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AI-DRIVEN HUMAN–MACHINE INTERACTION FOR AUTONOMOUS MECHATRONIC PLATFORMS

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ABSTRACT

The purpose of this study is to examine the ways in which artificial intelligence (AI) algorithms may be incorporated into human–machine interface (HMI) frameworks. The goal is to increase autonomy, safety, and responsiveness in advanced mechatronic systems, including autonomous robots, intelligent vehicles, and industrial automation platforms. The most important features are the combination of sensors in real time, predictive control based on machine learning, natural language processing for simple communication, and haptic feedback for immersive operator experiences. Experimental validations and simulation studies show that operational efficiency, situational awareness, and human confidence in autonomous systems may all be substantially improved. According to the findings, artificial intelligence-enhanced human-machine interaction (HMI) is of critical importance for the future generation of mechatronic platforms, as it serves to close the gap between human purpose and the autonomous execution of machines.

Keywords: Artificial Intelligence (AI), Human–Machine Interaction (HMI), Autonomous Mechatronic Systems, Machine Learning, Sensor Fusion.

INTRODUCTION

A common technique in engineering is to address mechatronics in a subsystem capacity. via the utilisation of subsystems that are technologically similar (mechanics, electronics, control, and software), integrated systems are created via the process of subsystem-based product development. Because of the fact that they were built concurrently, subsystems highlight the links between them. After the interfaces have been specified, the next step is to create each subsystem in the normal manner.

For the purpose of correctly developing interfaces, there has been a focus placed on the development of teams in order to promote communication and multidisciplinary understanding among engineers with varying degrees of experience. Due to the fact that the subsystem-based approach is more integrated, it removes the need to build technologies such as computer science and automated control. It is the successful integration of technology that contributes to the performance of the mechatronic system. In spite of the fact that the development process and the construction of teams are not well covered in the literature on mechatronics engineering, the subsystem-based approach is widely used. After the first chapter provides a definition of mechatronics, subsequent chapters address a variety of topics, including modelling, sensors, actuators, control, computer hardware, interfaces, communication, and more.

The use of digital electronics makes it possible to develop or upgrade dynamic systems that are based on mechanical principles. The key fields of study that must be studied simultaneously are computer engineering, software engineering, control engineering, and mechanical engineering. The transfer of functionality from mechanical hardware to computer software is the most significant paradigm change that mechatronics has brought about, despite the fact that mechanical end-effecting components are still there.

When it comes to the design of mechatronics, there is more potential for flexibility in terms of how specific functionality is carried out (i.e., technology and partitioning). Transfer functions, data flows, and energy transmission are all determined by the manner in which operational functionality is performed. It is uncommon for implementation features to be addressed for the purpose of improving design since the decision on functionality partitioning and implementation technologies is made early on in the design chain. In order to make the situation better, there is an immediate need for theories, models, and procedures that may facilitate the modelling, analysing, synthesising, simulating, and prototyping of a wide variety of technological systems, including mechatronic systems specifically. In place of a bottom-up, ad hoc design, this need to result in a conceptual development plan that is developed from the top down.

Novel Exoskeletons for Assistance and Training

As a result of the fact that "soft robots" are able to comply with the safety features of users, they are being used in every element of robotic assistance and training. Koh et al. proposed a soft robotic elbow sleeve that used elastomeric and fabric-based pneumatic actuators. The elbow sleeve had comprehensive design characteristics and functionality. It was fascinating to see the intent-based actuation control method. On healthy individuals, surface electromyography (sEMG) was able to identify the user's intent, and all of the participants were able to control the elbow sleeve by employing electromyography. In order to improve hand function, Yap et al. used soft robotic gloves that were equipped with fabric-reinforced soft actuators. In order to enhance the force required for finger extension, they used elastic fabric and soft actuators. A pilot study conducted on stroke survivors found that the soft glove improved their grasping ability. Through the use of soft modules, Oguntosin et al. demonstrated the functioning of an exoskeleton in a manner that was relatively distinct. The exoskeleton is made up of elements that have been manufactured using 3D printing technology and has passive joints and gravity adjustment. The exoskeleton was developed with the purpose of providing precise reaching control in the context of neurorehabilitation for individuals who are motor impaired. Based on the findings of these papers, soft modules are advantageous for the process of rehabilitation.

Advanced Human-Machine Interfaces in Biomechatronic

It is necessary to have sophisticated human-machine interfaces (HMIs) in order to achieve harmony between mechatronic systems and people in the loop. Because they do not have sufficient human-machine interfaces (HMIs) for interpreting user motion intention and states and providing haptic feedback, many systems fail.

In order to perform continuous and simultaneous decoding of multi-joint dynamic arm movements, Liu et al. developed a multichannel surface EMG signal-based model.

Through the use of myoelectrically controlled upper-limb rehabilitation exoskeletons, injured arms were able to be controlled with ease. The researchers Zhang et al. used sEMG data to predict the kinematics of the shoulder and elbow simultaneously and continuously. They did this by using principal/independent component analysis and artificial neural networks for electromechanical connection. For the purpose of exoskeletons, prostheses, and arm rehabilitation, the objective was to create a human-machine interface that was both natural and intuitive. In order to quantify grip force and three-dimensional push-pull force, Wu et al. used both surface electromyography (sEMG) and generalised regression neural networks. This research focused on the regulation of force in the intelligent prosthetic hand, which used electromyography (EMG) and grip force sensors to measure the amount of force that is generated by the human hand. In light of the fact that all of the earlier investigations made use of EMG sensors, there must be a more effective method to get stable signals. Jiang et al. propose the use of polypyrene-coated nonwoven fabric sheets in the construction of electromyographic (EMG) sensors. It is possible to individualise the design and sew it onto an elastic band in order to get skin contact and control of the prosthetic hand. The performance of the sensors was comparable to that of EMG sensors that used Ag/AgCl electrodes.

Human-machine interfaces (HMIs) that are based on electroencephalography (EEG) work by using brain impulses rather than muscle signals. In several non-invasive BMIs, the extraction of EEG features was accomplished by the use of Fourier time-frequency techniques. When applied to multichannel EEG recordings, this approach proved to be challenging. In order to improve multi-channel EEG classification, Wang and Veluvolu developed evolutionary algorithms that optimise features in order to decrease dimensionality and keep information relevant to classes. According to their findings, the Fourier-based approach combined with the covariance matrix adaptation evolution strategy works very well. Invasive brain-machine interfaces, as opposed to scalp EEG-based BMIs, make use of high-quality brain impulses to improve the dexterity of robotic arms or prosthetic hands. In order to decode lower limb muscle activity and kinematics from cortical neural spike recordings made during stand/squat movements, Ma et al. found that monkeys were the most effective method. They carried out an exhaustive data analysis and uncovered new insights into invasive BMIs for the purpose of controlling complex biomechatronic systems respectively.

The development of human-machine interaction in mechanical engineering

1980 was the year when the subject of human-computer interaction was first addressed in a professional setting for the first time. Computer science, ergonomics, engineering psychology, cognitive science, and other subjects that are connected to it are all included in this interdisciplinary field. This concept has been rapidly gaining popularity in a wide range of diverse fields ever since the turn of the century, when it was first introduced. On the other hand, there is no definition that is widely acknowledged despite the fact that it may be divided into two categories, which are as follows: (2) The process of developing, implementing, and assessing interactive systems while taking into consideration the user's work needs and surrounds is referred to as "human-computer interaction," and the word "human-computer interaction" represents the process. (1) Human-computer interaction is an area of research that concentrates on the design, development, and implementation of interactive computing systems for human use. This topic of study is becoming more popular. In the field of mechanical engineering, the interaction between humans and machines often takes place via the following stages: the early manual operation stage, the stage of operation control language and command interaction language, the stage of graphical user interface, and the stage of network user interface.

Industrial HMIS Work

Industrial Human-Machine Interfaces, often known as HMIs, are the essential connection that makes it possible for operators to interact with complicated gear in industrial environments. Panel-mounted buttons and indicator lights are the most fundamental of these interfaces, while complex touchscreen systems that are linked with real-time monitoring, diagnostics, and control features are the most advanced. By providing a user-friendly platform that allows human operators to oversee, interact with, and modify machine processes in a safe and efficient manner, the primary objective of any industrial human-machine interface (HMI) is to fulfil its primary function. The way in which a human-machine interface (HMI) functions in a specific industrial application is significantly reliant on the kind of equipment or system that it controls. An example of this would be a basic conveyor belt system that uses an HMI to provide simple start/stop instructions and speed changes. On the other hand, an HMI for a CNC machine or a robotic assembly line may provide tiered access to diagnostic data, tool path settings, sensor feedback, and remote access possibilities.

The operation of human-machine interfaces (HMIs) in industrial settings entails the integration of various layers of hardware and software. Programmable logic controllers (PLCs), industrial sensors, and actuators that are linked throughout the machine or plant are often the sources of data that are received by the human machine interface (HMI). This information is then processed and presented in a graphical manner, which may include meters, graphs, alerts, and control buttons. This gives the operator the ability to monitor the condition of the system in real time and react immediately to any changes that transpire. Commands may be sent by a variety of input methods, including touch displays, push buttons, keypads, and even gesture-based or voice-enabled input systems. This information is then sent back via the control system, which is responsible for causing the machine to respond in the appropriate manner, whether it be mechanically or electrically. In contemporary implementations, human machine interfaces (HMIs) are also networked with supervisory control and data acquisition (SCADA) systems and industrial Internet of Things (IIoT) platforms. This connectivity enables centralised control, cloud-based analytics, and remote monitoring.

As a result of their frequent deployment in difficult settings, industrial human machine interfaces (HMIs) are required to be durable and dependable. These conditions often include dust, temperature changes, vibration, and electromagnetic interference. It is thus necessary for the design and functioning of an HMI to strike a balance between use and durability. In addition, user access levels are often controlled via the use of password security and operator-specific interfaces in order to guarantee that only appropriately authorised staff are able to make modifications to essential system settings. The continued development of human machine interfaces (HMIs) in industrial systems has resulted in considerable improvements in operational efficiency, decreased downtime via the use of predictive maintenance warnings, and increased safety by enabling operators to respond in a proactive manner. When taken as a whole, human-machine interfaces (HMIs) in industrial settings are crucial components in contemporary production and automation systems.

They translate complicated machine activities into control experiences that are accessible and controllable for human users. HMIs are available in a variety of styles, including the following:

- Membrane Switches and Keypads
- Metal Keyboards and keypads
- Capacitive Touch buttons
- Silicone Rubber Keypads
- Touch display screens

Commonly used Industrial HMIs

Operators are able to enter data and take action via the use of touch-screen alternatives, which include buttons, switches, and other buttons and keypads. In addition to a wide variety of various alternatives, such as dashboards with intricate gauges that display accurate consumption data, human machine interfaces (HMIs) are also capable of transmitting information to the operator via the use of indicators. Indicators are often employed to indicate whether or not an appliance is working or when certain tasks are operating. An operator is able to interact with and operate equipment via the use of a computer interface, which is just a link between the operator and the machine. This connection allows for the transmission of inputs and outputs between the two parties.

Examples and Uses for Industrial HMIs

The Human Machine Interface (HMI) may be a solitary terminal for a single machine or it can be distributed for applications that are more vast and complicated. It is common practice in industrial settings to use them for the purpose of controlling processes and equipment. This involves connecting machines, sensors, and actuators located on the floor to a variety of systems, which may include applications for both I/O and PLC. Integrated human machine interfaces (HMIs) that are capable of transferring data to cloud systems or enterprise systems make it possible to aggregate data from hundreds of machines in order to ease central monitoring and management of the whole operation of a facility.

In the manufacturing shop floor, human machine interfaces (HMIs) have the ability to give crucial information that enables operators to maximise efficiency. For instance, they may relocate staff to accommodate slower output in another area of the factory or fine-tune machine settings in order to address issues and increase performance. Human machine interfaces (HMIs) might be installed on the machine or device itself, or they could take the shape of a handheld or portable device, or they could be positioned in the central control room.

In addition to its use in the automotive and industrial sectors, human-machine interfaces are also used in a variety of other industries, including the following:

- Food processing
- Manufacturing of pharmaceuticals
- Oil and gas
- Mining operations
- SCADA systems
- Applications of robotics
- Transportation

And many more.

HMI in the form of Membrane Keypad for Microwave Oven

The vast majority of individuals make frequent use of human-machine interfaces (HMIs) in their day-to-day lives; nevertheless, they may not be aware that anytime they use keypads to configure their microwaves or alter the temperature control in their vehicles, they are using a human-machine interface that interacts with their appliances and automobiles. High-level interfaces (HMIs) are often more resilient and sophisticated interfaces that are used in industrial settings. These interfaces are able to manage the number and complexity of outputs and inputs that are required to operate factories or machines.

OBJECTIVES

1. To create AI-driven HMI designs that let people and machines work together and talk to each other without any problems.
2. To identify and evaluate the acquired electro-oculogram (EOG) signal as the function f(x) for further modeling and assessment.

RESEARCH METHOD

We will refer to the obtained EOG as f (x). In this signal, there is a baseline drift that is not connected to any eye movement that may be occurring. This drift may be attributed to either the polarisation of the electrodes or the fact that sweating causes changes in the contact impedance. A subject's movement, noise from power lines, and muscular activity all contribute to the presence of high-frequency noise in addition to the noise that is already there. The fact that our system makes use of dry sensors, as opposed to sensors that make use of wetting gel, is another factor that contributes to negatively impacting the quality of the signal. To add insult to injury, the absence of a ground truth signal, which is devoid of artefacts, makes it challenging to simulate the genuine electroencephalogram signal. As a result, a signal denoted by the symbol f (x) undergoes preprocessing in order to analyse an input noise, fluctuations, and baseline-drift. De-trending is another name for the process of removing linear trends from a signal, which is done at the beginning of the process. The function that is obtained by computing the least squares fit of a straight line to a signal f (x) and then subtracting the function from the data is accomplished. In Figure 1, both the raw signal that was recorded and its de-trended variation are shown.

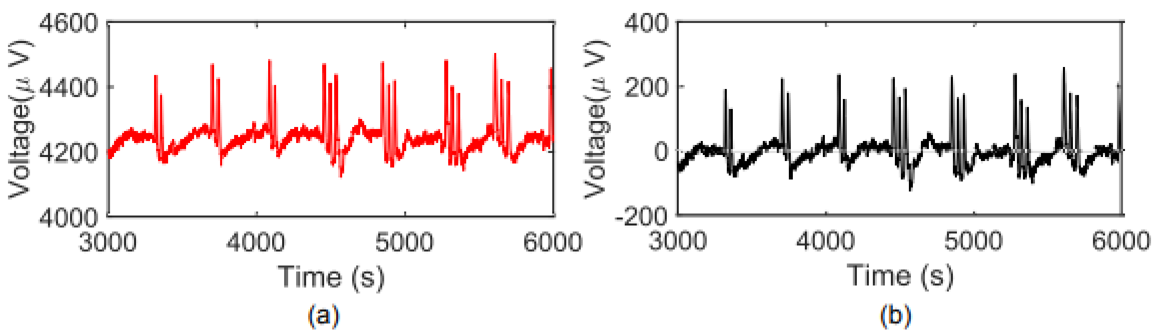


Figure. 1: The user's head was used to record EOG signals, which are shown below. The red waveform represents raw signals, whereas the black waveform represents de-trended signals.

In addition, a signal is denoised by using a Daubechies - 10 wavelet, which is characterised by ten vanishing moments and has a compact support of twenty samples. The decision to use the db-10 wavelet was made in order to enhance the smoothness of the signal, and it was based on preliminary experiments and comparisons with other wavelets.

A comparison is made between six different kinds of wavelets in order to determine which one is the most suitable. As a result of all of these wavelets, the output consisted of waveforms that had a maximum number of local peaks, which is not ideal for the threshold-based technique that we followed. This kind of forked output has the potential to be misinterpreted as a double blink, and as a result, it is not beneficial. It was discovered that the performance of the db-10 wavelet was superior than that of the Demay wavelet, despite the fact that the outputs from both wavelets are similar. Because of this, the selection of the db-10 wavelet was validated. The advantage of the dB-10 wavelet over other wavelets is seen in Figure (d). The difference between two signals was able to be seen once the de-noising process was completed.

The cooler black is used to symbolise a raw signal, whereas the colour blue is used to indicate a signal that has been smoothed out by noise. An important fact to learn is that wavelet de-noising helps increase the signal-to-noise ratio and contributes to the acquisition of a signal that is more distinct. Note the Figure.3.

After the signal has been smoothed, it is next put through a Butterworth band-pass filter of order four. After doing an analysis of the Power Spectral Density (PSD) of a signal, as seen in Figure 4 (a), the cut-off frequency, which ranged from 1 to 10 Hz, was determined. By lowering the 'cut-off', it is possible to remove baseline drift, and by raising the 'cut-off', it is possible to eliminate the influence of high-frequency noise. It is important to note that the use of a band-pass filter after the application of wavelet filtering led to the achievement of the necessary signal quality for the purpose of feature extraction. In comparison to the waveform that merely contains de-noised activity, which is represented by the blue-colored waveform, the magenta-colored waveform, which is a band that has been processed through the wavelet de-noising process, exhibits a trend that is smoother. This is seen in Figure 4 (b). The amplitude and duration values of voluntary and involuntary blinks for 41 participants are provided in Fig. 2. It is crucial to note that all of the signal waveforms that were utilised for illustration were taken from recorded data acquired from subject no. 7. These waveforms were chosen at random for the purpose of this presentation.

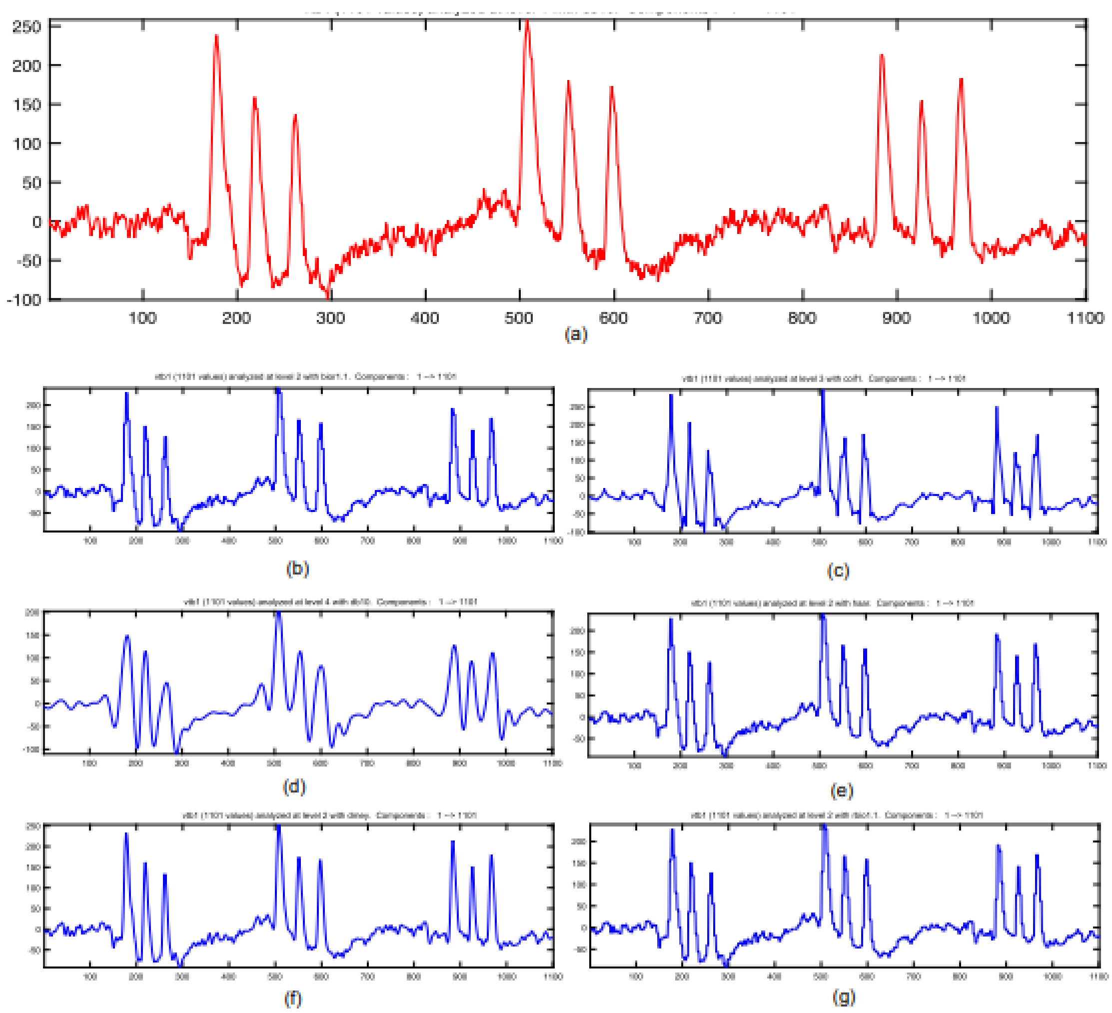


Figure 2: Figure shows de-trended, raw signal and its decomposition using different wavelets: a) Raw signal (red waveform) b) bior-1.1 wavelet at second level c) coif-1 wavelet at third level d) db-10 wavelet at fourth level e) h_{aar} wavelet at second level f) d_{mey} wavelet at second level g) rbio-1.1 wavelet

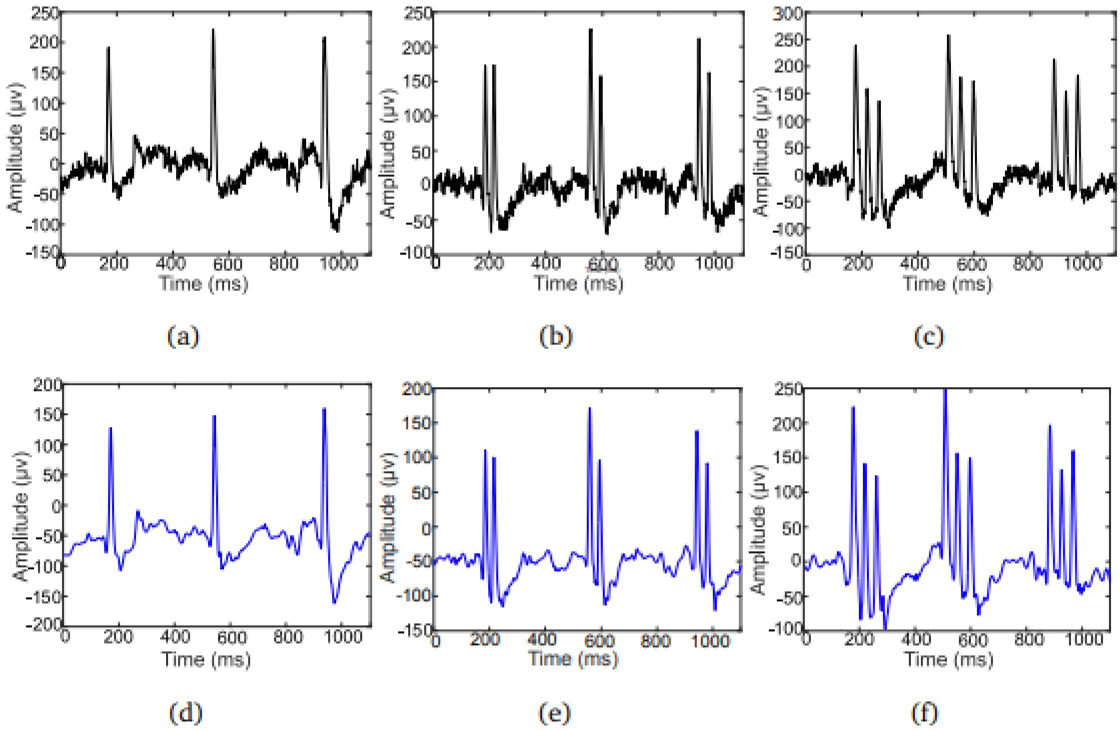


Figure. 3: Single, double, and triple voluntary blink waveforms (a-c) raw EOG signals. d-f exhibit wavelet-filtered EOG signals. The form is becoming clearer and smoother.

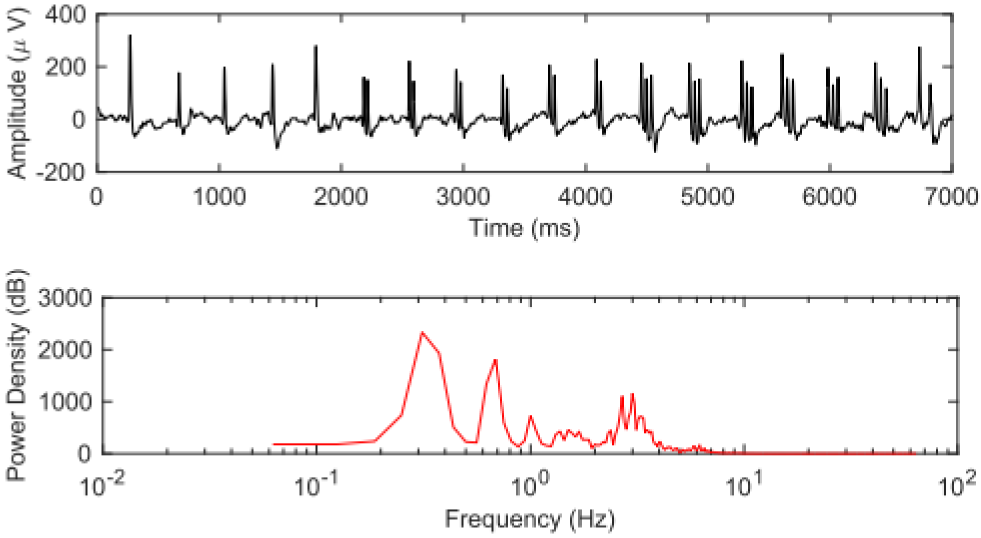
Feature Extraction and Blink Recognition

Band passing delays a signal, which must be adjusted before processing. Differentiation reveals aspects that are hard to see in raw form. Signals are further separated. The first-order derivative of a signal is Equation 1.

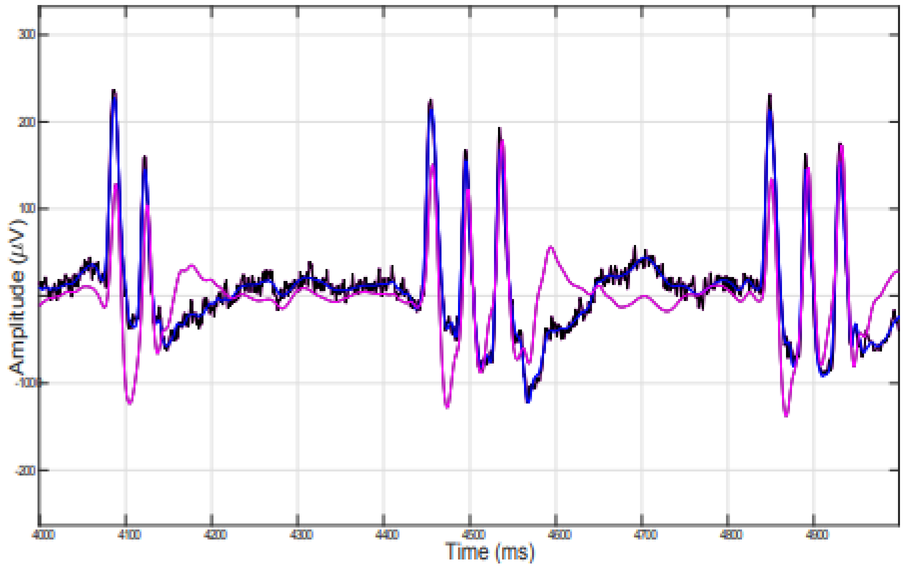
$$S = f_c(x) - f_c(x-1)$$

Where $f_c(x)$ is filtered EOG, and S is its first order differentiation with respect to time. along with its distinct waveform, which displays a variety of characteristics.

This picture depicts waveforms that exhibit unique and clearly recognisable characteristics, such as the speed, amplitude, and duration of the wave. A number of characteristics are retrieved from the data segment. These characteristics include the maximum amplitude of a filtered signal (Amax), the time length of a peak (tp), the peak amplitude of a differentiated signal (Smax), and the duration (dpn). tp is the amount of time that has passed from the beginning of an activity and the peak of a signal. When referring to the differentiated shape, the duration dpn is defined as the interval that extends from a peak to the crest of the form. Each of the three forms of voluntary blinks is shown in Figure 1. When it comes to a single blink, the same picture (a1 to a4) displays the filtered, wavelet de-noised, band-passed, and differentiated waveforms, respectively. similarly, for a double blink, you would use (b1 to b4), and for a triple blink, you would use (c1 to c4).



(a)



(b)

Figure. 4: A raw, de-trended EOG waveform (black) and power spectral density plot (red) is shown. PSD displays frequency components with log scale on the X-axis and amplitude in dB on the Y-axis. Raw (black), wavelet de-noised (blue), and band passed (magenta) EOG signals.

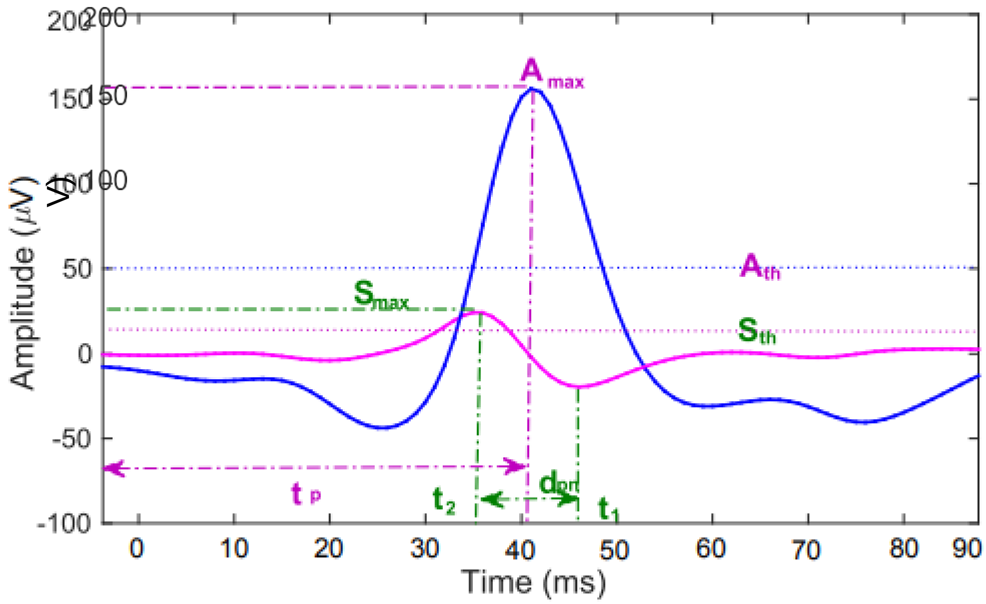


Figure. 5: A typical blink EOG and its distinct waveform demonstrate diverse qualities. A_{max}: maximum amplitude, A_{th}: threshold S_{max}: differentiated waveform maximum amplitude, S_{th}: threshold.

CONCLUSION

A major leap forward in the development and function of self-operating mechatronic platforms is the implementation of human-machine interface powered by artificial intelligence. These systems are able to deliver improved flexibility, safety, and efficiency via the integration of machine learning, sensor fusion, and predictive control. Multimodal communication and natural language processing increase the user experience and trust, while haptic feedback gives real-time operational awareness. The results provide verification that HMI boosted by artificial intelligence not only simplifies complicated jobs but also enhances the cooperation between people and machines. Research in the future need to concentrate on cross-domain applications, cybersecurity precautions, and scalable architectures in order to fully exploit the transformational potential of artificial intelligence in autonomous mechatronic systems.

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