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Biomedical signal processing for public health applications: a review of monitoring, detection, and diagnostic technologies

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ABSTRACT

Biomedical signal processing plays an important role in modern healthcare by transforming physiological signals into meaningful information for health monitoring, disease detection, and clinical diagnosis. Signals such as electrocardiograms (ECG), electroencephalograms (EEG), photoplethysmograms (PPG), and respiratory measurements provide valuable information about human physiological conditions. Advances in digital signal processing, feature extraction, pattern recognition, and machine learning have improved the ability to analyze these signals automatically and support continuous health assessment. This review examines fundamental biomedical signal processing techniques and their applications in public health, with particular attention to physiological monitoring, abnormality detection, diagnostic technologies, and wearable health systems. It also discusses technical challenges associated with signal noise, individual variability, computational limitations, and clinical validation. The review highlights the potential of biomedical signal processing to support accessible healthcare, early disease identification, remote monitoring, and population health management. All reviewed literature was published no later than 2013.

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1. INTRODUCTION

Biomedical signals provide important information about the physiological and functional conditions of the human body. These signals are generated by biological processes and can be acquired using various sensors and medical instruments, including electrocardiography (ECG), electroencephalography (EEG), pulse oximetry, and respiratory monitoring devices. Their analysis enables healthcare professionals to identify physiological abnormalities, evaluate disease progression, and support clinical decision-making.

Biomedical signal processing involves the acquisition, preprocessing, analysis, and interpretation of physiological measurements using digital signal processing techniques. Its development has enabled automated extraction of relevant information from complex biological signals that may be difficult to interpret through conventional visual inspection. Signal processing methods are particularly valuable for analyzing non-stationary physiological data, identifying abnormal patterns, and supporting continuous patient monitoring.

The relevance of biomedical signal processing extends beyond individual clinical diagnosis to broader public health applications. Continuous monitoring and automated detection technologies can support early identification of health abnormalities, remote healthcare delivery, and improved monitoring of populations with limited access to medical facilities. This review examines the principal technologies, analytical methods, applications, and challenges of biomedical signal processing based on literature published up to 2013.

2. BIOMEDICAL SIGNAL ACQUISITION AND PROCESSING TECHNOLOGIES

Reliable biomedical signal analysis begins with appropriate acquisition and preprocessing because physiological measurements frequently contain noise, artifacts, and variations caused by biological and environmental conditions. Different signal acquisition technologies are designed to capture specific physiological activities, depending on the intended monitoring or diagnostic application. The resulting measurements must be processed carefully before meaningful physiological characteristics can be extracted.

2.1. Electrocardiogram and cardiovascular signal processing

ECG is one of the most widely used biomedical signal acquisition technologies because it records the electrical activity of the heart. ECG signals provide information about heart rate, cardiac rhythm, electrical conduction, and abnormalities associated with cardiovascular conditions. Digital ECG processing enables automated identification of characteristic waveform components and supports the detection of abnormal cardiac events.

Pan and Tompkins [1] introduced an influential real-time QRS detection algorithm based on digital filtering, differentiation, integration, and adaptive thresholding. Their approach demonstrated that digital signal processing could reliably identify QRS complexes in long-duration ECG recordings, providing an important foundation for automated cardiac monitoring. Subsequent research expanded ECG analysis toward arrhythmia classification, heart rate variability assessment, and intelligent diagnostic systems.

Hegde *et al.* [2] reviewed ECG signal processing and heart rate variability analysis, emphasizing the importance of extracting physiological information from cardiac signals. Sansone *et al.* [3] further examined artificial neural networks and support vector machines for ECG pattern recognition and classification. These developments demonstrate the potential of combining conventional signal processing with computational intelligence for automated cardiovascular assessment.

2.2. Electroencephalogram signal processing

EEG measures electrical activity generated by the brain and is widely applied in neurological investigation and monitoring. EEG signals contain complex temporal and frequency characteristics associated with different physiological and neurological states. Their analysis can support the identification of abnormal brain activity, including epileptic seizures and other neurological conditions.

EEG preprocessing commonly involves filtering, artifact removal, segmentation, and normalization to improve signal quality. Frequency-domain analysis, time-frequency techniques, wavelet transforms, and statistical feature extraction can subsequently be used to characterize brain activity. Acharya *et al.* [4] reviewed automated EEG analysis for epilepsy and highlighted the potential of computational methods to distinguish normal and abnormal electrical activity.

Automated EEG analysis is particularly relevant when prolonged recordings generate large volumes of physiological data. Signal classification techniques can assist in identifying abnormal patterns and reducing the workload associated with manual interpretation. Nevertheless, EEG interpretation remains challenging because of signal variability, artifacts, and differences in neurological characteristics between individuals.

2.3. Photoplethysmography and physiological monitoring

Photoplethysmography (PPG) is an optical measurement technique used to detect changes in blood volume within peripheral tissues. It is commonly implemented in pulse oximeters and other non-invasive monitoring devices to obtain information about pulse activity and cardiovascular conditions. Allen [5] described the physiological principles and clinical applications of PPG, demonstrating its value as a relatively simple and accessible measurement technology.

PPG signal processing involves detecting pulsatile components, removing baseline variations, and identifying waveform characteristics associated with cardiovascular activity. These measurements can support heart rate estimation, pulse monitoring, and oxygen saturation assessment when combined with appropriate optical measurement techniques. Its relatively simple sensor configuration makes PPG particularly suitable for portable and wearable monitoring applications.

2.4. Wearable and remote biomedical monitoring

Wearable biomedical monitoring systems integrate physiological sensors, signal acquisition circuits, processing units, and communication technologies into portable devices. These systems can continuously collect physiological information while individuals perform daily activities, creating opportunities for remote monitoring outside conventional healthcare facilities. Baig *et al.* [6] reviewed wearable and wireless ECG

monitoring systems, particularly their potential for monitoring older adults and individuals requiring continuous cardiovascular assessment.

Wearable monitoring systems commonly employ ECG, PPG, accelerometers, temperature sensors, and other physiological measurement technologies. Signal processing algorithms are used to identify relevant physiological patterns, detect abnormal events, and generate information for remote healthcare applications. Banaee *et al.* [7] highlighted the growing role of wearable sensors and data analysis techniques in health monitoring systems, including the challenges of processing continuous sensor data.

3. FUNDAMENTAL BIOMEDICAL SIGNAL PROCESSING METHODS

Biomedical signal processing uses several complementary analytical techniques to transform raw physiological measurements into meaningful information. The principal processing stages generally include signal preprocessing, feature extraction, feature selection, and classification or interpretation. The effectiveness of these methods depends on signal characteristics, measurement quality, computational requirements, and the intended clinical application.

3.1. Signal preprocessing and noise reduction

Signal preprocessing is essential because biomedical measurements are frequently affected by noise, motion artifacts, baseline fluctuations, and interference from external electrical sources. Digital filters, including low-pass, high-pass, and band-pass filters, are commonly applied to remove unwanted frequency components while preserving relevant physiological information. Adaptive filtering and artifact correction techniques can provide additional improvements when interference changes over time.

Appropriate preprocessing is important because excessive filtering may remove clinically relevant signal characteristics. For example, ECG waveform morphology can be affected by inappropriate filter configurations, potentially reducing the accuracy of subsequent abnormality detection. Therefore, preprocessing parameters should be selected according to the physiological signal and the diagnostic features being investigated.

3.2. Feature extraction and signal characterization

Feature extraction identifies representative characteristics that describe the physiological information contained in a biomedical signal. Time-domain features include amplitude, duration, intervals, waveform morphology, and statistical measurements, while frequency-domain features describe spectral distributions and dominant frequency components. Time-frequency analysis provides additional information for signals whose characteristics change over time.

Wavelet transforms, Fourier analysis, statistical methods, and nonlinear analysis are among the techniques used for biomedical feature extraction. These methods can help characterize cardiac rhythms, EEG activity, respiratory patterns, and other physiological conditions. The selection of appropriate features is essential because irrelevant or redundant characteristics may reduce classification performance and increase computational complexity.

3.3. Pattern recognition and intelligent classification

Pattern recognition techniques support the automatic interpretation of physiological signals by identifying similarities and differences between signal characteristics. Artificial neural networks, support vector machines, decision trees, and statistical classifiers have been investigated for detecting and classifying biomedical signal abnormalities. Sansone *et al.* [3] demonstrated the relevance of neural networks and support vector machines in ECG pattern recognition and analysis.

Intelligent classification can support automated identification of arrhythmias, epileptic activity, and other physiological abnormalities. These methods can reduce dependence on manual signal inspection and provide decision-support information for healthcare professionals. However, their performance depends on representative training data, appropriate feature selection, and validation using independent patient populations.

4. PUBLIC HEALTH APPLICATIONS

Biomedical signal processing has significant potential to strengthen public health services through continuous physiological monitoring, early abnormality detection, and improved access to diagnostic technologies. Its applications are particularly relevant for chronic disease management, neurological monitoring, remote healthcare, and population-level health assessment. These technologies can complement conventional healthcare services by providing physiological information beyond occasional clinical examinations.

4.1. Cardiovascular disease monitoring and detection

Cardiovascular diseases require continuous or repeated monitoring because important physiological abnormalities may occur outside clinical environments. ECG processing can support the identification of abnormal heart rhythms, changes in cardiac activity, and potentially dangerous events requiring medical attention. Automated QRS detection and ECG classification provide important technological foundations for these applications.

Wearable and wireless ECG systems can extend cardiovascular monitoring into homes and community settings. Such systems may improve the availability of physiological measurements for individuals who require regular monitoring or have limited access to healthcare facilities. Nevertheless, automated detection should be considered a support mechanism rather than a replacement for comprehensive clinical assessment.

4.2. Neurological monitoring and early detection

EEG processing provides opportunities for monitoring neurological conditions through the analysis of brain electrical activity. Automated seizure detection can help identify abnormal neurological events during prolonged monitoring and may support timely clinical intervention. Acharya *et al.* [4] demonstrated the importance of signal analysis and intelligent classification in automated EEG-based epilepsy assessment.

Portable and wearable EEG systems may further extend neurological monitoring beyond specialized clinical environments. Balanou *et al.* [8] reviewed wearable EEG technologies and discussed their potential for personalized health applications. However, practical implementation requires reliable signal acquisition, comfortable sensor configurations, and validated algorithms that can operate under real-world conditions.

4.3. Remote patient monitoring and community healthcare

Remote patient monitoring uses physiological sensors and communication systems to collect health information outside conventional healthcare facilities. Biomedical signal processing enables continuous measurements to be converted into interpretable physiological indicators and potential abnormality alerts. Banaee *et al.* [7] highlighted the growing importance of wearable sensor technologies and intelligent data analysis in health monitoring systems.

These technologies may support community healthcare programs by enabling the monitoring of individuals with chronic conditions, older adults, and populations living far from healthcare facilities. Remote monitoring can also facilitate earlier identification of physiological changes and provide additional information for healthcare professionals. However, successful implementation requires reliable communication infrastructure, appropriate clinical response procedures, and affordable monitoring devices.

4.4. Preventive healthcare and population health assessment

Biomedical signal processing can contribute to preventive healthcare by enabling the repeated assessment of physiological indicators over extended periods. Continuous measurements may help identify changes in cardiovascular activity, sleep patterns, physical activity, and other health-related characteristics. Aggregated and appropriately anonymized physiological information may also support research into population health trends and preventive intervention strategies.

Nevertheless, individual physiological measurements cannot automatically be interpreted as indicators of population-level disease prevalence. Meaningful public health applications require representative sampling, appropriate clinical interpretation, and integration with demographic and epidemiological information. Therefore, biomedical signal processing should complement broader public health information systems rather than function as an isolated technological solution.

5. CHALLENGES AND LIMITATIONS

Despite significant technological advances, biomedical signal processing continues to face challenges associated with measurement reliability, computational performance, and clinical interpretation. Physiological signals are inherently variable and may be influenced by movement, environmental conditions, individual characteristics, and sensor placement. These factors can reduce the reliability of automated detection when algorithms are applied outside controlled clinical environments.

Another important challenge concerns the generalizability of signal classification algorithms. A model developed using a particular dataset may not perform consistently across different age groups, clinical populations, sensor configurations, or healthcare environments. Independent validation and evaluation under realistic monitoring conditions are therefore necessary before deploying automated diagnostic technologies.

Wearable systems also introduce practical limitations involving battery consumption, sensor comfort, wireless connectivity, data security, and device affordability. These considerations are particularly

important in public health settings where technological resources and healthcare infrastructure may vary considerably. Consequently, successful implementation requires balancing analytical accuracy with accessibility, operational reliability, and cost-effectiveness.

6. FUTURE DIRECTIONS

Future developments in biomedical signal processing are expected to strengthen the integration of physiological monitoring, intelligent analysis, and remote healthcare technologies. Advances in wearable sensors, low-power processing, wireless communication, and computational intelligence provide opportunities for more continuous and accessible health monitoring. Greater integration of multiple physiological signals may also improve the characterization of complex health conditions.

Another important direction involves developing robust signal processing algorithms capable of operating under real-world conditions. Research should emphasize artifact resistance, individual variability, computational efficiency, and validation across diverse populations. In addition, integration with electronic health records and public health information systems could improve the use of physiological measurements in longitudinal health assessment and preventive healthcare.

7. CONCLUSION

Biomedical signal processing provides essential technologies for transforming physiological measurements into useful information for health monitoring, abnormality detection, and diagnostic support. ECG, EEG, and PPG processing demonstrate the broad applicability of signal analysis techniques across cardiovascular, neurological, and general physiological monitoring. Integration with wearable sensors and remote monitoring platforms further creates opportunities to extend healthcare services beyond conventional clinical environments. However, reliable public health applications require accurate signal acquisition, robust preprocessing, appropriate feature extraction, validated classification algorithms, and effective clinical interpretation. Challenges involving signal variability, measurement artifacts, computational constraints, affordability, and population-level generalizability must also be addressed. Overall, biomedical signal processing represents an important technological foundation for more accessible monitoring, earlier detection, and evidence-based public health interventions.

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