

Advancements In Wearable Smart Devices for Biomedical Signal Processing: Technologies and Applications

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Abstract. This paper mainly discusses various technologies of wearable smart devices in biomedical signal processing, including hardware composition, biomedical signal types, signal processing technology, feature extraction, data analysis and result presentation. This paper introduces in detail the signal acquisition technology of PPG and EEG, as well as the signal preprocessing technology and EEG signal conversion process in brain-computer interface systems, including the function and working principle of PPG technology in various application scenarios such as heart rate monitoring, blood pressure monitoring, blood oxygen saturation monitoring and feature extraction of brain-computer interface equipment, and discusses the importance of feature extraction in the field of medical signal processing of intelligent wearable smart devices.

Keywords: Wearable smart device; signal processing; PPG; BCI; EEG; Biomedical signal.

1. Introduction

The use of wearable smart devices for tracking human medical health has been developed rapidly since the 21st century, bringing tremendous convenience in the field of healthcare, together with the development of the internet, artificial intelligence and big data. However, the concept of wearable smart devices can be traced back to the 1960s, proposed by a US mathematics professor, Edward O Thorp [1]. The wearable smart device is an accessory with interactivity and intelligence that can perform specific monitoring or supporting functions [1,2]. Some examples of wearable smart devices commonly used nowadays are smart watches, smart rings, smart glasses, electroencephalogram (EEG) headsets, etc. The different designs of wearable smart devices perform various functions, providing massive convenience to our daily lives and biomedical research. For example, smartwatches and smart rings are often used as fitness and sleep trackers as the cardiovascular system's activity is easily detected through the thin layer of skin on human hands. Smart glasses are indispensable in virtual reality (VR) technology and hand-free information display. EEG headsets can be applied to the Brain Computer Interface (BCI) technology to deal with the mind training of some patients with brain dysfunction. Some wearable smart devices strongly require portability and comfort properties, while others focus more on accuracy, instant analysis, etc.

2. Hardware of Wearable Devices

Usually, the hardware of a wearable smart device can be divided into three main components: (1) Biosensors that detect real-time health conditions and peripheral sensors that detect the surrounding environmental conditions. These sensors play the role of data collection and constitute the input of the smart device. (2) The computational hardware that analyzes the data input is typically formed by a microcomputer, enabling a preliminary medical diagnosis. (3) Customized clothing that supports the environment, cooperates with the sensor, or realizes a specialized function [2,3].

3. Signal Processing Technology

In general, signal conduct can be divided into four or five parts: Signal acquisition, signal transformation, feature extraction, data analysis, and some include feedback. The signal processing flow is shown in Fig. 1.

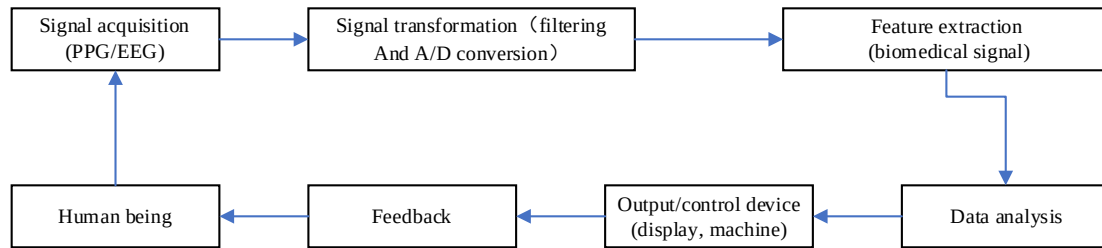


Fig. 1 Signal processing flow

3.1. Signal Acquisition

Wearable smart devices use a variety of sensors to capture physiological signals from the user's body. These sensors can include accelerometers, gyroscopes, optical sensors, and electrodes. The quality and accuracy of the acquired signals depend on several factors, including sensor placement, environmental conditions, and user behavior. For example, sensor placement must be optimized to ensure that the signals are captured accurately, while environmental conditions such as temperature and humidity can affect the performance of the sensors. User behavior, such as motion and posture, can also impact the quality of the signals captured. Therefore, these factors must be considered when designing wearable smart devices to ensure they can capture high-quality signals reliably.

To improve the accuracy and reliability of signal acquisition, advanced sensor fusion techniques can be employed. These techniques, such as Kalman filtering, use Bayesian estimation to combine data from multiple sources and account for uncertainties in the measurements [4,5].

3.1.1 Signal Acquisition of PPG

Photo Plethysmography (PPG) is a typical signal acquisition technology. This technology uses photoelectric detection to monitor the status of blood oxygen concentration, blood pressure, and breathing frequency. This monitoring technology does not require invasive procedures, thereby avoiding potential harm to the human body. It enables the development of non-invasive blood oxygen saturation monitoring models with simple and fast operation.

When light passes through human body tissue, it undergoes a complex process. Different structures and tissues, such as the epidermis, muscles, arterial blood, and veins, have varying absorptivity to light at different frequencies. The arterial pulse causes significant changes in light absorption at different frequencies at the test site, making it easy to measure. Therefore, blood oxygen saturation is usually determined based on arterial blood. The absorption of light by other tissues, such as skin, muscle, bone, and venous blood, is inevitable, and its measured value is the venous component or direct current component (DC). When the artery beats at the test site, the amount of light absorbed by each tissue also changes accordingly, resulting in the measurement of the arterial component or alternating current (AC). By measuring the amount of light absorbed through the tissue, the influence of non-blood tissue can be eliminated, allowing for the calculation of blood oxygen saturation.

3.1.2 Signal Acquisition of EEG

EEG signal is commonly used in the Brain-Computer Interface technology. Neuroscience studies have shown that the electrical activity of the brain's nervous system changes correspondingly after the generation of action consciousness and before the execution of the action or after external stimulation. This change can be detected by a specific means and used as a characteristic signal that the action is about to occur. By classifying and identifying these sign signals, the action intention that causes EEG changes can be distinguished. Through computer language programming, people's thinking activities can be transformed into command signals to drive external devices. Achieving the human brain's control of the external environment without the direct participation of muscles and peripheral nerves is the basic principle of signal acquisition under the brain-computer interface [6].

3.2. Signal Transformation

Raw signals collected by wearable smart devices are often contaminated with noise and artefacts that can arise from various sources, such as motion, environmental factors, or device malfunction. Preprocessing techniques are therefore necessary to remove these unwanted components and improve the quality of the signals. Standard preprocessing techniques include filtering, smoothing, and detrending. Filtering can be used to remove high-frequency noise, while smoothing can be used to reduce the impact of transient artefacts. Detrending can remove any linear or nonlinear trends in the data that may affect the accuracy of the subsequent analysis [7].

Fig. 2 shows the signal transformation flow. In the transformation of EEG signals in BCI technology, the system usually consists of a recording electrode, signal isolation amplifier, filter, analog-to-digital converter, etc. The subjects wear caps on their head to collect their EEG signal, EEG which is used as an information carrier of neuronal activity; in the signal acquisition step, selected input is recorded by the electrode and then sent to the magnifier to be amplified. Usually, the signal needs to be magnified about 10000 times. After the pretreatments, including the filtration and A/D conversion of the signal, it is finally translated to a digital signal that can be stored in the computer [6].

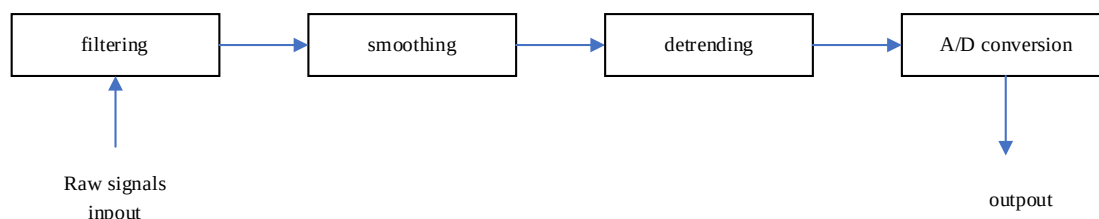


Fig. 2 Signal transformation flow

3.3. Feature Extraction

After preprocessing, the next step is featuring extraction, which involves extracting relevant information from the signals, including parameters such as heart rate, respiratory rate, and movement patterns. Feature extraction techniques include time-domain, frequency-domain, time-frequency domain analysis, wavelet transform, Principal Component Analysis (PCA), Independent Component Analysis (ICA), Nonlinear Dynamics, and Artifact Detection and Removal.

3.3.1 Key technologies

In the field of intelligent wearable smart devices for medical signal processing, feature extraction is a critical step that involves identifying and isolating meaningful information from the raw signals collected by the device. Here are some of the key technologies involved in this process, along with a detailed explanation of each:

1. Frequency Domain Analysis allows for the separation of signals into different frequency bands, which can help identify specific types of activity or abnormalities. Many medical signals, such as electrocardiograms (ECGs) and electroencephalograms (EEGs), contain frequency-specific information that can be extracted using Frequency Domain Analysis [5].
2. In the time domain, features such as amplitude, duration, and shape can be extracted from the signals. For example, the QRS complex in an ECG signal can be used to identify ventricular depolarisation. Time domain analysis is often used with frequency domain analysis to provide a more complete signal picture.
3. The features extracted by the first two methods are relatively simple and cannot represent the characteristics of typical non-stationary signals well. In contrast, the time-frequency combination method can extract the features of signals more accurately.
4. The wavelet transform is a powerful tool for analysing signals with non-stationary characteristics, such as those found in medical applications. It allows for the decomposition of signals

into different scales and resolutions, enabling the extraction of both time-domain and frequency-domain features simultaneously [7].

5. Principal Component Analysis (PCA) is a dimensionality reduction technique that can extract the most significant features from a set of signals. By projecting the signals onto a lower-dimensional subspace, PCA can help to reduce noise and redundancy while preserving the most critical information.

6. Independent Component Analysis (ICA) is a blind source separation technique that can separate mixed signals into their components. It is beneficial for applications where multiple signals are recorded simultaneously, such as in multi-channel EEG recordings [7].

7. Nonlinear dynamics techniques can provide insights into the underlying physiological processes and may help detect early signs of disease. For example, chaos theory and fractal analysis, can be used to extract features from signals that exhibit complex, nonlinear behaviour [6].

8. Artefact Detection and Removal is a crucial step in data preprocessing that involves identifying and removing unwanted or incorrect data points, known as artefacts, to enhance dataset quality and ensure reliable analysis. Artefacts, which can include motion or electrical interference, can significantly corrupt medical signals and bias feature extraction. To mitigate this issue, various techniques such as template matching, Kalman filtering, and spectral analysis can be employed to detect and eliminate artefacts prior to further processing, thereby improving the accuracy and reliability of the subsequent analysis [8].

By combining these and other techniques, intelligent wearable smart devices can extract various features from medical signals, enabling accurate monitoring, diagnosis, and treatment of various health conditions.

3.3.2 Application of feature extraction in various scenarios

Feature extraction is widely used in various scenarios of wearable devices, including applications based on EEG and PPG.

EEG-based feature extraction for various BCI scenarios involves recording the brain's electrical activity using electrodes placed on the scalp. The recorded signals are then processed and analysed to extract meaningful features that can be used to infer the user's cognitive state, intention, or behaviour. Here is a comprehensive overview of how EEG is used for feature extraction in different BCI applications:

1. EEG signals are recorded during sleep to extract features related to sleep stages and sleep quality. These features include time-domain characteristics like sleep latency, total sleep time, sleep efficiency and frequency-domain features such as power spectral density in different EEG frequency bands (delta, theta, alpha, sigma, beta, and gamma). Time-frequency domain analysis using wavelet transform can further reveal dynamic changes in sleep patterns.

2. EEG signals are recorded while the user performs tasks requiring concentration to extract features related to attentional focus. The time-domain signal can extract features such as amplitude, waveform length, and area under the curve. The frequency-domain analysis focuses on power spectral density and centre frequency of alpha and beta bands, which are associated with attentional processes. Time-frequency analysis using Short-Time Fourier Transform (STFT) or wavelet transform can provide insights into the temporal dynamics of attention.

3. EEG signals are recorded in response to visual stimuli to extract features related to visual processing. Visual evoked potentials (VEPs) are characterised by their latency and amplitude, which can be extracted from the time-domain signal. Frequency-domain analysis can be used to calculate the power spectral density of VEP signals. Time-frequency analysis using wavelet transform can reveal the time-varying characteristics of VEPs.

4. In motor imagery tasks, EEG signals are recorded while the user imagines performing a movement. Features related to event-related desynchronisation/synchronisation (ERD/ERS) are extracted from the mu (8-13Hz) and beta (13-30Hz) frequency bands. Time-domain features include the duration and intensity of ERD/ERS patterns, while frequency-domain features focus on power

spectral density changes. Time-frequency analysis using STFT, or wavelet transform provides insights into the temporal evolution of ERD/ERS patterns.

5. EEG signals are recorded in response to auditory stimuli to extract features related to auditory processing. Auditory evoked potentials (AEPs) are characterised by their latency and amplitude, which can be extracted from the time-domain signal. Frequency-domain analysis can be used to calculate the power spectral density of AEP signals. Time-frequency analysis using wavelet transform can reveal the time-varying characteristics of AEPs.

After feature extraction, further processing steps such as feature selection and optimisation are necessary to improve the performance of BCI systems. These steps help remove redundant and irrelevant features, thus enhancing the accuracy and reliability of BCI applications.

PPG technology plays a significant role in extracting features related to heart rate, blood pressure, blood oxygen saturation, and brain-computer interface (BCI) devices. Here is a detailed description of its main functions and working principles in each application:

1. PPG technology can measure the changes in light volume caused by the blood flow in vessels to obtain information about heart activity. It is called Heart Rate Monitoring. When the heart contracts, blood flows out of the heart and into the body, causing the vessels to dilate and the transmitted light to decrease; when the heart relaxes, blood flows back, causing the vessels to constrict and the transmitted light to increase. By analysing these changes in light volume, heart rate can be calculated.

2. PPG technology can measure pulse transit time (PTT), the time it takes for blood to travel from the heart to the measurement site. Pulse wave velocity is directly related to blood pressure, higher blood pressure results in faster pulse wave propagation, while lower blood pressure results in slower propagation. By establishing a characteristic equation and combining PTT with routine body parameters (such as height and weight), one can estimate the systolic and diastolic blood pressure, achieving non-invasive and continuous blood pressure measurement [3].

3. PPG technology can measure blood oxygen saturation (SpO₂), the percentage of oxygenated haemoglobin in the total haemoglobin available for binding. When the blood oxygen content increases, the binding capacity of haemoglobin with oxygen molecules strengthens, resulting in a decrease in transmitted light; conversely, when the blood oxygen content decreases, the binding capacity weakens, leading to an increase in transmitted light. Blood oxygen saturation can be calculated by analysing the changes in transmitted light.

4. PPG technology can be used in BCI devices to monitor physiological parameters such as heart rate, blood pressure, and blood oxygen saturation and extract features related to brain activity. These features can be used to decode brain signals and achieve brain-machine interaction. For example, by analysing heart rate variability (HRV), features related to autonomic nervous system activity can be extracted and used to control BCI devices [3,9].

In summary, PPG technology measures the changes in light volume caused by blood flow in vessels to extract features related to heart activity, blood pressure, blood oxygen saturation, and brain-computer interface devices, providing valuable information for health monitoring and BCI applications.

3.4. Data analysis

Once the features have been extracted, the next step is data analysis, which involves examining the data to identify patterns and trends. It can include statistical analysis, hypothesis testing, regression analysis, classification algorithms, clustering algorithms, time series analysis, machine learning, model validation and evaluation, interpretability and explainability, data fusion and data privacy and security.

1. Statistical techniques such as mean, median, standard deviation, variance, and correlation can describe the central tendency, dispersion, and relationships between features. These methods are essential for understanding data distribution and identifying potential trends or patterns.

2. To evaluate the significance of observed differences or relationships in the data, hypothesis testing methods such as t-tests, ANOVA, or chi-square tests can be applied. These tests help determine whether any observed variations are due to chance or genuine effects.

3. Regression analysis is used to model the relationship between one or more independent variables (features) and a dependent variable (e.g., disease status, patient outcome), which can help in predicting future outcomes or understanding the influence of different factors on the target variable.

4. Classification algorithms such as decision trees, support vector machines (SVMs), k-nearest neighbours (k-NN), and neural networks categorise patients or signals into different classes based on the extracted features. These algorithms are crucial for disease diagnosis, patient stratification, or activity recognition [2].

5. Unsupervised learning techniques like clustering algorithms (e.g., k-means, hierarchical clustering) can group similar signals or patients based on shared characteristics. It can reveal underlying patterns or subtypes within the data that may not be immediately apparent.

6. For signals that vary over time, time series analysis techniques can be employed to identify trends, seasonal patterns, and periodic changes. Methods like moving averages, exponential smoothing, and ARIMA models are commonly used for forecasting and trend analysis.

7. Advanced machine learning techniques, such as Machine Learning and Deep Learning, can be applied to medical signal data to extract complex patterns and relationships. Convolutional neural networks (CNNs) are handy for image-based signals, while recurrent neural networks (RNNs) and extended short-term memory networks (LSTMs) are effective for analysing sequences of data with temporal dependencies [5].

8. It is crucial to validate and evaluate the performance of any analytical model using appropriate metrics such as accuracy, sensitivity, specificity, precision, recall, F1 score, ROC-AUC, etc. Cross-validation, bootstrapping, and permutation tests are some standard techniques used for this purpose [5].

9. As medical decisions made by wearable smart devices can have significant consequences, there is a growing emphasis on the interpretability and explainability of the models. Techniques like Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive exPlanations (SHAP) can help understand how different features contribute to the model's output.

10. In situations where multiple data sources are available (e.g., multiple sensors on a wearable smart device), data fusion techniques can combine the information from different sources to improve the overall accuracy and reliability of the analysis.

11. When dealing with sensitive medical data, it is essential to ensure patient privacy and data security. Data anonymisation, encryption, and access control must be implemented to comply with regulations and protect patient confidentiality [2].

These technologies form the backbone of data analysis in medical signal processing for intelligent wearable smart devices, enabling accurate monitoring, early detection of abnormalities, personalised healthcare, and improved patient outcomes.

3.5. Feedback

In wearable smart device signal processing, the final step of feedback involves various techniques to improve the user experience and the accuracy of the device's responses. Here are some of the key technologies involved in this step:

1. Adaptive Feedback Control involves adjusting the feedback the wearable smart device provides based on the user's response or behaviour. For example, suppose a user is not responding well to a particular type of vibration feedback. In that case, the device may automatically adjust the intensity or pattern of the vibration to suit their needs better.

2. Machine learning can analyse user behaviour patterns and preferences over time, allowing the wearable smart device to provide more personalised feedback. For instance, a fitness tracker may learn that the user tends to move more during certain times of the day and adjust its activity goals accordingly.

3. The design and layout of the wearable smart device's user interface can significantly impact the effectiveness of feedback. Techniques such as visual, auditory, and haptic feedback can be optimised to convey information to the user clearly and intuitively.

4. Wearable smart devices can use sensors and data analysis to determine the user's current context (e.g., whether they are walking, running, or sitting) and provide relevant feedback to that context. For example, a smartwatch may vibrate differently when the user receives a call while driving compared to when they are at home.

5. To provide timely and accurate feedback, wearable smart devices must be able to process data in real-time, which requires efficient algorithms and hardware optimisations that can quickly handle large amounts of data without compromising battery life.

6. Wearable smart devices must also consider issues related to privacy and security when collecting and using personal data to provide feedback. Techniques such as data encryption, secure authentication, and anonymisation can help protect users' sensitive information.

7. By analysing the user's biomechanics (e.g., joint angles and muscle activity), wearable smart devices can provide feedback more closely aligned with their physical capabilities and limitations, which can help improve the accuracy and effectiveness of fitness training and rehabilitation programs [10].

8. Wearable smart devices can often integrate with other devices in the user's ecosystem (e.g., smartphones, smart TVs, etc.) to provide a more seamless and comprehensive feedback experience. For example, a wearable smart device may send notifications to the user's phone or display workout statistics on a smartwatch while they exercise.

9. Continuous feedback can consume significant power and shorten the wearable smart device's battery life. Therefore, effective battery management techniques are necessary to balance the need for real-time feedback with the need to conserve power. It may involve optimising algorithms, reducing the frequency of sensor readings, or using low-power modes when possible.

4. Conclusion

Wearable smart devices involve emerging technologies intersecting multiple disciplines, including neuroscience, signal detection, signal processing, and pattern recognition. The research on biomedical signal processing technology collected by these devices has important theoretical significance and broad application prospects. Due to the late development of the application technology of wearable smart devices, the corresponding theories and algorithms are not mature, and the research on its application is not perfect, so more scientific and technological workers are required to devote themselves to the research work in this field. The speed of signal processing and information conversion needs to be further improved, especially the accuracy of source signal extraction, which is beneficial to improving signal classification and processing speed and accuracy. The accuracy also needs to be further improved. Due to the limitation of signal acquisition accuracy and computing ability of wearable equipment, the improvement of biomedical signal, signal processing and information conversion speed contradicts the improvement of accuracy. Practical application can only be a compromise between the two.

There is still a gap between BCI technology and practical requirements. The current EEG technology is only suitable for laboratory research and application and sometimes needs the help of technicians. In the future, BCI will further develop in the direction of practicality.

Overall, the application field of wearable smart devices needs to be continuously expanded and combined with various technologies to increase its application scenarios.

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