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A Comprehensive Survey on Advanced Technologies Introduced for Rehabilitation

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ABSTRACT Following major accidents or illness, some patients may lose partially or completely some of their mental or physical function. Rehabilitation approaches and systems play an important role in patients' recovery. This manuscript focuses on rehabilitation systems. We provide insights on major and recent approaches, signals, and systems used to assist patient recovery. In order to help researchers, engineers, or physicians, this paper provides a comprehensive survey on recent approaches and systems used in the rehabilitation process. By highlighting the advantages and drawbacks of existing rehabilitation systems, this contribution can support initial studies or projects and encourage young researchers, as well as biomedical companies, to investigate and invest in new technologies. We hope that our study will participate in the global efforts paid to reduce patient suffering and help health care centers in their activities. To achieve this goal, we consider in our study recent technologies such as machine learning, artificial intelligence, signal processing, without missing to highlight various biomedical signals and exploring several developed systems.

INDEX TERMS Artificial Intelligence, Blind Source Separation (BSS), Dedicated Hardware and Software, Electrocardiogram (ECG), Electroencephalography (EEG), Electromyography (EMG), Empirical Mode Decomposition (EMD), Extra Training, Image Processing, Independent Component Analysis (ICA), Machine Learning, Myoelectric Signals, Rehabilitation, Signal Processing, Singular Value Decomposition (SVD), Surface Electromyography (sEMG), Wearable Devices.

I. INTRODUCTION

HUMANITARIAN reasons are our first motivation to conduct this study. Indeed, during the recent Covid-19 pandemic episode, many countries, societies, organizations, and definitely individuals have been more or less affected severely during that period. Following this pandemic, many healthcare centers were exhausted or overwhelmed, resulting in increased heavy burden for physicians and increased suffering for patients. A large number of patients from all over the world have been unable to access health centers or receive adequate care. Among them, patients with disability were the most affected in their everyday activities. Patients with complex chronic diseases (CCDs) become very vulnerable in such situations. Following major trauma caused by an accident or a severe illness, a long and hard rehabilitation procedure can be prescribed by doctors. According to [1], around 1.7 billion people from 204 countries suffer from musculoskeletal disorders. According to the World Health Organization [2], globally, an estimated 2.4 billion people are currently (April 2025) living with a health condition that may benefit from rehabilitation. The authors of [3] found that in 2016, the highest modeled spending was musculoskeletal disorders with an estimated \$380.9 billion in the USA. The authors of [4] highlighted the fact that the number of people suffering from a stroke will increase to 1.5 million per year just in Europe. They also mentioned the effectiveness of rehabilitation after a stroke, and that rehabilitation is the main cost of post-stroke

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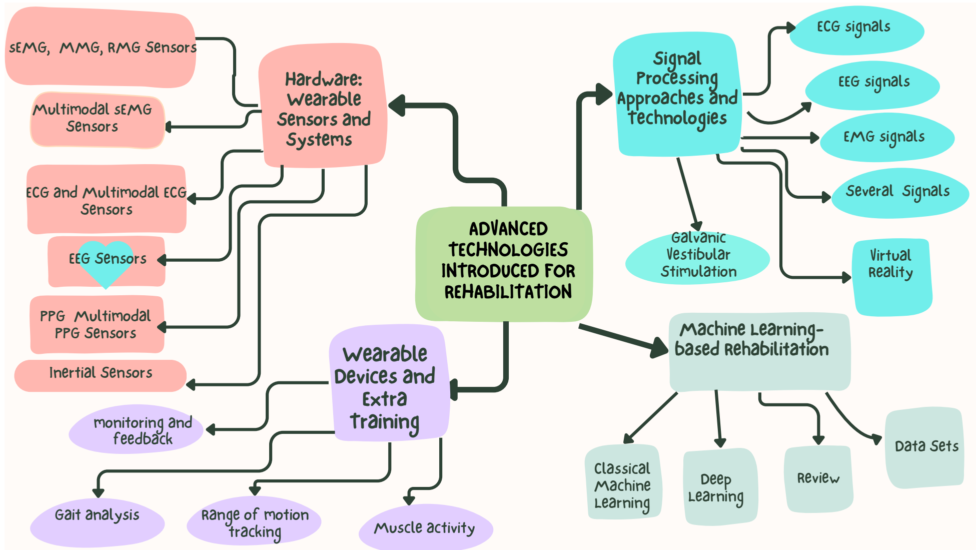

FIGURE 1. **Scientific publications on Rehabilitation Advanced Technologies Mind Map publications.**

care. In addition, they found that the rehabilitation cost for inpatients is about three times that of outpatients.

TABLE 1. **Rehabilitation technologies by application domains.**

Rehabilitation domains	Technologies
neuromuscular	non-invasive brain simulation, brain-machine interface (BMI) system, magnetic resonance imaging (MRI), machine learning, radiomics, neuromuscular and muscular electrical stimulation (NMES)
motor	exoskeleton, prosthesis, EMG, robotic glove, serious game system, inertial measurement unit (IMU)
post-stroke care	sEMG sensors, EEG sensors, physiotherapy, speech therapy, irtual reality, brain simulations
brain disorder	EEG sensors, virtual and augmented reality, neuroprostheses, BMI system, neurostimulation, neurodevices

This study is a joint project between four senior researchers coming from research centers in different countries. We should highlight that during their long careers, the authors have been involved in various research or industrial projects related to biomedical systems. In fact, they published several original papers related to different biomedical applications. We can mention a few of them, such as the ones considering: coronary artery disease [5], [6], bone tumor [7], analyzing electromyography (EMG) signals [8]–[11], Alzheimer detection [12], non-invasive health systems [13], monitoring electrocardiogram (ECG) signals [14]–[16], electroencephalography (EEG) signals [17], carotid atheroma risk stratification [18], diagnosis of deep vein thrombosis (DVT) [19], detection of the Gougerot-Sjögren syndrome [20], diagnostic of skin cancer [21], impact of corona virus [22], and burden of non-communicable diseases [23].

This paper focuses on recent and advanced technologies used in rehabilitation, including wearable devices and sensors, hardware and software for rehabilitation. Table 1 lists typical rehabilitation domains and associated technologies. Signal processing algorithms and techniques for these devices are reviewed. Machine learning and deep learning models and approaches for rehabilitation are presented. This paper is intended for a wide range of readers, including researchers, physicians, electronics and biomedical engineers. As there is a plethora of papers in the area of rehabilitation, it is impossible and not the intention of the paper to compile an exhaustive list of them. Instead, by highlighting the advantages and drawbacks of existing rehabilitation systems, we hope that this contribution can support initial studies and encourage young researchers as well as biomedical companies to investigate and invest new technologies, contributing to global efforts in improving the efficiency of the rehabilitation process and reducing patients suffering.

This paper's mind map information and organization is in Fig. 1.

The remainder of the paper is organized following the sequential order of signal flow and functional modules of advanced technologies for rehabilitation. Firstly, we review various hardware sensors and devices for acquiring biomedical signals from human bodies such as EMG, ECG, and EEG sensors in Section 1. These sensors are key components of any wearable medical device and are fundamentally the physical enablers of the overall rehabilitation system architecture. Then, Section 2 presents wearable devices and the training of these devices. Section 3 discusses a range of biomedical signal processing approaches and technologies for various signals including ECG, EEG, and EMG signals. These algorithms are core of rehabilitation systems. This section also introduces complex systems using the combination of several biomedical signals. In Section 4, we present the application of machine learning models and algorithms for rehabilitation, including both classical machine learning and deep learning. Finally, the paper is ended by general conclusions. We should highlight that our study focuses on recent references. Indeed, in our statistical study, curves or tables we only consider references published between 2007 and 2024. However, less than 10% of all cited references in this manuscript are published earlier than 2007 mainly for some reasons, such as: references well-known or with high citation, mathematical approaches, survey papers, or papers targeting specific research areas.

II. HARDWARE: WEARABLE SENSORS AND SYSTEMS

Recently, due to the pandemic situation that has hit the world in the last three years, home rehabilitation has become increasingly popular due to the safety and familiarity of the home environment, as well as the ease of potential long-term rehabilitation training. In addition to the advantage of reducing the financial burden, the need to relieve the pressure of public hospitals and private clinics, the home environment also has the advantage of flexibility of training time. Evaluation of the effectiveness of rehabilitation procedures has been limited to the laboratory context, and relatively little is known about rehabilitation at home or in real life situations. Therefore, this new rehabilitation scenario has become a research topic for many scientific and academic institutions that are involved in finding new methodologies and technological systems to reduce the burden on hospitals and healthcare systems with physical rehabilitation therapies and monitoring processes.

Recent advances in signal processing, electronics, and wireless networks [24] (particularly with 5G and the incoming 6G) have provided the means to help overcome these challenges. Wireless wearable systems have appeared as gold standard solutions to aid in continuous monitoring as part of a diagnostic procedure, optimal maintenance of a chronic condition, or during supervised recovery from an acute event or surgical procedure, or more in general, in cloud-based or edge-based remote rehabilitation therapies such as rehabilitation for myocardial infarction, rehabilitation after stroke, rehabilitation for traumatic brain injury, and physical rehabilitation after hip or knee surgery [25], [26]. By implementing these technologies, the rehabilitation process can be performed remotely, from home or during normal daily activities, with the virtual supervision of a doctor/therapist. By definition, wearable medical devices should be worn by patients to monitor their daily living activities without interfering with or limiting the patient's normal range of action/motion. The use of wearable devices for medical therapies can help reduce costs in healthcare systems and hospitals and reduce the number of excess patients. Furthermore, these should allow patients to perform the required rehabilitation exercises comfortably at home, without compromising their daily routine. Using cutting-edge communication technologies to provide healthcare services, patients' conditions can be assessed remotely and doctors can provide the necessary help [27]. Doctor records can also be stored for later use or for more complex data analysis to understand health trends within the same community.

Biomedical sensors are key components of any wearable medical device and are basically the physical enablers that play a fundamental role in the overall eHealth architecture. The accuracy of the acquired data depends on the sensors. Therefore, they are responsible for the overall performance of wearable devices. Physiological signals are acquired from various sensors such as ECG, EEG, phonocardiography (PCG), surface electromyography (sEMG) [28]–[32], photoplethysmography (PPG), and inertial measurement unit (IMU) [33]. Recently, optical fiber-based sensors have been developed for smart health monitoring [34], detecting and quantifying cortisol [35], detecting tyramine [36] and aflatoxin [37]. In a physical rehabilitation scenario, aimed at the healthy locomotion of the patients, gait (walking) pattern analysis is of utmost importance. Understanding how we walk and why we walk the way we do can reveal several postural and musculoskeletal disorders, which need to be addressed before they become a pathology. This analysis can be carried out through the use of video technologies or detection platforms. However, the most accurate ones are those worn by patients, which reflect the correct movement of their limbs, hands or fingers, especially when applied during normal daily activities [28], [38]–[42]. Over the last two decades the use of wearable sensors, placed on the body for rehabilitation purposes, has gained more and more interest due to the lowering of their cost, the increase in their miniaturization in terms of weight and size, and finally thanks to their long autonomy linked to low-power circuits with which they are built [24], [43], [44]. Furthermore, wearable textile electrodes have proven to be a decisive component of such sensors in the acquisition of critical bio-potential signals for routine monitoring, assessment, and exploitation of cardiac and neural muscle functions [45], [46].

To show the diffusion of wearable technologies for sensing body signals in rehabilitation activities, we used Scopus and Web of Science (WoS) servers to conduct a statistical study on indexed published papers related to these topics using keywords. To this goal, we plotted in Fig. 2 the number of published items (journal articles, book chapters, and conference proceedings) with respect to their publishing year from to 2007 and 2024 and considering different sensors. As can be easily observed from Fig. 2, starting from 2012 there has been a rapid increase in the number of articles in the scientific literature which reflects the growing research

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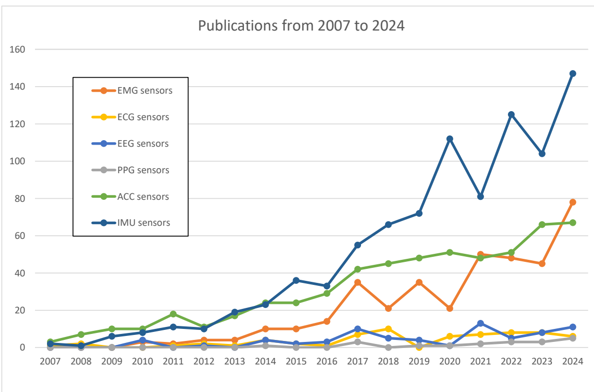
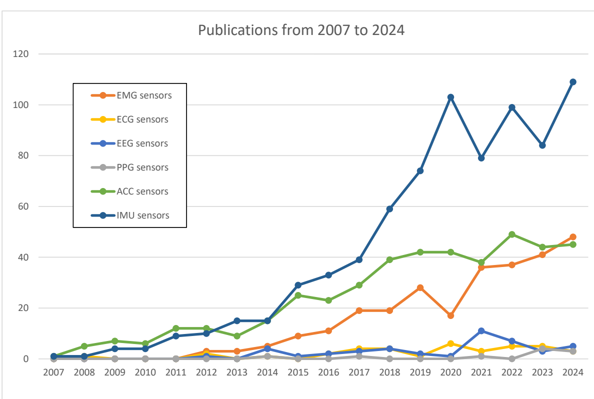
for wearable sensors for rehabilitation purposes enabled by the progress in circuit integration and miniaturization. Based on Fig. 2, we can see the growing number of published scientific articles focusing on the design of wearable sensory devices for rehabilitation purposes for the most common type of signals. Therefore, in this section we classify ongoing research on wearable sensors applied to rehabilitation into six categories. The first four categories consider sensors capable of capturing different biomedical signals: EMG, EEG, ECG and PPG. The remaining last two categories are related to accelerometer sensors and inertial sensors, also known as IMUs, which are popular today due to their easy implementation and integration into existing wearable sensor devices.



a) Number of publications per year (Scopus).



b) Number of publications per year (WoS).

FIGURE 2. Scientific publications on different wearable sensors used for rehabilitation purposes with respect to year. The search was limited to peer reviewed journal papers, book chapters, and conference proceedings published between 2007 and 2024 and indexed in the a) Scopus and b) WoS database, last accessed: April 14, 2025.

However, to sake of completeness, in the rest of this section we performed our keyword-based searches using different well-known databases such as Scopus, WoS, IEEE Xplore, PubMed Central and the Google Scholar search engine. Finally, some commercial websites describing prototypes, systems, and devices were included when the published scientific literature did not offer adequate descriptions of these relevant or well-known products.

A. *sEMG and Multimodal sEMG-Based Sensors*

The sEMG signal is well suited for monitoring person's body posture, physical performance, and fitness level due to the fact that it can be obtained using intrinsically non-invasive measurement devices and is relatively easy to acquire [47]–[52]. Indeed, sEMG signals are generated from electrical potentials produced during muscle contractions [53], [54] and can be collected simply by placing electrodes on the skin surface. However, these electrical signals have relatively low amplitudes and, for processing, they need carefully designed high input-impedance, low-noise amplifiers [55]. In [56] and [57], [58], a couple of human activity detection systems based on sEMG signals and inertial data have been proposed that can be used in a variety of scenarios like in the rehabilitation settings. In particular Fig. 3 reports the flow chart and the hardware as printed circuit boards (PCBs) of the sEMG system presented in [55], [57], [58] called WiSE and consisting of several ultralight wireless sensing nodes that are able to acquire, process and efficiently transmit the sEMG and inertial data to one or more base stations through a 2.4 GHz radio link using a communication protocol customized on top of the IEEE 802.15.4 physical layer. The base stations are connected through a USB link to a personal computer (PC) on which a user interface software was implemented to view, record and analyze the data. Fig. 4 displays for the proposed system the placement of the mobile nodes on the right arm for the recognition of some daily human activities.

In [59], a waterproof wearable device with sEMG sensor and an IMU sensor was designed and tested to help therapists and trainers in aquatic rehabilitation. More in general, many systems and wearable devices based on sEMG sensors and inertial sensors have been implemented in the last decade for rehabilitation.

On the one hand, sEMG sensors are useful for exoskeleton technology which has proven crucial in helping patients with stroke, incomplete spinal cord injuries, and other deficits that impair walking functions. For exoskeleton technology, using the sEMG signal (or the remaining part of it) information is essential for controlling purposes, instead of using the more invasive implantable myoelectric sensors for intramuscular EMG signal recording [60], [61]. To this end, implementing sEMG sensors that are able to capture and process in real-time the neural signals from the muscles was a matter of research in the last two decades for a Japanese company that developed and commercialized an exoskeleton technology, called Hybrid Assistive Limb (HAL), to aid people with disabilities. It includes both arm and leg assistance (which can be used separately or in tandem) actuating the knee and hip joints by using the sEMG signals [62], [63].

On the other hand, having tiny sEMG sensors integrated into a shirt or clothing is very useful in rehabilitation [45],

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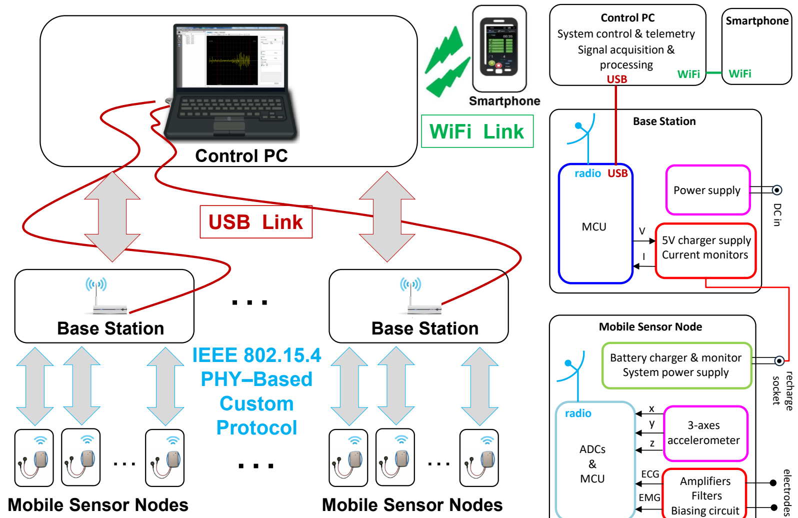
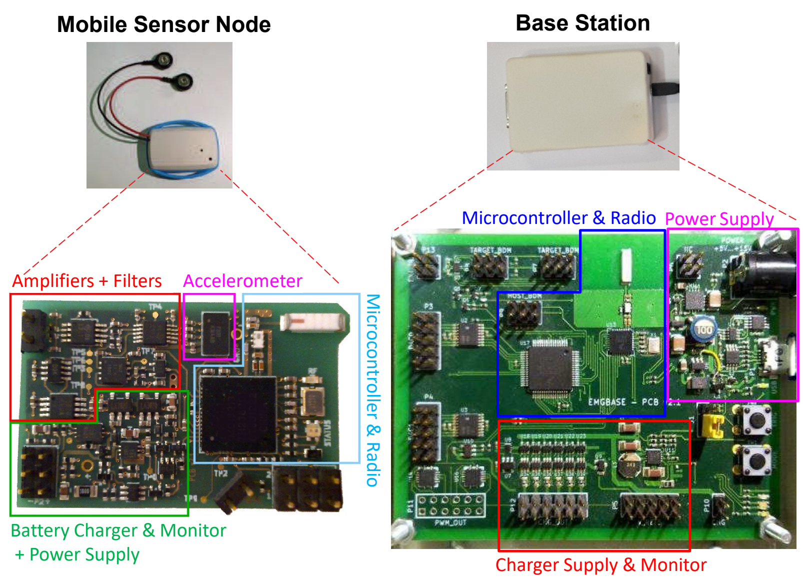


a) sEMG signal acquisition system: flow chart.



b) sEMG system hardware: PCB of the single-channel mobile sensor node (left) and the base station (right).

FIGURE 3. sEMG global system [55], [57], [58].

[64]. In [65], a low-cost sensorized shirt incorporates a six-channel sEMG sensor and a heart rate data acquisition module to provide the patient with objective audiovisual and haptic biofeedback. The shirt is interfaced with a smartphone application, for patient use at home, and with the online database, for remote therapist supervision from the hospital.

For the same purposes, sEMG sensors are used to monitor repetitive hand movements that are often used in rehabilitation protocols to regain hand movement and strength. In [28], a robotic glove was designed to aid in the movement and coordination of gripping exercises through a cable system actuated by servomotors that opens and closes the patient hand. The glove can be controlled in terms of finger position and grip force through the switch interface, software program, or sEMG signal. Surface EMG sensors are also used in [39] for the design and implementation of a robotic system for assisted hand rehabilitation based on mirroring healthy hand movements. The healthy hand opening and closing is detected by sEMG sensors and this is used to guide a robotic glove moving the paretic hand. In [66], the design and evaluation of a wearable robot addressing the limitations of the soft robot gloves for rehabilitation and assistance of stroke and spinal cord injury patients is presented. The system is composed of a soft hand exo-sheath based on electric actuation and integrated with a soft fabric EMG sensor designed to be compact and portable.

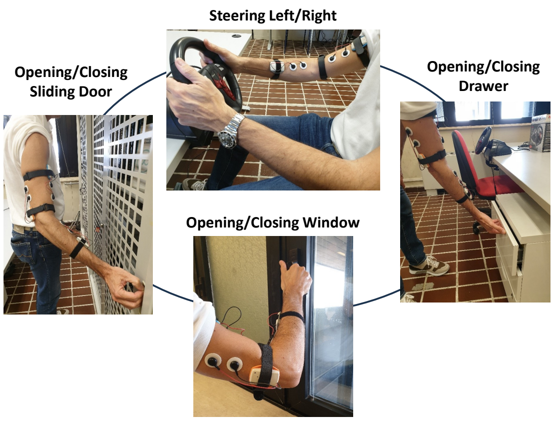


FIGURE 4. Example of activities recognized by the sEMG system in [57], [58].

In [32], a novel wearable sEMG sensor was proposed for muscle strength evaluation and rehabilitation training. It consists of a flexible sEMG acquisition system that combines a flexible graphene-based electrode with a flexible printed circuit board (PCB) for signal acquisition. The system utilizes a polydimethylsiloxane substrate combined with graphene transfer technology to develop a flexible sEMG sensor. The single-lead sEMG acquisition system was designed and the PCB was fabricated considering the requirements of flexible bending and twisting.

In [67], an innovative wearable sensor is developed that can be placed over clothing or installed in a nearby off-body apparatus such as armrests and wrist pads and can monitor superficial and deep muscles without requiring direct skin contact. This sensor is based on a novel muscle monitoring technique, named RMG, which can directly measure the muscle motion by coupling radio frequency (RF) energy to superficial and deep internal muscles. The proposed RMG sensor employs four pairs of sensing antennas attached to a wearable armband on the middle forearm and connected by cables to off-body transceiver for fast and flexible prototyping purposes to obtain an all-in-one wireless system. Operation over clothing without direct skin touch allows to noninvasively monitor both surface and internal muscles. Coupled with sEMG, the RMG can potentially lead to new methods for assessment of muscle functions, diagnosis of neuromuscular disorders, monitoring of muscle fatigue and physical training, all activities that are involved in many rehabilitation systems and protocols.

1) Multimodal sEMG-Based Sensors

New sEMG-based biosensors with multimodal signal acquisition, based on ECG, near-infrared spectroscopy (NIRS), MMG, force myography (FMG), EEG, acceleration, temperature, and vibration detection, have recently been proposed.

Multimodal sEMG and ECG wearable sensing systems are reported in [68]–[70] that can be used in medical applications and rehabilitation settings. In particular, in [68] the acquisition system consists of an intelligent electrode device (which performs amplification, filtering, analog-to-digital (A/D) conversion, binary encoding, and wireless transmission of biosignals) and a data acquisition host that receives them using ZigBee wireless technology. In [69], a low-power wearable sensor networks platform with high sensitivity electric potential dry surface sensors in proposed that can be used in either contact or non-contact mode to measure ECG and EMG signals. The sensor nodes perform runtime directly the heart and respiration rates, thus reducing the amount of data to be transmitted and the radio power consumption. Finally, in [70] a low-cost, low-power prototype is proposed that is characterized by very high sensitivity allowing to capture and identify small muscle movements quite distinctly.

A prototype of a hybrid sEMG, NIRS, and MMG sensor system was proposed in [71]. Here, the acquisition circuits were assembled into an all-in-one sensor, which can measure the muscle motion and fatigue from the modalities of electrophysiology, optics, and acoustics through the fusion of EMG, NIRS, and MMG signal data. To improve the reliability and safety of myoelectric prosthetic control, a modular multimodal EMG-FMG acquisition system is proposed in [72]. The whole system contains one data acquisition unit for A/D conversion and wireless data transmission and eight identical sensor modules for signal conditioning and amplifying. The sensor modules are based on floating electrodes that can be used for measuring EMG signal and for the force probe of FMG simultaneously. With this solution, the FMG and EMG signals could be detected at the same positions of the muscle.

A low-cost wearable multimodal sensing system for EMG, ECG, acceleration, and temperature signal acquisition was proposed in [55], [58]. The system consists of wearable sensing modules that transmit the biological and accelerometer signals to one or more base stations using a custom wireless protocol based on the IEEE 802.15.4 standard. Finally, each base station is connected via USB to a control PC running a user interface software for data processing and storage. The RF communication protocol allows a high data rate compared to other devices using the same physical layer and an accurate microsecond-level synchronization, between nodes connected to the base station. The signals thus acquired can be combined and processed to detect and recognize human activities and help clinicians monitor rehabilitation sessions.

As a sort of improvement of the previous system, a three-channel wireless sensor for either EMG or ECG signal acquisition with an inertial platform for simultaneously capturing movement information has been proposed in [73] and displayed in Fig. 5. The wearable sensor can acquire three independent bioelectrical channels at 24-bit resolution and a sampling rate up to 3.2 kHz. It has a 6-DoF inertial platform measuring linear acceleration and angular velocity. The Bluetooth low-energy was chosen for the wireless link as easy interface with many consumer electronics devices, such as smartphones or tablets, that can work as data aggregators. Furthermore, to take into account the cost of computation, the compression efficiency and energy consumption of some lossless algorithms suitable for wireless transmission of EMG signals were studied in detail [74].

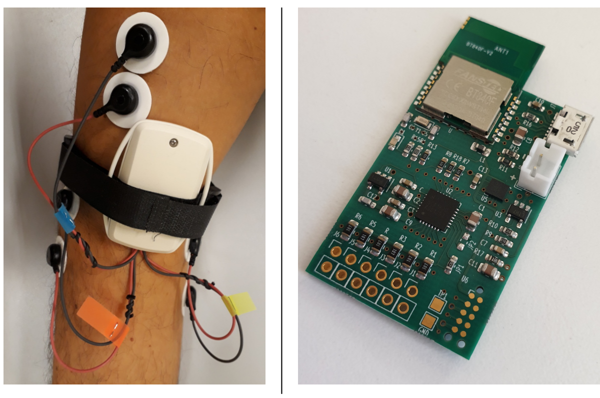


FIGURE 5. EMG/ECG signal acquisition with inertial platform system proposed in [73]. The left picture displays the placement of the electrodes and device on the upper portion of a right arm. The electrodes identified by the yellow tab contact the biceps brachii, those identified with the orange tab the triceps brachii, and those with the blue tab the deltoideus medium muscle (licensed under CC BY 4.0). The right picture displays the assembled prototype circuit board: the EMG/ECG sensing chip is U2, the inertial sensor is U5 and the overall circuit measures 51 mm$\times$27 mm.

In [75], EEG and EMG signals were collected during dynamic elbow flexion-extension motion at different speeds, while holding different weights. These biosignals were used to develop different EEG-EMG fusion models to classify the weight the user was holding while moving, which can be used to improve the adaptability and robustness of wearable mechatronic rehabilitation devices. Bioelectrical signals were acquired using an Intronix (Intronix Technologies, Bolton, Canada) 2024F Physiological Amplifier System, configured to collect EEG and EMG signals at 4000 Hz sampling rate. A ground electrode was placed over the elbow bone of the subject's non-dominant arm to act as the system ground for the differential amplifier used by the Intronix 2024F Physiological Amplifier System. In order to provide a sufficient electrical connection through the subject's hair, EEG signals were measured using gold-cup electrodes with conductive paste.

A prototype of a multimodal EMG, ECG, vibration and temperature sensing system to be incorporated into clothing and worn by the patient was reported in [76]. Here, in addition to the sensor readout circuit for collecting the bio-potential signals, the analog front end (AFE) includes a piezoelectric wave detection circuit for vibration sensing, a low-power analog-digital circuit with pulse-width modulation (PWM) digital signal output, and a bandgap circuit for temperature monitoring. The digital signal processing part integrates a digital signal controller for AFE control and calibration, an ARM-like microprocessor for compression and communication, a 4 kB SRAM, and a 4 kB ROM.

Stroke survivors often have difficulties in completing activities of daily living (ADL) independently. Thus, ADL-related training for gross and fine motor function together is important in the rehabilitation of these patients. In [77], an ADL-based serious game rehabilitation system was proposed for the training of motor function and coordination of arm and hand movements, where the patient performs the corresponding ADL movements to interact with the target in the serious game. A custom system based on sEMG, FMG, and inertial multi-sensor was proposed to estimate the natural upper limb movement using a sensor-fusion model. In particular, to implement the proposed multi-sensor, six commercial sEMG sensors were placed evenly around the user's forearm, eight barometric pressure sensors were attached evenly around the inner side of the wrist to measure the FMG, and two 9-axis IMUs were placed one on the middle of the forearm, and the other on the upper arm.

In [78], a system called SKYRE for the remote assessment of patients undergoing knee rehabilitation was proposed. The system is based on a multi-sensor wearable garment, which can provide a real-time objective evaluation of physical exercises, and an ICT architecture, which can support clinicians in their decision-making process and provide guidance to the patients. The system is composed of two units on the thigh and calf, which are battery-powered and independent from the perspective of power management as well as from the computational point-of-view that adopt two IMUs placed on the lower limbs, a couple of four EMG sensors located on relevant muscles in the lower limbs, and two electrical muscle stimulation (EMS) circuits to electrically stimulate specific muscles.

B. ECG and Multimodal ECG-Based Sensors

Patients recovering from ischemic cardiac episodes and similar acute events or heart surgery may require rehabilitation sessions in which remote health monitoring status can be accurately assessed using wearable sensors based on ECG. In [79], a prototype system called Wealthy allows the monitoring of health conditions using ECG (Fig. 6), heart rate, oxygen saturation, impedance pneumography and activity wearable sensors.

The design and implementation of the prototype of a multisensor wearable patch (MultiSense CardioPatch) for remote cardiac monitoring aiming to provide more detailed and complete cardiac status diagnostics was presented in [80]. The system integrates multiple sensors into a single patch to detect both electrical (ECG) and mechanical (heart sounds) cardiac activity, as well as physical activity via a 3-axis accelerometer. The prototype comprises a microcontroller board with a radio communication unit and is powered by a rechargeable lithium-ion battery to enable remote monitoring of cardiac function in chronically ill patients undergoing home cardiac rehabilitation programs.

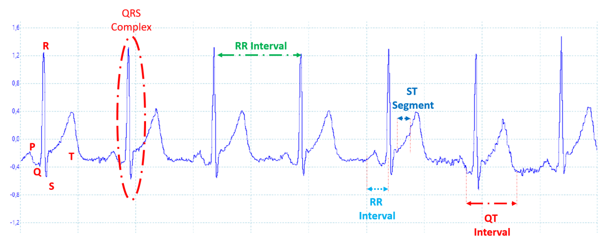


FIGURE 6. ECG signal with some important features.

In [81], a wearable monitoring device was proposed for upper limb rehabilitation that integrates ECG and EMG sensors and uses data acquisition boards to obtain accurate signals during training aided by robotic gloves. The collected ECG/EMG signals were filtered, amplified, digitized, and then transmitted to a remote receiver (smartphone or laptop) through a low-energy Bluetooth module. A data analysis software platform was developed to visualize ECG/EMG information and integrated into the control module of the robotic glove. During the course of training, various hand activities (that is, hand closure, forearm pronation, finger flexion, and wrist extension) were monitored by the EMG sensor and changes in patient physiological state were monitored by the ECG sensor. In a previous project and to monitor patients in an operating room and simplify the connection and monitoring tasks of physicians, we proposed a small wireless device to collect ECG signals and transmitted to a remote monitoring PC [82]. That device has been shown to be most easily in practice and requires almost no effort from physicians to maintain and operate, see Figs. 7 and 8 .

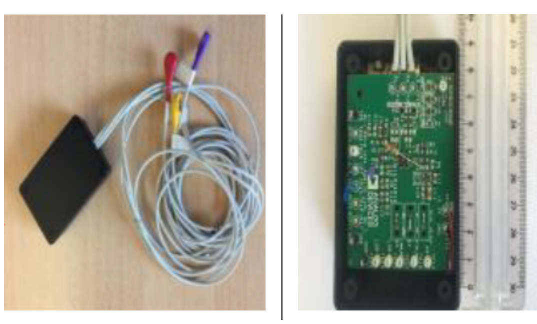


FIGURE 7. In a previous project [82], we developed a wireless ECG circuit for monitoring patients in operating room.

In [83], a cyber-physical cardiac monitoring system called Big-ECG for stroke management, consisting of a wearable ECG sensor, data storage and analysis in a big data platform, and healthcare consultancy services using data analytics and medical ontology has been proposed. This system can help healthcare companies in prognosis and rehabilitation management during post-stroke treatment. A wearable continuous ECG/EMG monitoring system that can transmit data to a smartphone/laptop for real-time monitoring, data recording and analysis, was proposed in [84]. The wearable wireless sensor is implemented in a compact size (30 mm $\times$ 30 mm $\times$ 4.5 mm) and 24 hours of continuous ECG and EMG recording were conducted to demonstrate the robustness and stability of the device based on extended time wearability on a daily routine.

FIGURE 8. Wireless ECG has been used in real operating room and compared to classic wired ECG system.

In [85], a telemonitoring system composed of an acquisition, a transmission, and an elaboration unit is proposed. The first one includes a shirt, a pair of socks and a belt embedding accelerometer and inertial sensors, pressure sensors, single-lead ECG, pulse oximeter, and temperature sensors. These sensorized clothes are able to transmit the collected data to a single database and provide physicians with the processed information, allowing them to monitor the rehabilitation activities performed by patients and assess whether corrective measures are necessary. The design and implementation of a wearable system, called Twinmed, composed of an exoskeleton and a smart shirt that records cardiac and muscle signals through 3D silver-based textile electrodes was proposed in [86]. The system was developed with the aim of evaluating the progress of rehabilitation and the correct use of crutches during walking with the exoskeleton through the use of the ECG and EMG signal.

C. EEG Sensors

With the progress of microelectronics, communications and signal processing, wireless EEG systems have attracted increasing attention in the last ten years and research studies have recognized their potential [87]. The use of wearable EEG systems has demonstrated their validity in the monitoring of rehabilitation activities and in the detection of neurological and developmental disorders such as the autism spectrum disorder (ASD), where early diagnosis is an urgent need for the treatment and rehabilitation of these patients.

In [88], a brain-computer interface (BCI) and brain-machine interface (BMI) system is proposed to control an upper limb robotic arm. The whole system includes electrodes, shield wires, preprocessing chip, wireless communication, central control system, arm machinery, PC software, and APP on the mobile terminal. The recorded EEG signal is transmitted to the computer and the upper limb robotic arm interface via Bluetooth. To obtain effective commands from the brain, the recorded EEG signal is processed by filtration, noise reduction, feature extraction and classification, while the PC software and the upper limb arm are driven by commands based on EEG. Through the encoders and gyroscopes on the upper limb arm, some feedback signals are acquired in real time, such as the joint angle, acceleration, and angular velocity of the arm. In [89], tremor suppression in human hand and forearm was studied, where EEG sensors were used as cap head for tremor recording as shown in Fig. 9.

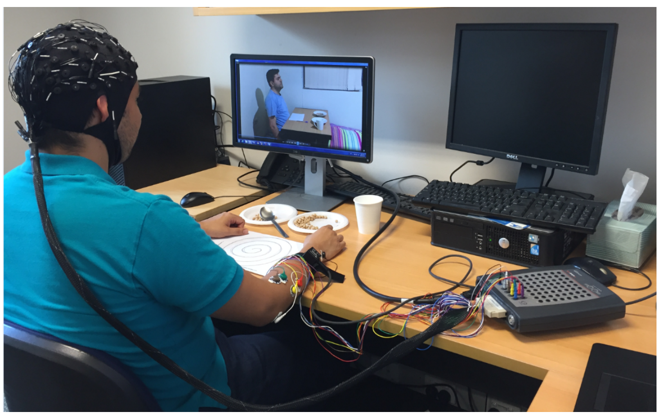


FIGURE 9. EEG sensors used as cap head for tremor recording.

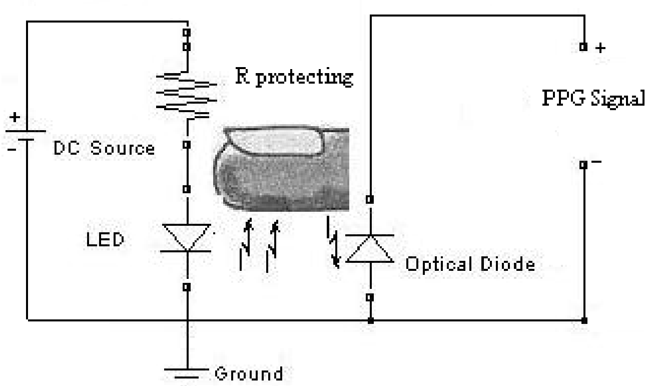
In order to perform an effective treatment for rehabilitation of severe motor impairment after stroke, a novel closed-loop neurofeedback system prototype called REINVENT was proposed in [90] to promote the patient motor recovery. REINVENT (Rehabilitation Environment using the Integration of Neuromuscular-based Virtual Enhancements for Neural Training) leverages recent advances in neuroscience, wearable sensors and virtual technology, and integrates low-cost EEG and EMG sensors with feedback in a head-mounted virtual reality (VR) display to provide neurofeedback when an individual's neuromuscular signals indicate movement attempt, even in the absence of actual movement. In [91], an EEG-based ASD classification processor that targets a patch-form factor sensor that can be used for long time monitoring in a wearable environment was proposed. The selection of frontal and parietal lobe electrodes causes minimum uneasiness to the patient. The proposed and implemented algorithm utilizes only four EEG electrodes. The processor is implemented and validated on Artix-7 FPGA which requires only 26k lookup tables and 15k flip flops. A hardware feasible shallow neural network architecture is used for the ASD classification. The system classifies the ASD with a high classification accuracy of 85.5% using the power and latency of 8.62 μW and 2.25 ms, respectively.

D. PPG Sensors and Multimodal PPG-Based Sensors

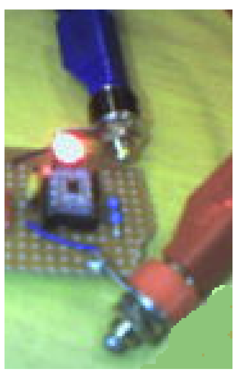
Recent advances in wearable healthcare sensor technology have triggered radical changes in rehabilitation. In the last years, the PPG signal has gained in popularity as a further biosignal that could easily provide interesting information about patient cardiac activity (heart rate and body pressure), and wearable systems involving wireless PPG sensors are becoming used in long-lasting rehabilitation programs. As an example, pulmonary rehabilitation exercises and patient management for long periods of time are required for chronic lung illnesses which usually worsen over time such as the chronic obstructive pulmonary disease caused by chronically poor airflow that makes breathing difficult. In [92], a remote rehabilitation system for a multimodal sensors-based application is proposed. It involves the fusion of sensory data – captured motion data by stereo-camera and PPG signal by a wearable sensor – that are the input variables of a detection and evaluation framework.

Many consumer wearable devices are capable of measuring heart rate information using PPG signal processing. However, the sampling intervals of these wearable devices tend to be longer than those of traditional instruments in clinical applications and research environments. Therefore, in [93] data interpolation was applied to PPG data acquired with low sampling rates, so that traditional heart rate variability (HRV) methods like power spectrum analysis can be utilized for stress evaluation. Additionally, motion artifacts (MA) caused by the interfacial dynamic change between PPG wearable sensors and human skin are making accurate measurements still challenging in personal healthcare and rehabilitation training. In [94], a wristwatch-type PPG-based heart rate (HR) wearable sensor was proposed that uses a novel interface sensor to remove MA through adaptive filtering avoiding conventional accelerometer-based MA techniques. The interface sensor is able to detect non-contact proximity and contact pressure between wearable sensors and human skin. This sensor employs natural piezo-thermic transduction of human skin and enables direct interfacial proximity/pressure detection by using simple thin-film thermistors to detect the interfacial thermal field change. Using natural transduction of human skin and simple thermometry, this interface sensor provides an advantageous MA removal for wearable monitoring devices during physical activities and thus broadens wearable monitoring applications such as rehabilitation.

In [95], a wearable low-cost PPG sensor for simultaneous hand gesture and force level classification was proposed, that can be very useful in a wide range of application scenarios in post-stroke home rehabilitation. Here, a customized wristband embedded with green, red, and infrared light PPG sensors was developed, in order to improve the accuracy achievable with single-signal or two-signal combinations. In [96], a prototype PPG sensor was developed for continuous measurement of oxygen saturation level, as shown in Fig. 10, where the circuit model consists of a infrared light emitting diode (LED) and a photo-diode with other supporting components.



a) Circuit model of PPG sensor.



b) Prototype of PPG sensor circuit.

FIGURE 10. Prototype PPG sensor for continuous measurement of oxygen saturation level.

For the sake of completeness, due to its low invasivity, low cost and easy-to-acquire characteristics, the PPG signal is often used in combination with other biosignals related to cardiorespiratory activity such as ECG. As an application example of home-based mobile-health (mHealth) rehabilitation system, a design based on mobile visible light communication (mVLC) technology for clinical data transmission was proposed in [97]. In the proposed system, multiple biosignals such as PPG, ECG, and respiration signal are acquired by wearable body sensors, transmitted through LED, and received by a smartphone camera at 30 fps thus avoiding the use of RF communication channels that can be risky for a human body in term of long term usage (as in rehabilitation programs) due to RF exposure and electromagnetic interference (EMI). Furthermore, an Android-based mobile monitoring application was also available for local data analysis, visualization, and storage.

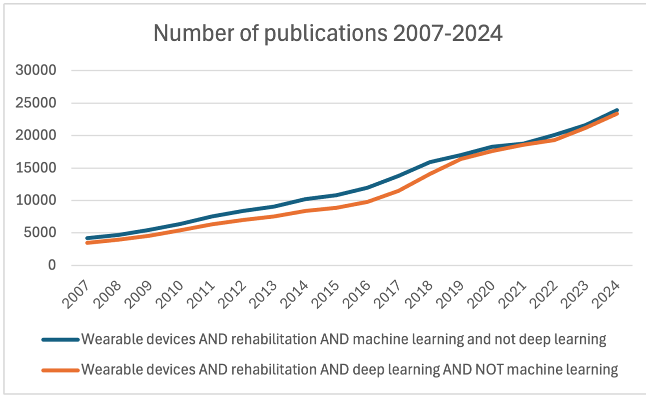
E. Inertial Sensors

Due to their relative ease of operation and low cost, inertial measurement units (IMUs), which incorporate a combination of accelerometers, gyroscopes, and sometimes magnetometers, are used for a wide range of applications requiring measurements of speed, accelerations, angular velocity, and orientation of the human body. These include sports performance, gait analysis, and rehabilitation (e.g., Parkinson's disease monitoring or post-stroke assessment) [98], [99]. In particular, inertial and multimodal platforms exploiting commercial IMU sensors have been widely proposed over the last two decades in most rehabilitation scenarios where knowledge of position, acceleration and orientation of the human body and its parts is essential for monitoring and evaluating patient activity [100]–[109]. In [89], IMU sensors were used for data recording in a tremor suppressing project as shown in Fig. 11.

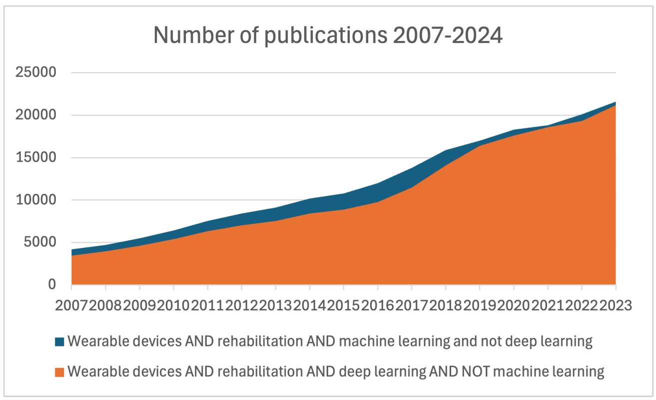
FIGURE 11. IMU sensors attached on a subject's wrist.

III. Wearable Devices and Extra Training

Wearable devices for rehabilitation that use machine learning and require specific training are gaining traction in the field of physical therapy. Wearable devices are being used in rehabilitation with the help of machine learning algorithms. These devices collect physiological signals from users and can induce emotional states to assess patients' rehabilitation outcomes [110], [111]. Machine learning algorithms are then applied to the collected data to classify the emotional state based on a two-dimensional model of emotion, achieving high accuracy [112]. Additionally, machine learning algorithms can be used to estimate clinical scores and track the motor recovery process in patients with upper-limb motor impairments [113]. The combination of wearable devices and machine learning provides an accurate, objective, and effective solution for clinical rehabilitation assessment and remote rehabilitation without the presence of physicians [114]. These advancements in wearable technology and machine learning offer new possibilities for personalized and precision rehabilitation interventions.



a) Number of publications per year in linear scale.



b) Comparison among the number of publications.

FIGURE 12. Publication of references on machine learning-based wearable devices for the years 2007–2024.

As Fig. 12 shows, the field of wearable devices for rehabilitation using machine learning has seen significant growth since 2017. Here is a general overview of the publication trend:

- 2007–2016: These years saw a relatively small number of publications as it was less than 10000 up to 2014 and 2017 for normal machine learning and deep learning respectively, as the field was still emerging.
- 2017–2018: There was a noticeable increase in publications as researchers began to recognize the potential of combining wearable technology with machine learning for rehabilitation purposes.
- 2019–2020: The field experienced rapid growth, with a substantial increase in the number of publications. This period likely saw the introduction of more sophisticated deep machine-learning algorithms and improved wearable sensor technology.
- 2021–2024: These recent years have likely seen the highest number of publications, with continued growth in the field. The COVID-19 pandemic may have further affected research in monitoring and rehabilitation using wearable devices before it accelerated again.

Wearable devices integrated with machine learning algorithms have demonstrated significant potential in the field of rehabilitation. These technologies provide innovative solutions for monitoring and enhancing various aspects of rehabilitation processes. For example, wearable sensors combined with machine learning have been employed in post-stroke rehabilitation assessments, enabling more precise and objective evaluation of patient progress [115]. Additionally, the utilization of machine learning algorithms in wearable devices has facilitated the development of systems for personalized rehabilitation assessment, allowing for tailored and effective rehabilitation plans [116].

Furthermore, the integration of machine learning into wearable devices has enabled the creation of Internet of Things (IoT)-based systems for upper limb rehabilitation assessments, expanding the accessibility of rehabilitation services beyond traditional healthcare settings [117]. These advancements have not only enhanced the monitoring of rehabilitation progress, but have also improved the overall effectiveness of rehabilitation interventions, particularly in cases of stroke rehabilitation [118], [119].

Moreover, wearable devices equipped with machine learning capabilities have played a crucial role in providing biofeedback during rehabilitation, assisting in balance and gait outcomes in neurological diseases [120]. The portability and user-friendly nature of the wearable devices have rendered them suitable for both clinical and home-based rehabilitation settings, thereby increasing patient compliance and engagement in the rehabilitation process [120]. These devices offer several advantages over traditional methods, including:

- Continuous monitoring: Wearable devices can collect data continuously, providing a more comprehensive picture of a patient's progress compared to periodic assessments in a clinical setting.
- Remote monitoring: Patients can use these devices at home, allowing therapists to monitor their progress remotely and adjust rehabilitation plans as needed.
- Personalized feedback: Machine learning algorithms can analyze data collected by wearable devices and provide personalized feedback to patients, helping them improve their form and adherence to their rehabilitation program.

Here are some examples of how wearable devices are being used for rehabilitation with machine learning and specific training:

- Gait analysis: Wearable devices with sensors such as gyroscopes and accelerometers can be used to track a patient's gait pattern, helping therapists identify abnormalities and design targeted exercises to improve walking mechanics.
- Range of motion tracking: Wearable devices can track the range of motion in a joint, allowing therapists to

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monitor progress and ensure that patients are performing exercises within safe and effective limits.
- Muscle activity monitoring: EMG sensors in wearable devices can measure muscle activity, helping therapists assess muscle activation patterns and identify potential muscle imbalances. Fig. 13 displays an augmented reality-based illusion system (ARIS) architecture, which was developed by one of the co-authors. It mixes EMG and a camera tracking system [121].

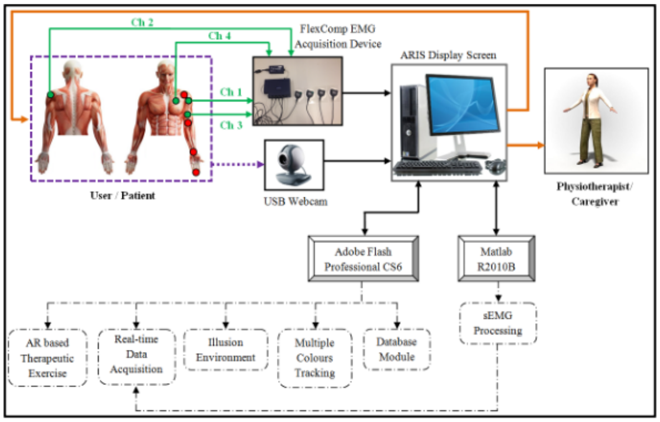


FIGURE 13. ARIS system Architecture, red dot represents the location of four colour markers while green dot represents the site of electrodes.

Specific training is often required to use these devices effectively, as therapists need to understand how to interpret the data and use it to guide their treatment decisions. Additionally, patients may need training on how to wear the devices and perform exercises correctly. Here are some examples of companies developing wearable devices for rehabilitation that use machine learning and require specific training:

- MindMaze is a brain technology company that aims to accelerate humanity's ability to recover, learn and adapt. With over a decade of work at the intersection of neuroscience, biosensing, engineering, mixed reality and artificial intelligence, it has enhanced patients' recovery potential with neurological diseases. The company use digital therapeutics with best-in-class motion analytics, AI and cloud technologies to create a universal platform for brain health [122].
- Neofect promotes motor learning and brain reorganization to improve function for adults rehabilitating from stroke. It integrates treatment, provides real-time feedback on exercises, incorporates devices into session activities, simultaneously views client and device usage, and digitally assigns in-session activities and home exercise programs [123].
- Rehabtronics company develops robotic rehabilitation devices and robot-assisted therapy systems for people with physical and neurological disabilities. Its technology uses machine learning algorithms to optimize therapy and improve rehabilitation outcomes [124].
- Bionik develops robotic devices and AI-based rehabilitation solutions for people with neurological and musculoskeletal disabilities. The Company's product includes three InMotion® Robots for rehabilitation following stroke and other neurological conditions intended to restore upper-extremity motor control for a broad range of neurological conditions and recovery stages, including early recovery from acute stroke. InMotion® Robots also provide objective evaluation assessments intended to measure and report the patient's level of motor impairment and progress during the course of therapy. A home version of the InMotion® upper-extremity technology is in development [125].

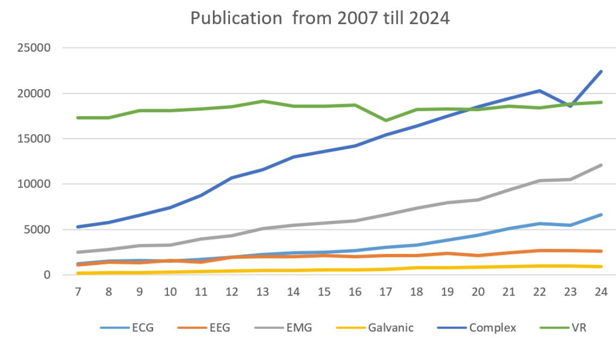
In conclusion, the synergy between wearable devices and machine learning algorithms holds significant potential for transforming rehabilitation practices. By leveraging these technologies, healthcare professionals can deliver more personalized, efficient, and data-driven rehabilitation interventions, ultimately enhancing patient outcomes and the quality of care.

Wearable devices are meant to be used as a complementary tool to enhance the effectiveness of rehabilitation programs. It is important to note that wearable devices are not totally a replacement for traditional physical therapy. It is crucial to consult with a healthcare professional before using any wearable device for rehabilitation purposes.

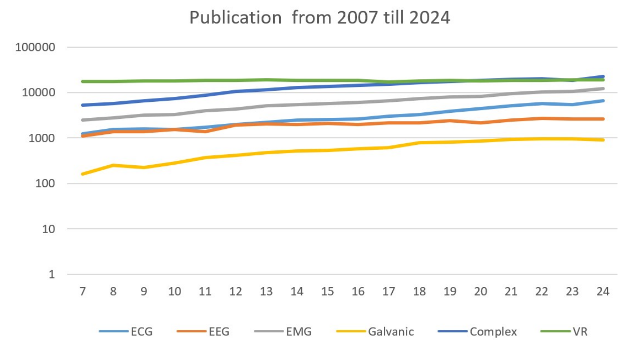
IV. Signal Processing Approaches and Technologies

From the beginning of this century, the processing of biomedical signals (ECG, EEG, EMG, etc.) using different advanced processing tools [126] (such as wavelets, deep learning, machine learning, time-frequency representations, adaptive filters) has been an active research field for a wide range of applications going from human/brain-computer interference (H/B-CI), to brain gaming, and rehabilitation robotics [127]. In [43], the authors provide a review on common physiological systems used in the rehabilitation field and they target commercial wearable devices.

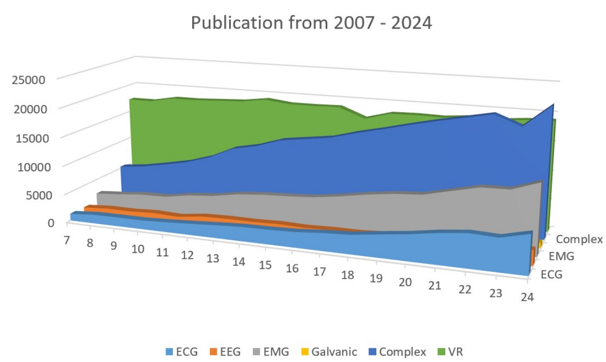
To illustrate the high dynamic research activities in the field of signal processing applied in the rehabilitation aspects, we used the server of Google Scholar to conduct a statistical study on published papers and other online resources related to these topics. To this goal, we plotted the number of publications (papers, conferences, online resources) with respect to their publishing year in Fig. 14. To make a better and fast comparison, we provide four sub-figures to show the number of publications with respect to year and considered signal in linear scale (a), in logarithmic scale (b), the steepest growth of publication is provided in (c), and the percentage of publication is shown in (d).



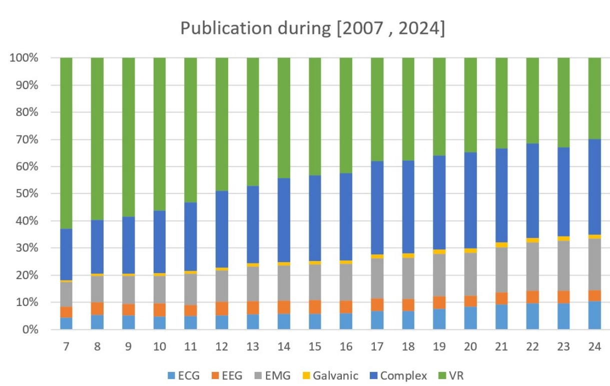
a) Number of publications per year in linear scale.



b) Number of publications per year in logarithmic scale.



c) Comparison among the number of publications.



d) Percentage of publications per year.

FIGURE 14. Publication of references on biomedical signals used in rehabilitation with respect to year.

Based on Fig. 14, we can notice the large number of published papers focusing on biomedical signal processing approaches applied to rehabilitation purposes. Therefore, in this section, we classify the existing and ongoing researches in signal processing applied to rehabilitation into six categories. The first three categories consider the applications based on different biomedical signals including ECG, EEG, and EMG. In the fourth category, we consider the stimulation of the galvanic vestibular. The fifth subsection considers complex systems using simultaneously more than one biomedical signals. The final category focuses on rehabilitation applications using biomedical signals coupled with virtual reality.

A. Electrocardiographic Signals

The most important muscle in the whole body can be identified as the heart. Indeed, our life depends on the health of our heart. The heart is responsible to circulate the blood among different body organs through the arteries, veins, and capillaries. The blood circulation provides the nutrients and oxygen to all our cells and at the same time helps to get ride of the metabolic waste. As all muscles, the motion of the heart is generated by electrical signals. The electrical signals of the heart can be described by electrocardiographic signals, as shown in Fig. 15. To enable the heart to fulfill its pumping role, it needs an electrical source. This corresponds to a pre-existing electrical impulse coming from the cells of the heart tissue more precisely in the sinus node (SN). This impulse propagates along the muscle fibers, causing the heart to contract. In fact, each cell is a membrane exchange center where different ions are involved [128], such as sodium (Na), potassium (K), calcium (Ca), and chlorine (Cl). In order to measure and record ECG, biopotential electrodes[1] are provided as interfaces between the body and the measuring instrument. The potentials measured on the outer surface of the chest through the electrodes are recorded on moving chart paper in the form of ECG.

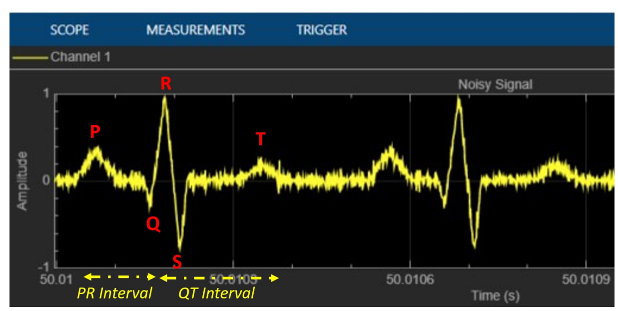


FIGURE 15. An example of ECG signal and its major features.

We can mention that the ECGs are usually very noisy. The noise can be generated by the sensors or the electronic circuits. It can be also caused by electrical signals generated by other organs such as the diaphragm which is the main muscle to control the volume of lungs used for breathing, or

[1]Generally, Silver/Silver Chloride (Ag/AgCl) electrodes are used.

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other muscles such the suboccipital muscles act to rotate the head and move the neck, etc. In order to clean ECG signals form electrical artifact that can be generated by external electrical sources, notch filters are largely used. However, to reduce the impact of other signals generated by various muscles and remove artifacts from electrocardiographic signals, the authors of [14] propose an approach based on independent components analysis [129]. Using an adaptive blind signal processing approach, the same authors [130] succeeded to reduce artifacts in ECG signals. Blind source subspace separation [131], [132] and classification of ECG are developed in [133].

To ensure patients safety, physiological parameters (cardiac rhythm, heart rate, blood pressure and blood oxygenation) are monitored during a surgery [15]. During a surgical procedure, the use of the electrosurgical units (ESUs) becomes nowadays indispensable. Indeed, the ESU produces a RF alternative current to cut or/and to coagulate the tissue. However, the electrical pulses generated by the ESU can strongly disturb the ECG recording and monitoring. To remove electrical artifacts, we have proposed different methods based on singular value decomposition (SVD), wavelets, and empirical mode decomposition (EMD) [16], [134].

For developing a complex home monitoring system, the authors of [135] elaborate a digital system, called "System for Prevention, Care and Rehabilitation of Subject with Cardiovascular Risk", to acquire and process ECG and extract the HRV, which is defined as the time interval difference between two adjacent heartbeats [136]. According to [135], the HRV is used to estimate the beat-to-beat heart rate dynamics and respiratory modulation in real time by using their previous system "Windows Media Center". Finally and in order to extract the respiration information, the authors filter the obtained ECG by a cascade of two median filters, with respectively 200 ms and 600 ms temporal windows. The first filter removes the QRS complexes, while the P and T waves are eliminated by the second filter. We should mention that their device can be considered a medical-making support for characterizing ECG patterns and discriminate normal versus pathological cardiovascular patterns [137].

B. Electroencephalography Signals

It is well known that our brain is a very crucial and complex organ in our body. Indeed, our brain generates our feelings, maintains our memories, creates our thoughts, and controls almost all our conscious or unconscious activities by electrical signals transmitted through our neurons to different muscles or organs. The EEG is used to measure the electrical activities of our brain using small metal discs (electrodes) attached to the patient's scalp. EEG can be measured during any activity of an alive brain (even during a sleeping period or being fainted), as shown in Fig. 16. In particular, the EEG data reported in Fig. 16 were collected in a hospital setting during routine diagnostic procedures using a Galileo BE Plus PRO Portable, Light version, with electrodes applied in the standard 10-20 configuration.

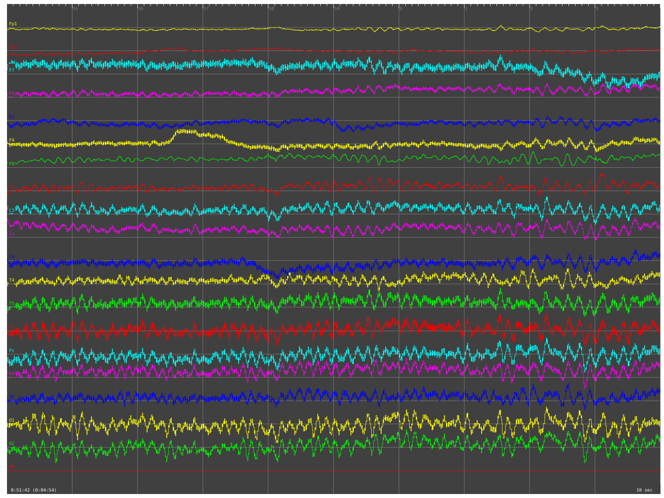

FIGURE 16. An example of EEG signals with 19 channels with electrodes applied in the standard 10-20 configuration as in [138].

Usually EEG signals can be used to diagnose neurodegenerative diseases (e.g. Alzheimer's disease, frontotemporal dementia, dementia with Lewy bodies, progressive supranuclear palsy, vascular dementia, etc.) [138]. They can also be used to diagnose multiple brain disorders (epilepsy, seizure disorder, sleep disorders, tumors, stroke, Creutzfeldt-Jakob disease, etc.) [139]. EEG and its features are widely used in BCI systems, as shown in Fig. 17.

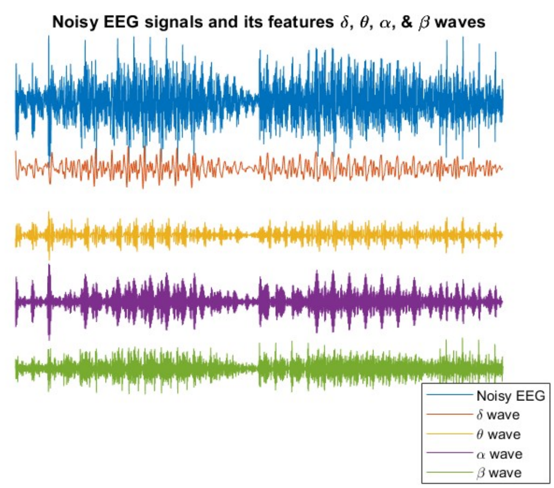

FIGURE 17. Noisy EEG signal during one minute with its features: Delta (δ) wave 1–4 Hz, Theta (θ) wave 4–8 Hz, Alpha (α) wave 8–12 Hz, Beta (β) wave 12–30 Hz. The sampling frequency is $f_s = 256$ Hz.

Using independent component analysis (ICA) [140], the authors of [141] removed artifacts and noise from EEG signals. Then, the cleaned EEG signals were filtered by band-pass filters to focus around the desired frequency components. Then, several features have been extracted based on the time, frequency, or time-frequency domains, and using

Morlet or Bump wavelets. Using the extracted features to control a finger rehabilitation system, the authors of [141] applied several classifiers such as support vector machine (SVM), K-nearest neighbors (KNN), linear discriminant analysis (LDA), and random forest on modified and reduced dimensions features obtained by the principal component analysis (PCA) techniques.

Oral communication is the most effective way to engage in a conversation and enhance our social connection. Unfortunately, people suffering from auditory processing disorders (APD) [142] face a big challenge to participate in common conversations among several persons. In fact, recent hearing devices (hearing aids or cochlear implants) use advanced signal processing algorithms. The latter devices are very helpful to maintain a conversation between two individuals. Unfortunately, they reach their limit if many people talk simultaneously. To help suffering individuals in these cases, the authors of [143] propose an auditory attention decoding (AAD) hearing device using EEG. In order to develop their system, the authors use several approaches based on CNN, minimum mean-squared error (MMSE), least absolute shrinkage and selection operator (LASSO), and canonical correlation analysis (CCA).

Using virtual reality gloves and neurophysical signals such as EEG and EMG, the authors of [144] identify and classify four different hand actions for human motor actions. To remove environmental artifacts from EEG signals, the authors used three methods of referencing (average ear reference, common average reference, and the small Laplacian, i.e. the average of four electrodes around the target electrode) as suggested in [145]. To improve the classification of EEG signals, several finite impulse response (FIR) filters of order 100 have been used to decompose the EEG into many subbands [144], including α waves (8-10 Hz, 10-12 Hz, and 8-12 Hz) and β waves (12-15 Hz, 15-18 Hz, 19-30 Hz, and 12-30 Hz). The authors reach around 75% correct classification using several classifiers, including naive Bayes, alternating decision trees, multinomial logistic regression with a ridge estimator, functional trees, naive Bayes trees, and SVM.

C. Myoelectric Signals and Surface Electromyography

In a similar way to our heart, all other skeletal muscles generate various electrical pulses during their actions, these impulses are called the myoelectric signals. The EMG represents the measured biomedical signal related to myoelectric signals. EMG can be divided into two categories depending on the methods used during the measurement: sEMG and intramuscular EMG (iEMG). The sEMG is a safer non-intrusive method compared with iEMG. For this reason, many systems have been proposed to deal with sEMG, specially to operate a robotic exoskeleton, see Fig. 18.

According to [146], 85% of the stroke, or cerebrovascular accident (CVA), are of ischemic origins and 15% are hemorrhagic. A stroke can be the cause of severe consequences such as level of consciousness, visual deficits, eye movement abnormalities, language impairment, facial paralysis, or even hemiplegia. In many cases, rehabilitation therapy for hemiplegia can be highly recommended. Many researchers are building rehabilitation training robots to help patients, and are also investigating exoskeleton for rehabilitation purposes or to enhance their motor function. To build an effective exoskeleton, researchers should pay attention for the weight of the device, the accuracy of the requested actions, the action time, the robustness of the system, the volume of the device, its degrees of freedom, its price, usability, its ability to enhance the mobility, and its acceleration of the rehabilitation process. Recently, exoskeletons are used in various applications such as military, helping workers in their hard tasks, and assisting patients with their daily life activities. We should mention that exoskeletons are widely used in the rehabilitation process. The authors of [147] proposed a limb exoskeleton rehabilitation system based on the processing and the classification of sEMG signals. In their system, they applied random forest to achieve pattern recognition, and they used a complete ensemble empirical mode decomposition (EEMD) [148], [149] to filter the signals and wavelets [150] were used as tool for features extractions. Their experimental results showed about 94% of accurate classification. In order to improve the physical human-robot interaction control, the authors of [151] proposed a variable stiffness exoskeleton with sEMG-based torque estimation. In [152], EMG-driven robot hand assisted upper limb training has been tested in clinical service. In order to extract valuable muscle information and also describe muscles' activities from noisy multi-channel sEMG, ICA [140] and spectral curve descriptors have been used in [153]. Using SVM [154], KNN [155], and LDA [156], myoelectric pattern recognition of hand motions for stroke rehabilitation has been derived in [157]. Similar approaches have been proposed [158], [159].

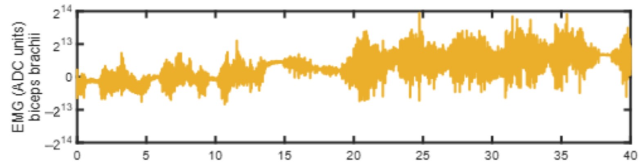

FIGURE 18. An example of sEMG signal recorded from biceps brachii muscles.

D. Galvanic Vestibular Stimulation

To cope with neural declines affecting elderly people, several non-invasive brain simulation (NBIS) methods have been investigated. Depending on the required simulation and the corresponding neurological disorder, NBIS can be applied through various means [160], such as electroconvulsive therapy (ECT), repetitive transcranial magnetic stimulation (rTMS), single-pulse transcranial magnetic stimulation (sTMS), transcranial electrical simulation (tES), galvanic vestibular stimulation (GVS), and transcranial focused ultrasound (tFUS).

While the vestibular integrates signals from muscles, joints, the skin, and our eyes, and is an essential organ in our body, it is incompletely understood and it influences a number of brain systems. Indeed, our brain through the vestibular system senses information about our body position and allows rapid compensatory movements in response to any external force to maintain our balance. According to [161], around 28 out of 100000 US adults suffer from bilateral vestibular hypofunction (BVH), which is equivalent to more than 64 thousand cases of severe to profound BVH only in the United States, and 1.8 million worldwide (by extrapolation of US estimates to the 2008 world population). As there is no medical treatment for bilateral vestibular deficit (BVD), vestibular implants have been tested for the rehabilitation of patients suffering from BVD. These implants offer possibilities to evaluate balance. It seems that GVS is a promising field to enhance vestibular reflex [162].

According to [163], GVS can help us understand our sensory signal processing in the vestibular system under normal and pathological conditions. In addition, GVS may be used to block or activate the discharge in the vestibular nerve by electrical currents. During a GVS session, small electrical currents (less than 3 mA) are administrated to the subject behind its ears. Modern brain imaging technologies[2] can be used to study and design GVS stimuli by inferring brain activity at various spatial and temporal scales [160]. In therapeutic intervention, GVS becomes an essential means. During GVS, EEG signals can be used to capture rapid dynamic brain activities. As EEG contains very noisy signals, blind source separation [129], [140], [164], [165] methods can be used to clean these signals from artifacts and other noises. Data analysis and GVS can be used in neurorehabilitation [160].

E. Complex Systems Using Several Biomedical Signals

In [166], the authors review several studies related to interpreting volitional movement intent from biological signals [166] used to create artificial limb for amputated people. According to their study, more than one million people worldwide are unfortunately suffering every year from limb amputations. In order to propose an artificial limb, various biomedical signals are used, such as EEG, electrocorticography (ECoG), electroneurography (ENG), and EMG. They present as well a generic block diagram of a movement intent decoder used to action the artificial limb. This decoder works in two phases: a training or an exercise. Both phases start by signal acquisition, then signal filtering and enhancement operations, before extracting useful features. During the training period, the extracted features are fed into the decoder to link these features to specific motion or gesture. During the exercise period, the extracted exercise features are compared to the decoder outputs. Then the intent motion is predicted, which should go through a post processing stage before going to various servomotors to realized the desired motion. The extracted features are tightly related to recorded signal. For example, in the case of EEG signals, the signals are split into different frequency bands, including the delta ($\delta < 4$ Hz), the theta ($4 < \theta < 7$ Hz), the alpha ($8 < \alpha < 15$ Hz), and the beta ($\beta > 15$ Hz) waves [167]. Mostly, the alpha signals are used in the movement intent decoders. However, a low-frequency amplitude modulation extracted from ECoG signals can be correlated to the limb movements [167]. Finally, several advanced signal processing approaches based on Kalman filtering (KF), machine learning, artificial neural networks (ANN) and specially multilayer perceptron (MLP) have been used in different approaches to extract features and manipulate artificial limbs.

F. Virtual Reality and Signal Processing for Remote Monitoring Rehabilitation Systems

It has been mentioned before that signal processing methods applied to biomedical signals (ECG, EEG, EMG, etc.) are widely used in various fields and are very valuable for diagnostic and clinical tests. The same signals can be used as well in the rehabilitation procedures. Often, a patient wearing many senors should do some exercises under the supervision of a practitioner to evaluate the states of its recovery. To extend the application of such process to home-based rehabilitation support activities, recent studies have proposed different approaches [168], [169].

Using Microsoft Kinect systems, the authors of [168] customize a virtual reality system allowing a subject to carry out physical and cognitive rehabilitation therapies. The virtual reality platform they developed encourages a patient to rehabilitate its strength, aerobic, motion or cognitive capacities through specified exergames. The system can be used in home activities without the active need or presence of a therapist. At the end of every session, the system generates a log report and sends it to a therapist for further offline evaluation if required. To add more comfort to patients, the users are monitored and they are provided with audio-visual feedback during their session. This feedback allows a user to know in real time if the ongoing exercises are well performed according to their specific therapy program.

Using the IoT technology, the authors of [170] designed a remote-monitoring validation engineering system (ReMoVES)[3], which is a remote care solution for frail elderly individuals. This system also proposed a list of exergames to encourage and enhance therapy performance of a patient. Knowing that biomedical signals are noisy and based on the proposed ReMoVES, the authors of [169] proposed a pre-processing approach of the acquired signals. In their study, they consider different kind of noises, including additive white Gaussian noise (AWGN) and multiplicative

[2] Modern brain imaging technologies used: functional magnetic resonance imaging (fMRI), EEG, magnetoencephalography (MEG), and positron emission tomography (PET).

[3] ReMoVES was designed by the University of Genoa [170] to support motor and cognitive rehabilitation using exergames and digital tests. This system relies on Microsoft Kinect v2, Leap Motion and a touchscreen.

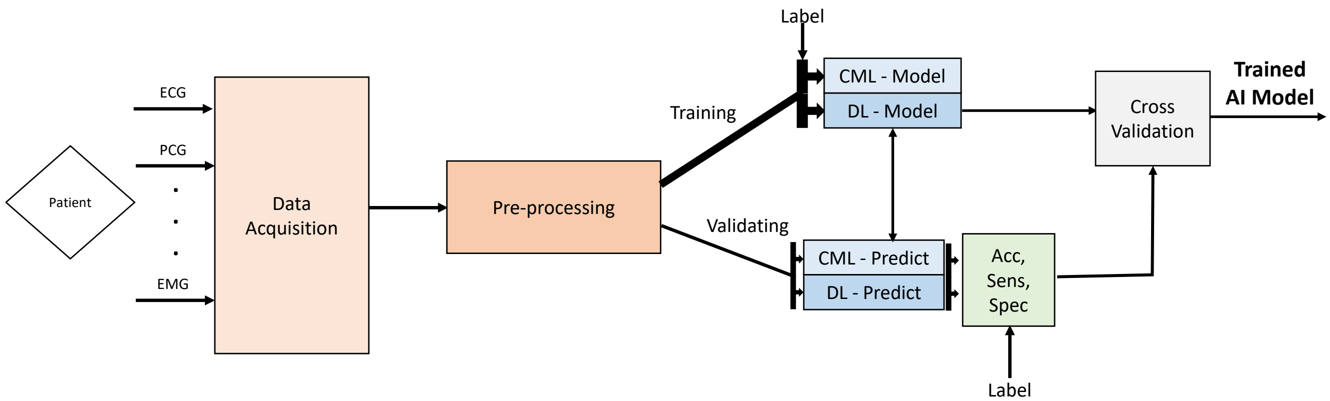

FIGURE 19. **Methodology of machine learning-based rehabilitation research; CML – classical machine learning, DL – deep learning, Acc – accuracy, Sens – sensitivity, Spec – specificity.**

noise (such as speckles used in radars, the impulse or shot noises that could alter randomly some signal samples). Their approach consists of applying at first a spline interpolation over the raw data, then filtering the outputs by nonlinear filters. The filtered data go through a segmentation procedure as an initial phase of feature extraction before ending by data analysis. The ReMoVES platform helps the authors to have a certain feedback on potential moves of the upper limb of the subject. In their original study, they mention that the feature extraction phase was done by experts and they suggest the possibility to do this task automatically.

V. Machine Learning-based Rehabilitation

Conventional rehabilitation approaches usually require regular evaluations from doctors and/or physiotherapists on the physical activities of patients during the course of rehabilitation based on visual observations complemented by clinical measurements. While these approaches are effective in many aspects of speeding up the recovery process, they are limited by the high medicare expense and the availability of medical doctors and physiotherapists [171]. Some of these constraints can be effectively mitigated by machine learning approaches which have been proposed and applied in a variety of areas of physiotherapy and rehabilitation. Machine learning is a rapidly evolving area with new tools emerging every couple of months, which provide great opportunities to improve the rehabilitation procedure and reduce the cost of medicare and the workload of physiotherapists [115].

The main purpose of applying machine learning is to leverage its strong signal and data analysis capabilities to assist the rehabilitation process by providing patients with conveniently accessible real-time measurement and guidance, particularly in the context of home-based or telerehabilitation settings. Machine learning includes classical machine learning and deep learning [172], with the latter receiving an increasing attention. The methodology of machine learning-based rehabilitation research is illustrated in Fig. 19.

A. Classical Machine Learning

In general, the steps of applying classical machine learning in rehabilitation include data collection, signal acquisition, preprocessing, feature extraction, and classification. As the first step, general patient data such as age, gender, and medical history information are collected. Physiological signals are acquired from various sensors such as ECG [115], PCG [173], EMG [174], EEG [175], and IMU [115]. Recently, functional near-infrared spectroscopy (fNIRS) has been used to monitor the brain activity in rehabilitation [176]. These sensors can be worn conveniently by patients at home to provide real-time physiological signal measurement, which reduces the time and efforts required by patients to travel to hospitals or physio clinics. As an example, Fig. 20 shows the waveforms of the real-time PCG and ECG signals measured by a wearable vest holding six PCG sensors and one three-lead ECG sensor illustrated in Fig. 21.

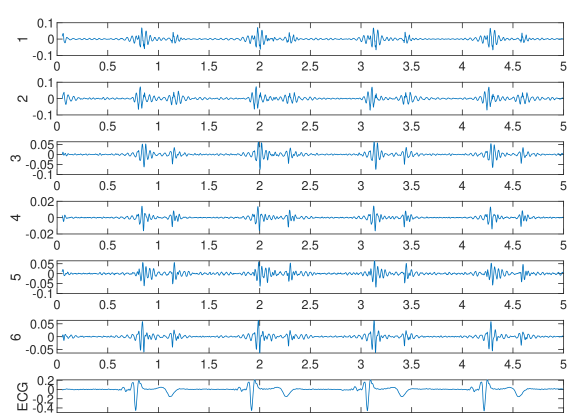

FIGURE 20. **Waveform of PCG signals and ECG signal recorded from a wearable vest.**

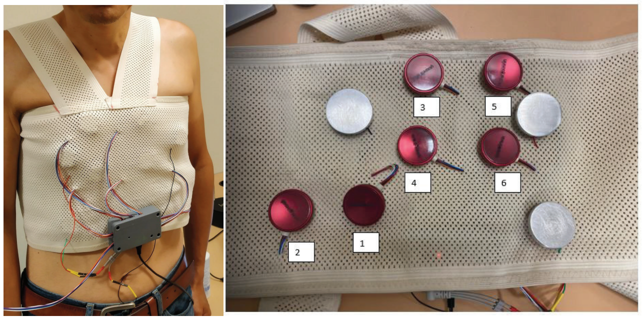

FIGURE 21. Prototype wearable vest holding six digital stethoscopes and one three-lead ECG sensor.

As the acquired signals are often contaminated by various external noise and interference, in the preprocessing step, the raw signals are amplified and filtered to remove noise and interference [177]. Simple frequency-selective filters can be used to suppress out-of-band interference and noise. If the interference lies in the same time-frequency band as that of the signal-of-interest, more advanced filtering algorithms such as the adaptive Wiener filter [173], [178] and the recursive least squares (RLS) filter [177] can be applied to enhance the signal integrity. Another important aspect in preparing signals for machine learning is that the signals need to be properly normalized before they are input into the neural network.

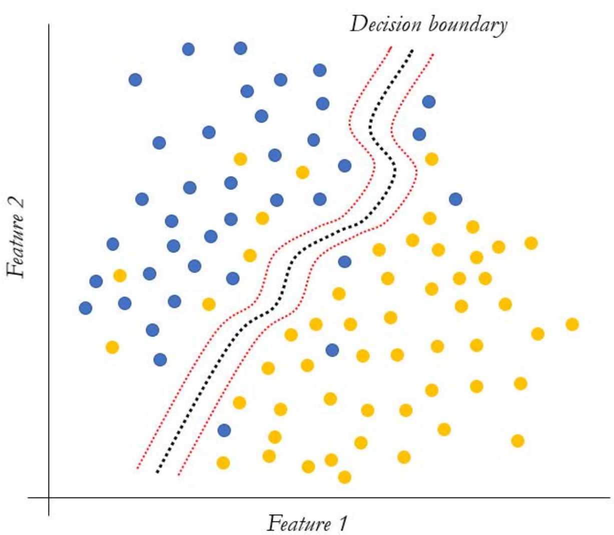

FIGURE 22. Decision boundary of an SVM-based classifier.

After preprocessing, features-of-interest such as the heart cycle obtained from the ECG and PCG signals, and gait information acquired from the IMU sensors are then extracted from the filtered signals. These features can be obtained directly from the time-domain signal waveform or from various transform domains such as the Fourier transform and the wavelet transform. Ideally, extracted features should present significant difference for the signal categories to be classified. Feature selection techniques such as the Student's t-test and the maximum relevance and minimum redundancy method can be employed for this purpose [179]. The selected features are input to a classifier or an estimator. Examples of classical classifiers include SVM [5], random trees, and random forest [180]. Fig. 22 illustrates the decision boundary of an SVM-based classifier. In [181], SVM is used to distinguish between normal and coronary artery disease (CAD)-affected heartbeats, obtaining an accuracy of 80.44% and an F1-score of 81.00%.

B. Deep Learning

Recently, deep neural network-based classifiers such as the convolutional neural network (CNN) and the recurrent neural network (RNN) have seen wide applications due to their enhanced capabilities compared with classical machine learning approaches [115], [178]. Note that unlike classical machine learning, in deep learning-based neural networks, the feature extraction operation is often implicitly embedded/incorporated in the deep neural networks employed. For deep learning, the architecture of the neural network and its associated hyper-parameters play an important role in a successful application of machine learning. In general, its capability increases with the depth of the network. General guidelines on designing deep neural networks and tuning the hyper-parameters can be found in [172].

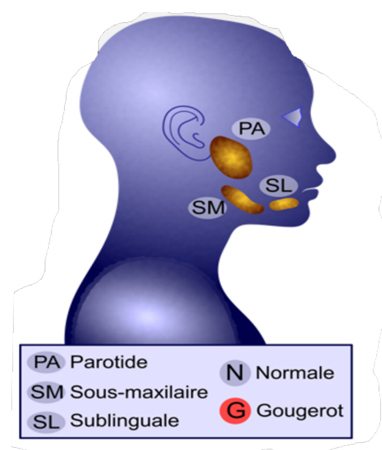

FIGURE 23. Salivary glands.

CNNs are useful for data with a grid-like structure such as image, spectrogram, and scalogram. They employ multiple layers of convolutional filters to extract features from the input signal, followed by pooling layers to reduce the dimension of the data. The output of the last convolutional layer is usually fed into fully connected layers for classification or regression tasks [6]. On the other hand, RNNs are developed to handle data with temporal dependencies such as ECG and PCG signals. They process the input data sequentially based on the current input unit and hidden states that capture information from previous time steps [172]. Using deep learning, we proposed in [182] an automatic diagnosis of

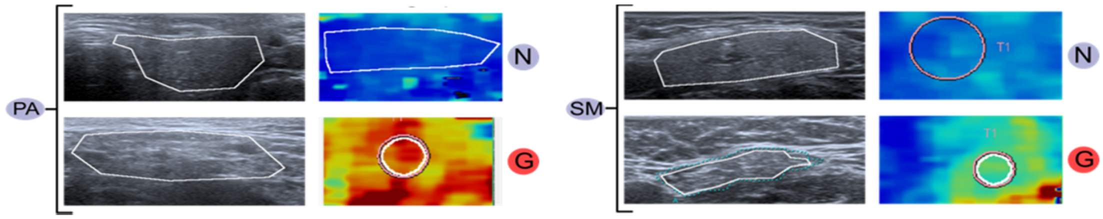

FIGURE 24. Machine learning to automatic detection of Gougerot-Sjörden syndrome.

the Gougerot-Sjörden syndrome that may affect the salivary glands, see Fig. 23, at different severity levels between 0.1 and 5% of the total population, see Fig. 24.

Recently, the transformer architecture attracted significant research interests in many areas such as automatic speech recognition (ASR) and natural language processing (NLP). Similar to the RNN, a transformer-based neural network is applied to sequential input data. However, unlike RNNs, a transformer network can process the entire input sequence simultaneously using the attention mechanism, which enables it to focus on specific parts of the input sequence based on their relevance [183].

For both classical machine learning and deep learning, the accuracy of models is evaluated through statistical metrics, including sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve. Explainable AI tools such as guided-backpropagation, gradient-weighted class activation mapping (Grad-CAM), and local interpretable model-agnostic explanations (LIME) can be applied to understand and interpret the machine learning results. In two different joint projects [19] and [184] between ENSTA, the Medical school in Brest, and Brest Hospital, we proposed two systems to detect and characterize a thrombus in deep veins using elastography and echography, see Fig. 25. We should highlight that the classification performance shown in both projects are good and quite comparable.

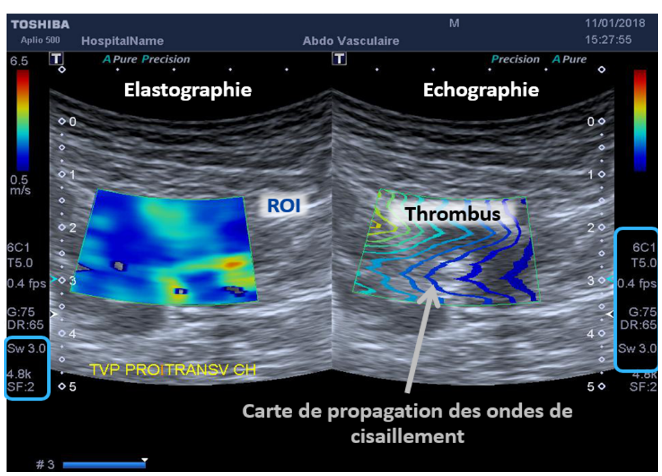

FIGURE 25. Elastography and echography of a blood clot.

C. Literature Review

As can be seen from Fig. 26, there is a plethora of papers in the area of machine learning in rehabilitation and it is not possible to compile an exhaustive list of them. Therefore, in this section, we mainly focus on the most recent works in this area. It is noticeable from Fig. 26 that there is a surge of publications during the Covid-19 time. For upper-limb rehabilitation, an intelligent wearable robotic exoskeleton prototype was developed [185]. It can be used to provide support for diagnostic and rehabilitation processes of neuromotor functions. These intelligent exoskeleton devices apply machine learning to detect motion intentions during rehabilitation [186]. Thus, physical therapy sessions can be adjusted according to the special needs of each individual patient. An overview of how machine learning is used in EMG signal-driven upper-limb prosthesis control was provided in [174] along with a discussion about how it could be employed to improve the robustness and reliability of future devices. In [187], a federated learning-based consensus model was developed for post-stroke assessment. This study proposed the adoption of federated learning to develop a scalable AI model for post-stroke assessment while protecting patients' privacy.

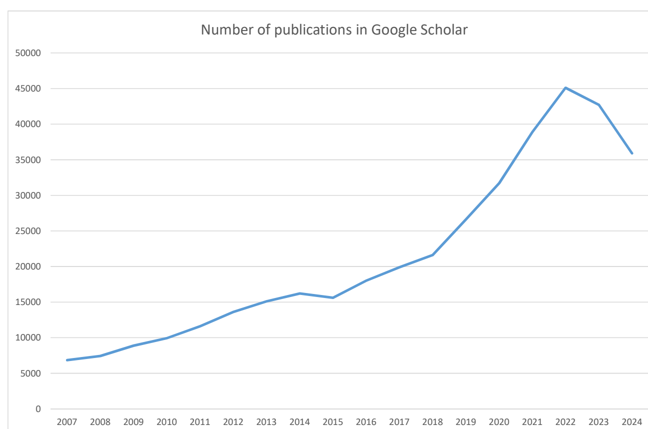

FIGURE 26. Number of publications per year between 2007 and 2024 on machine learning with applications in rehabilitation, retrieved from Google Scholar on April 24, 2025.

In [188], machine learning approaches were proposed to predict rehabilitation success based on both clinical and patient reported outcomes. Regression algorithms were applied to estimate the rehabilitation success in terms of admission and discharge value differences. Classification models were then developed for predictions based on a three-class grading scheme. A review article in [189] summarized the state-of-the-art works combining AI and the IoT to help the elderly live easier and better. Paradigms of both classical machine learning and deep learning were introduced. Activity classification and fall detection [190] were chosen as two important application examples in elderly care to showcase the potential, limitations, and perspectives of machine learning.

A tutorial on reinforcement learning (RL) methods implemented in a reproducing kernel Hilbert space was presented in [191]. These methods can be used to address challenges in decoder design for the BMI system in online continuous learning of tasks, which is required for the full restoration of motor function. A transformer-based neural network for gait prediction in lower limb exoskeleton robots was presented in [183], which showed a significant reduction of the mean-squared error compared with the CNN model.

A recent review on wearable sensors and machine learning in post-stroke rehabilitation is published in [115]. The authors followed the guidelines of preferred reporting items for systematic reviews and meta-analysis (PRISMA) to select 33 papers in the review. The objectives and limitations of each paper are summarized in [115]. A logistic regression and a feed forward neural network were used in [192] to identify patient orientation for the purpose of mitigating pressure injuries, which are a common problem for patients who have limited mobility, particularly for those who are confined to a bed. Machine learning techniques for Alzheimer's disease diagnosis and prediction were proposed in [175], [193] based on magnetic resonance imaging (MRI) results, see for example Fig. 27. In [194], the authors presented an automatic clustering algorithm to detect anomaly in the perfusion MRI of the brain, see Fig. 28.

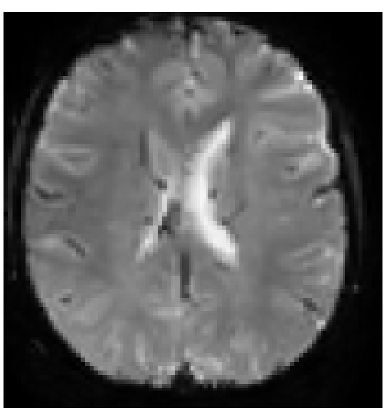

FIGURE 27. Brain MRI image.

Digital twins is a promising approach to personalize rehabilitation by creating virtual replicas of patients [195], enabling simulations of different treatment scenarios and personalized therapy plans based on real-time data and individual needs. These models can predict patient outcomes, allow real-time monitoring of rehabilitation progress, and adjust therapy accordingly, leading to optimized recovery.

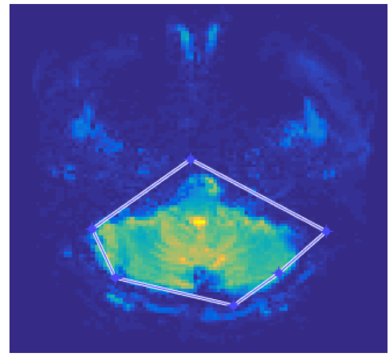

FIGURE 28. Using machine learning for automatic anomaly detection in MRI.

D. Data Sets

Machine learning algorithms can be classified as unsupervised and supervised learning [172]. Unsupervised algorithms are well-known for feature extraction and do not require any supervision signals/labeled data. For supervised learning, access to labeled data plays a key role in developing machine learning based classification algorithms in rehabilitation. As the training of the neural networks greatly depends on the labeled data, the domain knowledge of doctors and physiotherapists is instrumental. Obviously, incorrectly labeled data usually leads to a performance degradation. In [188], data from a thousand rehab patients were used to build models that are able to predict the rehab success for a patient upon treatment start. A list of the currently available open access data sets of PCG recordings is provided in a recent paper [196]. Table 2 shows some open access datasets which can be used for the purpose of training machine learning algorithms in rehabilitation.

In contrast to areas such as ASR and NLP with easy access to a large amount of training data, in many rehabilitation applications, there is only limited labeled data available. Moreover, in general, the amount of data required for training increases with the size of the neural network. This may lead to problems such as overfitting, where the neural network performs well only on the training data set, but fails to generalize to other data. In such a case, transfer learning can be used to leverage the strong capability of pre-trained large neural networks in feature extraction and classification [6]. Utilizing a pre-trained network allows data limitations to be overcome, including issues around limited labeled data.

Another approach to solve the neural network overfitting problem is through data augmentation and data generation [201]. Data augmentation reduces overfitting by training models on slightly modified copies of existing data, for example through adding noise, modifying the contrast, hue, and saturation of the original image, etc. Data generation refers to the creation of synthetic data, which can be achieved using generative AI networks.

TABLE 2. Examples of currently available open access datasets for training machine learning algorithms in rehabilitation

Data class	Data description	Data set
Heart sound	PCG recordings	Various data sets summarized in [196]
Heart signal	ECG recordings	Incentia [197]
Stroke	Data of patients recovering from stroke	SCOAR [198]
Movements	Physical rehabilitation movements	IRDS [199]
Alzheimer's disease	Commonly used Alzheimer's disease datasets	Summarized in [175]
Neurocritical care	Transcranial Doppler ultrasound	[200]

E. Concerns

As shown in the works mentioned above, machine learning provides potential benefits for rehabilitation, compared with conventional rehabilitation approaches. However, the use of machine learning may raise ethical and operational concerns. Ensuring the diversity of training data is paramount to prevent biases, as witnessed in other deep learning applications [6]. Overfitting remains a technical concern, where algorithms might be overly tailored to specific datasets, compromising their broader applicability. Variability of signals and motion artifacts may also reduce the generalisability of AI-based rehabilitation models. Moreover, societal unease about AI-driven decisions in rehabilitation emphasizes the need for human oversight and transparent accountability. Furthermore, ethical concerns related to patient privacy and confidentiality present a challenge for the collection of data. As a result, in contrast to other areas such as image and speech recognition, where a large open-access database is available, only limited medical datasets are available. Extensive processes are required to anonymize medical data and make them available for use in machine learning models. Despite these challenges, AI's supportive role, aiming to enhance, not replace, human expertise, presents promising advancements in rehabilitation.

VI. CONCLUSION

This paper considers technologies for rehabilitation from various points of view. It is well known the impact of rehabilitation therapies on patients as well as on the health care system. Rich countries can pay hundreds of billions per year to cover the need of their citizens. While rehabilitation therapies are almost as old as the medicine practices, during the last two decades, rehabilitation techniques have been largely improved by introducing new technologies such as machine learning, cutting-edge electronic devices, advanced signal processing approaches, etc. Through this study, we considered four major research fields recently introduced in rehabilitation therapies. The need of our societies for such therapies will continue to increase. The budget allowed for such medical acts will also be soaring.

APPENDIX

A. Publication Tables

The number of publications on rehabilitation related to specific biomedical signals from 2007 to 2024 is shown in Tables 3 and 4. The number of publications on wearable devices for rehabilitation related to acquired body signals from 2007 to 2024 is listed on Table 5.

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TABLE 3. Number of publications on rehabilitation related to specific biomedical signals. Data on this table were obtained using a research done on Google Scholar on May 6, 2025.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015
ECG	1220	1540	1570	1550	1730	1960	2230	2460	2510
EEG	1110	1390	1360	1560	1380	1920	2030	2000	2120
EMG	2470	2790	3190	3260	3970	4340	5100	5480	5680
Galvanic	161	254	225	277	366	417	482	517	533
Complex	5290	5750	6550	7410	8730	10700	11600	13000	13600
VR	17300	17300	18100	18100	18300	18500	19100	18600	18600

TABLE 4. Number of publications on rehabilitation related to specific biomedical signals. Data on this table were obtained using a research done on Google Scholar on May 6, 2025.

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024
ECG	2000	2130	2130	2390	2150	2450	2680	2650	2600
EEG	2460	2910	3280	3710	4380	4790	5770	5370	5260
EMG	5970	6600	7370	7950	8280	9360	10400	10500	12100
Galvanic	572	620	782	819	849	932	961	955	915
Complex	14200	15400	16400	17500	18500	19400	20300	18600	22400
VR	18700	17000	18200	18300	18200	18600	18400	18800	19000

TABLE 5. Number of publications on wearable devices for rehabilitation related to acquired body signals. Data on this table were obtained using a research done on Scopus (left columns) and WoS (right columns) web servers on April 14, 2025.

Year	Scopus						WoS					
	EMG	ECG	EEG	PPG	ACC	IMU	EMG	ECG	EEG	PPG	ACC	IMU
2007	0	0	1	0	3	2	0	0	0	0	1	1
2008	0	0	2	0	7	1	0	0	1	0	5	1
2009	0	0	0	0	10	6	0	0	0	0	7	4
2010	3	0	0	4	10	8	0	0	0	0	6	4
2011	2	0	1	0	18	11	0	0	0	0	12	9
2012	4	0	2	1	11	10	3	0	2	1	12	10
2013	4	0	1	0	17	19	3	0	0	0	9	15
2014	10	1	4	4	24	23	5	1	1	4	15	15
2015	10	0	2	2	24	36	9	0	0	1	25	29
2016	14	0	1	3	29	33	11	0	2	2	23	33
2017	35	3	7	10	42	55	19	1	4	3	29	39
2018	21	0	10	5	45	66	19	0	4	4	39	59
2019	35	1	0	4	48	72	28	0	1	2	42	74
2020	21	1	6	1	51	112	17	0	6	1	42	103
2021	50	2	7	13	48	81	36	1	3	11	38	79
2022	48	3	8	5	51	125	37	0	5	7	49	99
2023	45	3	8	8	66	104	41	4	5	3	44	84
2024	78	5	6	11	67	147	48	3	3	5	45	109
Total	380	19	66	71	571	911	276	10	37	44	443	767

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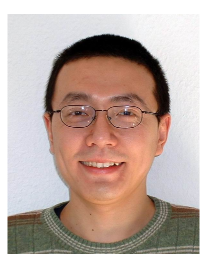

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