Signal Processing for Motion Artifact Removal and Noise Reduction

Signal processing is an important part of wearable biomedical devices because physiological signals such as **ECG (Electrocardiogram), PPG (Photoplethysmography), and accelerometer signals** are easily affected by noise and motion artifacts. Wearable devices are used while a person is walking, running, exercising, sleeping, or performing daily activities. During these activities, movement of the body and changes in contact between the sensor and skin can introduce unwanted components into the recorded signal. If these unwanted components are not removed, they can affect feature extraction, heart-rate estimation, activity recognition, fall detection, and other healthcare applications. Therefore, suitable signal-processing techniques are required to improve the quality and reliability of wearable sensor data.

1. Noise and Motion Artifacts in Wearable Signals

Biomedical signals obtained from wearable sensors contain both useful physiological information and unwanted disturbances. **Noise** refers to unwanted electrical or environmental components that interfere with the desired signal. Common sources include power-line interference, electromagnetic interference, sensor electronics, and thermal noise. **Motion artifacts** are unwanted signal variations caused by physical movement of the user, movement of the sensor, or changes in sensor-skin contact. Motion artifacts are particularly significant in wearable ECG and PPG systems because the sensors are attached to the moving body.

In an ECG signal, motion may cause changes in electrode contact and electrode impedance. This can introduce baseline fluctuations and large amplitude disturbances. In PPG, motion is even more problematic because the signal is obtained by measuring changes in light absorption caused by blood volume changes. Movement of the wrist, fingers, or sensor can change the amount of light reaching the photodetector and produce variations that are not related to blood circulation. Accelerometers are often used along with ECG or PPG sensors to identify the user's movement and help remove motion-related components.

2. Signal Processing Pipeline

A typical wearable signal-processing system consists of several stages. The basic processing sequence can be represented as:

Sensor → Signal Conditioning → Filtering → Motion Artifact Detection → Artifact Removal → Feature Extraction → Classification/Monitoring

First, the physiological signal is acquired using an appropriate sensor. The raw signal is generally very small and may contain noise. Therefore, amplification and initial conditioning are performed. The signal is then passed through appropriate filters to remove unwanted frequency components. Motion information obtained from an accelerometer can be used to identify periods of movement and estimate motion artifacts. Advanced algorithms can then suppress these artifacts while preserving important physiological information. The cleaned signal can subsequently be used for feature extraction and machine-learning applications.

3. Filtering Techniques

Filtering is one of the simplest and most commonly used techniques for noise reduction. A **low-pass filter** allows low-frequency components to pass while reducing high-frequency

noise. It can be used to remove high-frequency disturbances from ECG or PPG signals. A **high-pass filter** removes very low-frequency components such as baseline drift. A **band-pass filter** combines the characteristics of high-pass and low-pass filters and allows only a selected range of frequencies to pass. For example, an ECG processing system may use a suitable band-pass range to reduce baseline wander and high-frequency noise while preserving important cardiac components.

A **notch filter** is commonly used to reduce power-line interference. Electrical equipment can introduce interference around the power-line frequency, typically 50 Hz in India. A notch filter is designed to suppress a narrow frequency band around this interference while retaining most of the useful signal. However, filter parameters must be selected carefully because excessive filtering can remove important physiological information.

4. Baseline Wander Removal

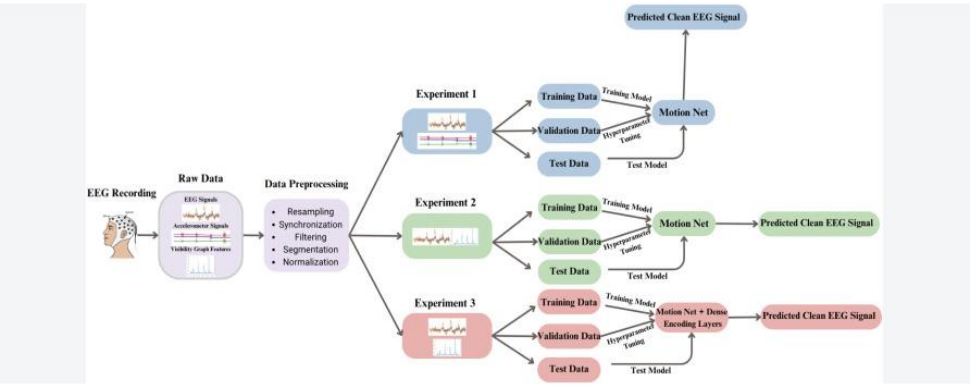
Baseline wander is a low-frequency variation in a biomedical signal. It can occur because of respiration, body movement, electrode movement, or changes in sensor contact. In ECG, baseline wander can make it difficult to identify the P wave, QRS complex, and T wave accurately. In PPG, slow variations can also affect the detection of pulse characteristics.

Baseline wander can be reduced using a high-pass filter, moving-average filtering, polynomial fitting, or adaptive techniques. The objective is to remove the slowly changing baseline while retaining the actual physiological waveform. Care must be taken because aggressive baseline correction may distort the morphology of the signal. Proper selection of filter characteristics is therefore important for reliable biomedical signal analysis.

5. Motion Artifact Removal Using Accelerometer Data

One of the important techniques in wearable signal processing is the use of an **accelerometer as a reference sensor**. The accelerometer measures body movement along different axes, such as X, Y, and Z. When a person moves, the accelerometer records the corresponding motion. This information can be used to identify whether an ECG or PPG disturbance is caused by actual physiological activity or motion.

For example, consider a smartwatch measuring PPG while a person is running. The PPG signal contains the pulse waveform, but wrist movement introduces additional variations. At the same time, the accelerometer records the movement of the wrist. The accelerometer signal can therefore be used as a reference for estimating the motion component present in the PPG signal. Signal-processing algorithms can then reduce the correlated motion component from the PPG signal.



6. Adaptive Filtering

Adaptive filtering is an effective method for removing motion artifacts because the characteristics of motion noise can change continuously. Unlike a fixed filter, an adaptive filter automatically changes its parameters according to the input signal.

In a typical adaptive filtering system, the physiological signal is treated as the primary input and the accelerometer signal is used as the reference input. The adaptive filter estimates the noise component that is correlated with the accelerometer signal. This estimated noise is then subtracted from the primary signal.

The basic concept can be represented as:

Primary Signal = Desired Physiological Signal + Motion Noise

Accelerometer Signal → Adaptive Filter → Estimated Motion Noise

Clean Signal = Primary Signal − Estimated Motion Noise

Adaptive filtering is useful in wearable devices because human movement is not constant. For example, a person may remain stationary for some time, walk slowly, and then start running. The characteristics of the motion artifact change during these activities, and the adaptive algorithm can adjust accordingly.

7. Wavelet-Based Noise Reduction

Wavelet transform is another useful technique for biomedical signal denoising. Unlike traditional Fourier analysis, wavelet analysis provides information about both time and frequency. This is particularly useful for biomedical signals because physiological events occur at specific time intervals.

In wavelet-based denoising, the signal is decomposed into different frequency levels. Components mainly associated with noise can be reduced or removed using thresholding. The remaining components are reconstructed to produce a cleaner signal. Wavelet techniques are widely applicable to ECG and PPG because important features such as QRS complexes and pulse peaks can be preserved while reducing noise.

8. Moving Average and Median Filtering

Simple digital filters such as **moving-average filters** can be used to smooth noisy sensor signals. In a moving-average filter, several consecutive samples are averaged to produce a smoother output. This can reduce random fluctuations in the signal. However, a very large averaging window may smooth out important physiological features.

A **median filter** replaces each sample with the median value of a group of neighboring samples. It is particularly useful for removing sudden spikes or impulse noise. Median filtering can be useful when the signal contains isolated abnormal values caused by sensor disturbances. The filter size should be selected carefully to avoid changing the shape of important physiological features.

9. Signal Quality Assessment

Before using a processed signal for medical analysis, its quality should be evaluated. Signal quality assessment determines whether the signal contains sufficient physiological information for further processing. Parameters such as **signal-to-noise ratio (SNR), correlation, amplitude stability, baseline stability, and waveform morphology** can be considered.

For example, if an ECG signal has a high level of motion artifact, an algorithm may identify that particular segment as poor-quality data instead of using it for heart-rate or arrhythmia analysis. Similarly, a PPG system may reject signal segments collected during intense motion if reliable pulse information cannot be obtained. Signal-quality assessment is therefore an important step in wearable healthcare systems.

10. Importance in Wearable Healthcare Applications

Motion artifact removal and noise reduction are essential for many wearable healthcare applications. In **heart-rate monitoring**, a clean ECG or PPG signal improves the accuracy of heart-rate estimation. In **activity recognition**, accelerometer signals must be processed to distinguish activities such as walking, running, sitting, and standing. In **fall detection**, reliable motion signals are necessary to identify sudden changes in acceleration and body orientation. In **anomaly detection**, noise reduction helps machine-learning models distinguish genuine physiological abnormalities from sensor-related disturbances.

The quality of the processed signal also directly affects machine-learning performance. If noisy data are used for training, the model may learn unwanted patterns instead of meaningful physiological features. Therefore, preprocessing and artifact removal are important before feature extraction and model development.

11. Example of a Wearable ECG/PPG System

Consider a smartwatch designed for continuous heart-rate monitoring. The device contains a PPG sensor and a three-axis accelerometer. When the user is sitting, the PPG signal is relatively stable and the heart-rate waveform can be extracted easily. When the user starts running, wrist movement introduces strong motion artifacts. The accelerometer detects this movement, and an adaptive filtering algorithm uses the accelerometer information to estimate the motion component. The estimated artifact is removed from the PPG signal. Additional band-pass filtering can further reduce unwanted frequency components. The cleaned signal is then processed to detect pulse peaks and calculate heart rate.

A similar approach can be used for wearable ECG systems. Electrodes acquire the ECG signal, while an accelerometer provides information about body movement. Filtering and adaptive artifact-removal algorithms can reduce motion-related interference. The processed ECG can then be used for QRS detection, heart-rate calculation, and other physiological analyses.