare monitoring. Nat. Biotechnol. 2019, 37, 389–406.

23. Ansari, M.S. Analog front-end design for biomedical signal acquisition systems. CSI Trans. ICT 2019, 7, 199–204.

24. Rajeswari, J.; Jagannath, M. Advances in biomedical signal and image processing—A systematic review. Inform. Med. Unlocked 2017, 8, 13–19.

25. Gohel, V.; Mehendale, N. Review on electromyography signal acquisition and processing. Biophys. Rev. 2020, 12, 1361–1367.

26. Houssein, E.H.; Kilany, M.; Hassanien, A.E. ECG signals classification: A review. Int. J. Intell. Eng. Inform. 2017, 5, 376–396.

27. Faust, O.; Hagiwara, Y.; Hong, T.J.; Lih, O.S.; Acharya, U.R. Deep learning for healthcare applications based on physiological signals: A review. Comput. Methods Programs Biomed. 2018, 161, 1–13.

28. Rahul, J.; Sora, M.; Sharma, L.D. An overview on biomedical signal analysis. Int. J. Recent Technol. Eng. 2019, 7, 206–209.

29. Ielpo, N.; Calabrese, B.; Cannataro, M.; Palumbo, A.; Ciliberti, S.; Grillo, C.; Iocco, M. EMG-Miner: Automatic Acquisition and Processing of Electromyographic Signals: First Experimentation in a Clinical Context for Gait Disorders Evaluation. In Proceedings of the 2014 IEEE 27th International Symposium on Computer-Based Medical Systems, New York, NY, USA, 27–29 May 2014; pp. 441–446.

30. Uktveris, T.; Jusas, V. Development of a modular board for EEG signal acquisition. Sensors 2018, 18, 2140.

31. Aljalal, M.; Ibrahim, S.; Djemal, R.; Ko, W. Comprehensive review on brain-controlled mobile robots and robotic arms based on electroencephalography signals. Intell. Serv. Robot. 2020, 13, 539–563.

32. Merletti, R.; Botter, A.; Cescon, C.; Minetto, M.A.; Vieira, T.M. Advances in surface EMG: Recent progress in clinical research applications. Crit. Rev. Biomed. Eng. 2010, 38, 347–379.

33. Drost, G.; Stegeman, D.F.; van Engelen, B.G.M.; Zwarts, M.J. Clinical applications of high-density surface EMG: A systematic review. J. Electromyogr. Kinesiol. 2006, 16, 586–602.

34. Campanini, I.; Disselhorst-Klug, C.; Rymer, W.Z.; Merletti, R. Surface EMG in Clinical Assessment and Neurorehabilitation: Barriers limiting its use. Front. Neurol. 2020, 11, 934.

35. Demeco, A.; Marotta, N.; Moggio, L.; Pino, I.; Marinaro, C.; Barletta, M.; Petraroli, A.; Palumbo, A.; Ammendolia, A. Quantitative analysis of movements in facial nerve palsy with surface electromyography and kinematic analysis. J. Electromyogr. Kinesiol. 2021, 56, 102485.

36. Kumari, P.; Mathew, L.; Syal, P. Increasing trend of wearables and multimodal interface for human activity monitoring: A review. Biosens. Bioelectron. 2017, 90, 298–307.

37. Zhao, S.; Liu, J.; Gong, Z.; Lei, Y.; OuYang, X.; Chan, C.C.; Ruan, S. Wearable Physiological Monitoring System Based on Electrocardiography and Electromyography for Upper Limb Rehabilitation Training. Sensors 2020, 20, 4861.

38. Liu, S.H.; Wang, J.J.; Tan, T.H. A Portable and Wireless Multi-Channel Acquisition System for Physiological Signal Measurements. Sensors 2019, 19, 5314.

39. Biometrics Ltd. Available online: Https://www.biometricsltd.com/index.htm (accessed on 24 April 2021).

40. Surface EMG Sensor. Available online: Https://www.biometricsltd.com/surface-emg-sensor.htm (accessed on 15 April 2021).

41. Biosignalsplux. Available online: Https://plux.info/12-biosignalsplux (accessed on 3 March 2021).

42. Delsys. Available online: Https://delsys.com/ (accessed on 3 March 2021).