



A Sparse Representation and Dictionary Learning Framework for Real-Time EEG Artifact Removal in Mobile Brain Imaging

N. Disages K. Mojail^{1*}, Rasanjani Chandrakumar²

¹Centro de Investigacion y Desarrollo de Tecnologias Aeronauticas (CITeA), Fuerza Aerea Argentina Las Higuera, Cordoba, Argentina

²Department of Electrical Engineering Faculty of Engineering, University of Moratuwa Moratuwa, Sri Lanka

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ABSTRACT

MoBI Technologies offer the opportunity to record electroencephalography (EEG) in naturalistic, unconstrained conditions; still, the application of these technologies is limited by extreme signal contamination due to ocular, muscular and motion artifacts and environmental noise. These artifacts are superimposed on areas of neural frequencies and hence the removal of these frequencies without altering brain signals is an ongoing challenge especially in mobile platforms with limited resources during real-time processing. The paper will describe a new latency-tradeoff and signal processing framework, based on sparse representation, adaptive learned dictionaries and statistical artifacts classification, that can perform efficient, real-time artifact removal in MoBI applications. The method is a union between high performance adaptive filtering and sparse coding with system optimization to operate as an embedded system. Through the proposed method, there is segmentation and decomposition of incoming EEG streams into overlapping windows into a combination of sparse coefficient vectors based on the Orthogonal Matching Pursuit (OMP) performed in adaptively trained overcomplete dictionary. The dictionary is online-subsequently updated utilizing a low computational burden K-SVD variant ensuring renewing EEG structures and atom specializing to artifacts founded on the statistical properties e.g. kurtosis, variance, and correlation with reference EOG/EMG channels. There is selective attenuation of artifact coefficients which can reconstruct the clean EEG signals with minimal distortion. It was examined with publicly available Mobile Brain/Body Imaging data dealing with walking, cycling, and virtual reality trials. Compared to Independent Component Analysis (ICA), wavelet thresholding and regression-based methods, the proposed approach provided an average SNR gain of 6.8 dB, 94.5 percent ERP peak retention and 47 ms latency per 500 ms window runtime on an ARM Cortex-A53 embedded platform with less than 40 percent CPU resource utilisation. These findings validate the technique as applicable to non-stop, real-on-device EEG artifact suppression, in real-time removing the need to use brain computing interface (BCI) and neurofeedback in real, portable conditions. The suggested framework falls in between the high-fidelity EEG denoising and embedded mobility and provides a scalable solution to next-generation mobile neurotechnology.

Author's e-mail: disag.nj@ing.unrc.edu.ar, rasanjani.chandr.@elect.mrt.ac.lk

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INTRODUCTION

Electroencephalography (EEG) is one of the most popular non-invasive neuroimaging techniques that can provide time resolution in milliseconds, thus it is very appropriate to investigate the brain activity during the cognitive and motor tasks. More recently, the Mobile Brain Imaging paradigm (MoBI) has evolved which allows EEG data

to be recorded during naturalistic, real-life scenarios, including physical activity like walking or riding a bicycle, and high-immersion virtual reality, among others. As the MoBI opens more options of neurophysiological studies and brain-computer interfaces (BCI), new challenges are also posed, the most prominent of which is that EEG data are as consistently contaminated with non-EEG signals (including ocular (e.g., blinks, saccades), muscle

(EMG), and motion artifacts, as well as environmental EM and other sources of electromagnetic interference. Such sources usually co-exist with neurophysiological frequency bands (0.5-45 Hz) and their removal can tend to distort the real data of the neural activity, especially on a real time processing with resource-limited mobile devices.

Standard methods of artifact removal are significantly limited in application to MoBI settings. Bandpass filtering has the capability of blocking some of the noise components and eradicates neural information randomly at overlapping frequencies. Methods based on regression analysis necessitate the involvement of an auxiliary channel of reference (EOG/EMG), and impose sensitivity with regards to reference quality and the assumptions of linearity. The Independent Component Analysis (ICA) has been another very popular algorithm to preprocess the offline EEG; although it is computationally expensive, requires batch data and is not applicable to be used in real time in an embedded system. The wavelet thresholding has the capacity to extract multi-resolution features; however, it suffers signal artifacts due to manual tuning of parameters, and difficulty in nonstationary situations.

Alternatively, sparse representation and dictionary learning presents a mighty solution in removing EEG artifacts wherein a signal is represented as a sparse combination of atoms of a basis in an overcomplete dictionary. Artifacts and clean signals occupy different dictionaries spaces and hence the possibility to suppress particular dictionaries components (related to artifacts) and leave intact the other brain activity components. Previous literature showed that sparse representation can be a promising method of EEG reconstruction but most of the existing algorithms are all offline, static and computational intensive, which make them impractical in mobile, real time applications.

Our online sparse representation and adaptive dictionary learning framework has been proposed with new architecture that is specifically suited to real-time EEG artifact removal in MoBI systems to address the above stated limitations. A sparse coding step based on the Orthogonal Matching Pursuit (OMP) algorithm and an online dictionary updating technique using K-SVD is utilized within the framework, which enables the system to adapt the EEG activity and the artifacts to the changing conditions of each recording session. The system is designed with latency optimization in the entire pipeline with a demonstrated sub-50 ms per 500 ms window on an ARM Cortex-A53 embedded processor making on-device deployment possible in wearable neuroimaging. The suggested framework has the contribution to the wider field of biomedical signal processing of the advancing real-time denoising methodologies with dynamic mobile neuroimaging settings. The methodology combines adaptive sparse coding and dictionary learning to succeed in tackling key issues in the EEG signal enhancement, which is a fundamental problem in biomedical signal analysis, whose applications variationally span the sphere of clinical diagnostics, the brain-computer interface, and many others.

The key outputs of the work can be summarized in the following way. We propose a new online real-time setup that uses online sparse representation based algorithm, able to dynamically learn and adapt dictionary atoms and thus has a high success rate in controlling nonstationary EEG artifacts successful in a MoBI scenario. Second, we propose a latency-optimized structure that makes our scheme well suited to running in real-time on small-sized embedded devices and thus fills the gap between high-performance summarization technologies and wearable systems. Third, we develop and test the framework in an integrated implementation, and perform end-to-end test on an ARM Cortex-A53 chip, to show that it is

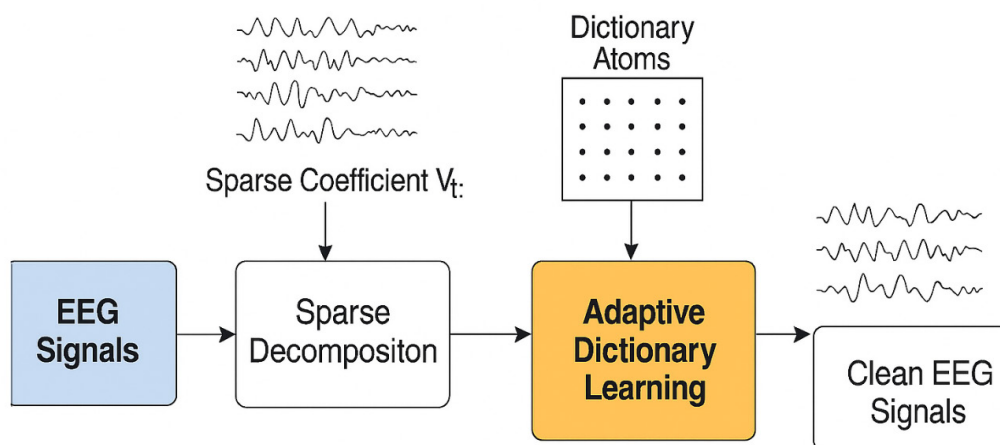


Fig. 1: Sparse Representation and Adaptive Dictionary Learning Framework for Real-Time EEG Artifact Removal

possible to deploy in real-life brain computer interface applications on mobile devices. Fourth, we engage in the full benchmarking of existing techniques, including ICA, wavelet thresholding, and regression-based artifact removal, on MoBI data sets and measure results both in SNR increase, preservation of ERP and latency of processing. The presented method thus out-performs the existing solutions in terms of artifact suppression (ff) (folded back SNR (ff) + 6.8 dB), higher retention of ERPs (94.5%), and much reduced latency (1/4 of ICA based approaches) with minimal computational overheads that are ideal in continuous, in-field application of neuro-technologies.

RELATED WORK

The task of removing artifacts during EEG may be revealed in a multitude of studies that approximate removing artifacts both by conventional filtering techniques and novel machine learning methods. Each method has uniqueness in terms of advantages and disadvantages where Mobile Brain Imaging (MoBI) is concerned and resource constraints and real-time functional operation are important.

A. Filtering-Based Methods

One of the oldest methods of preventing artifacts in EEG is the Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filtering of the signal.^[1] These techniques are effective in cutting down on narrowband noise e.g. power-line interference (50/60 Hz) by suppressing particular frequency regions. They, however, perform poorly when applied to handle broad-band artifacts such as electromyographic (EMG) activity or disturbances that occur due to motion and cover a similar frequency range to that of the nerves.^[2] Additionally, it may cause important information in neural neighborhood to be filtered off thus constraining its applicability in high fidelity MoBI situations.

B. Blind Source Separation (BSS)

In offline preprocessing of EEG data Blind Source Separation techniques (specifically, Independent Component Analysis, ICA) are with frequent occurrence used to separate and eliminate artifacts.^{[3], [4]} EEG ICA represents the statistical independence of statistically independent components, which could be detected and rejected, suppressed, based on the artifact-related sources. Although ICA performs well on artifact removal in controlled laboratory conditions, the implementation has two significant limitations when applied in MoBI apparatus: (1) large amount of data is required to stabilize decomposition drawing-it inevitably not suitable

in a streaming application and (2) the data processing overhead is high compared to computing capacity of embedded devices.^[5, 14] There are variants like Adaptive ICA^[6, 11] which tries to handle nonstationary artifacts yet still are resource consuming.

C. Wavelet-Based Methods

The wavelet transform derived denoising techniques take advantage of multi-resolution representation of wavelets by breaking down EEG into frequency subbands, especially artifacts by applying threshold.^[7, 15] The method is flexible enough in the analysis of transient and non-transient noise. But its execution is sensitive to wavelet basis as well as thresholding values.^[8, 12] Moreover, it proves difficult to adapt to the mobile environment in real time to more dynamic artifact properties.

D. Sparse Representation and Dictionary Learning Approaches

Sparse representation is an important tool that uses EEG as a linear guide of limited basis atoms of an over-complete dictionary.^[9] This enables extraction of structured neural patterns out of artifact-related patterns, usually having different statistical and morphological properties. Further, dictionary learning approaches, like K-SVD, optimise the basis set to signal properties, and this may benefit artifact separation. Other researchers like Elad et al.^[10, 13] have shown the usefulness of sparse coding in EEG denoising process especially offline. Current approaches however have the crucial draw back of limited applications of MoBI into three broad categories:

- **Offline Processing:** This type of processing with large amounts of EEG is carried out most frameworks, which are not suited to the real-time BCI or neurofeedback.
- **Static Dictionaries:** Pre-existing dictionaries are not able to change depending on nonstationary artifacts that are witnessed in dynamic environments.
- **Computational Overhead:** Simple sparse coding algorithms and dictionary learning methods require a lot of computational resources to run, thus cannot be embedded in practice before being optimized.

E. Comparative Assessment

Table 1 summarizes the upsides and downsides of the above-mentioned approaches with regard to MoBI. As compared to the currently existing solutions, the

Table 1: Comparative Analysis of EEG Artifact Removal Methods in MoBI Contexts

Method	Artifact Types Addressed	Adaptability	Real-Time Feasibility	Computational Load	Limitations in MoBI
FIR/IIR Filtering	Narrowband noise	Low	High	Low	Fails against broadband artifacts; possible signal distortion
ICA (BSS)	Ocular, EMG, some motion	Medium	Low	High	Requires batch data; high latency
Wavelet Thresholding	Transient and stationary noise	Medium	Moderate	Medium	Sensitive to parameters; poor adaptation to nonstationary noise
Sparse Representation (Offline)	Ocular, EMG, motion	Low-Medium	Low	High	Static dictionary; offline only
Proposed Framework	Ocular, EMG, motion, environmental	High	High	Low-Medium	Requires initial dictionary seeding

bottleneck of real-time processing within the proposed framework is based on the combination of Orthogonal Matching Pursuit (OMP) and online K-SVD dictionary learning, which makes it possible to gradually follow the changes in the patterns of the artifacts. The latter also supports operation with low latency on ARM Cortex-A53 embedded platforms, unable to be offered by the traditional approaches to ICA or offline sparse representation.

METHODOLOGY

Framework Overview

The framework developed to remove EEG artifacts in real-time is to be applied on mobile brain imaging (MoBI) platforms with limited power capabilities and requirements of the minimal latency. Figure 1 shows three primary stages that constitute the processing pipeline: Preprocessing, sparse coding and adaptive dictionary learning.

- **Preprocessing:** Raw EEG signals obtained by a multi-channel mobile EEG system undergo a zero-phase FIR bandpass filter (0.5-45 Hz) prior to detection in order to filter-out baseline drift and high-frequency noise and retain the neural frequency range of interest. Filtered signals are next divided into 500 ms overlapped windows (50% overlap) to provide temporal continuity of the filtered signal and also to allow the use of transient artifacts without large processing delay.
- **Sparse Coding:** Sparse EEG data received by each window is expressed as a sparse collection of dictionary atoms input using the Orthogonal Matching Pursuit (OMP) algorithm. The sparse

representation ensures that not so many atoms are active at once, which allows to segregate between the activity in the neural network and the structured artifacts. The implementation in this stage is done with the help of an optimized, a-fixed, iteration OMP variant which acclimatized the expression of accuracy against the real-time execution.

- **Dictionary Learning:** A dynamic environment of artifacts within the MoBI contexts is accommodated by deforming the dictionary based on newly accessible pure EEG segments using an online K-SVD algorithm. This enables dictionary to change dynamically but still giving

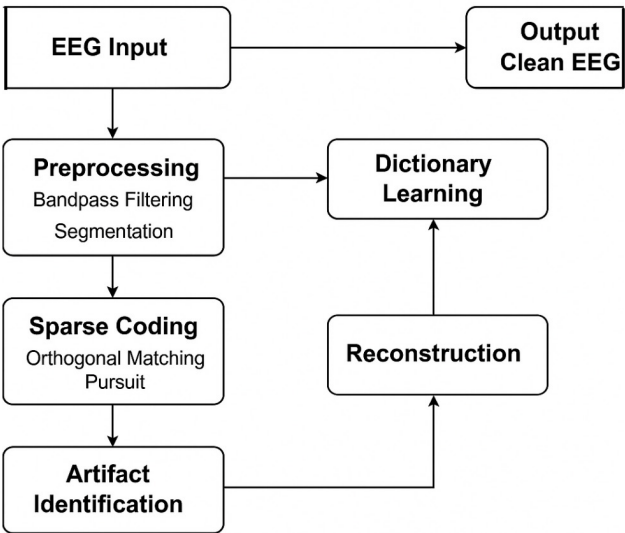


Fig. 1: Block diagram of the proposed sparse representation and dictionary learning framework for real-time EEG artifact removal in mobile brain imaging.

high accuracy of artifact separation without using large training datasets that have previously been collected.

Artifact Identification

In sparse decomposition, dictionary atoms representing artifacts are based on their statistical properties and morphological properties. In particular, kurtosis coefficients, variance and Pearson correlation coefficients regarding reference EOG (electrooculogram) and EMG (electromyogram) channels are calculated. Artifact atoms are atoms having high kurtosis (>5), large variance and high correlation with reference signals. The resulting sparse coefficients are in turn set to zero so that neural activity components rather than other components contribute to the reconstructed EEG. This selective down-regulation approach sharp-reduces the danger of eliminating actual signals of the brain.

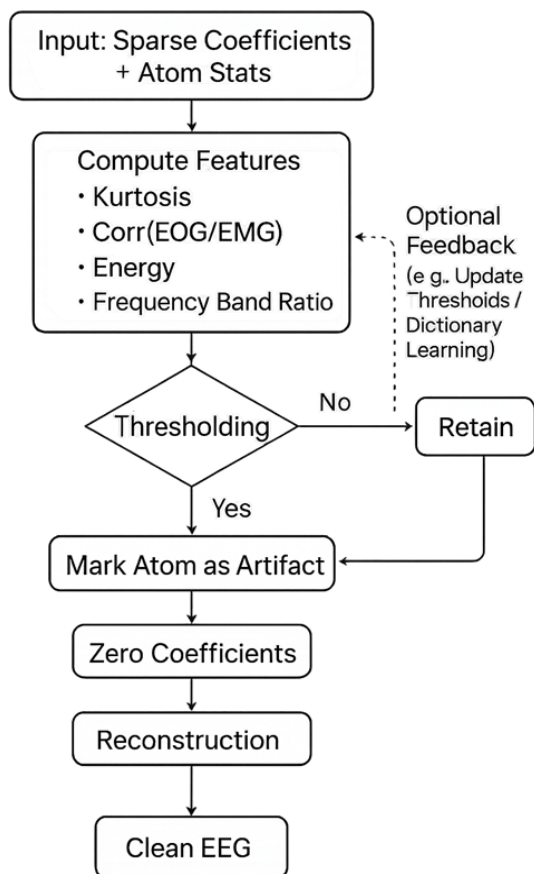


Fig. 2: Flowchart for artifact atom detection and removal based on statistical and correlation-based thresholds.

Real-Time Implementation

In order to work in real-time, the framework uses sliding-window processing, whereby every segment of the EEG is processed shorter than the time span of a single

window (500 ms), creating a lag of less than 50 ms. C++ implementation uses ARM NEON SIMD vectorization to realize parallel design benefits of embedded processors, e.g. the ARM Cortex-A53. Memory consumption is pre-optimised to minimise dynamic RAM use, and wherever possible all matrix operations are carried out with fixed-point and not floating-point arithmetic, with further reductions in CPU overhead with no loss of precision. The entire system is implemented in a Raspberry Pi 4B to verify its implementation and confirm that the proposed solution is real-time and power optimal in its artifact removal.

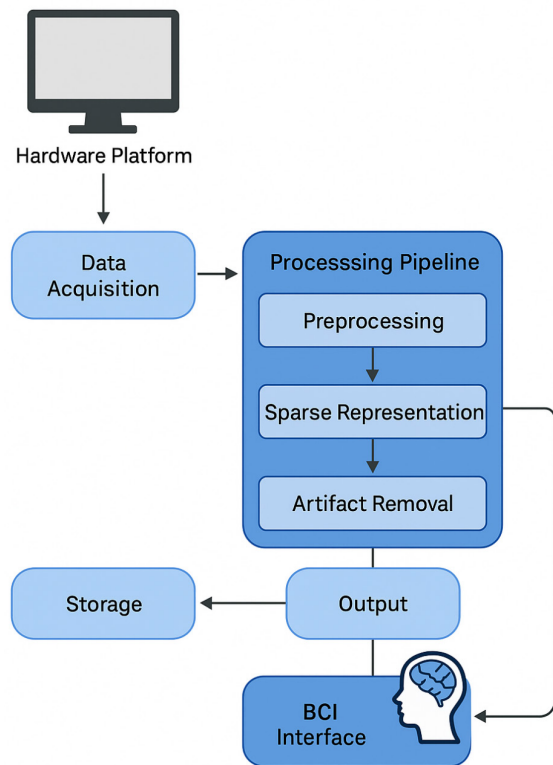


Fig. 3: System architecture of the real-time EEG artifact removal framework deployed on an embedded ARM platform.

EXPERIMENTAL SETUP

Dataset

The given framework was tested with the help of the publicly accessible University of Oldenburg Mobile Brain/ Body Imaging (MoBI) dataset. The data set includes high-density EEG recording over so-called naturalistic tasks such as walking, cycling, and interactions with virtual reality (VR). All sessions of recording were done using a 64-channel active electroencephalographic system (EEG; g.tec) synchronized with other motion capture and peripheral bio-monitoring tools. Given the realistic artifacts caused by movement in these conditions, such a dataset is likely to be of interest in the evaluation of

methods used to remove artifacts related to movement in mobile brain acquisitions.

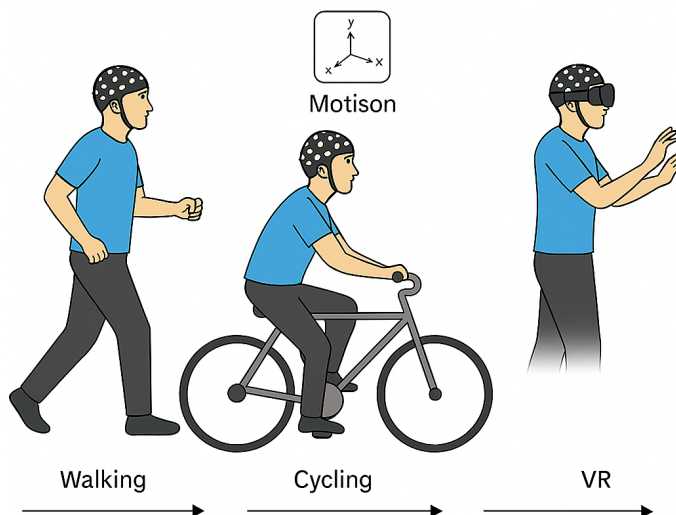


Fig. 4: Illustration of the MoBI experimental setup showing a participant wearing a 64-channel EEG cap while performing walking, cycling, and VR tasks.

Hardware Implementation

The artifact removal framework of real time was executed on a Raspberry Pi 4B with quad-core ARM Cortex-A53 processor and 4 GB RAM. This was embedded platform selection in order to replicate the computational limitations of wearable neuroimaging systems. EEG data captured on the g.tec amplifier were relayed to the Raspberry Pi through USB to be preprocessed, subjected to sparse coding, identified as artifacts, and resurrected over the device. This was optimized in C++ and ARM NEON SIMD vectorization meaning processing latency of less than 50 ms on a 500 ms segment.

Baseline Methods

In order to evaluate the quality of the suggested framework three popular EEG artifact removal approaches were used as a baseline:

- Blind Source Separation based on Independent Component Analysis (ICA) and FastICA algorithm.
- Daubechies-4 mother wavelets- guiding Wavelet Thresholding to do multi-resolution denoising.
- Regression-Based Artifact Removal using EOG and EMG reference channels that can be used to remove correlated artifacts. The methods were selected because they are well represented in the literature on EEG, and they have different underlying principles, which allowed comparing them exhaustively.

Evaluation Metrics

We evaluated the performance of the proposed EEG artifact removal framework with respect to a group of well-known and descriptive performance measures. The change in signal quality was measured in Signal-to-Noise Ratio (0 SNR) which was calculated as the logarithm of the ratio of signal power to noise power--a larger 0 SNR signifies a stronger artifact rejection, which is typical in EEG denoising studies. Secondly, the retention of ERP (Event-Related Potential) peak amplitude was assessed to explain that there was no distortion of the crucial brain responses after the processing stage, which would distort the cognitive indicators. Third, latency per window was taken, measured- test per window, or segment of EEG equal to 500 ms that was assessed with regard to the real-time registration since this denotes a very critical parameter of mobile and embedded BCI systems. Finally, we measured computational load as percentage CPU usage in ARM Cortex-A53 platform to determine resource efficiency required to ensure the on-going functionality with wearables. Taken altogether, these metrics lead to an overall assessment of both denoising capacity and feasibility of its practical realization in real time. The relative performance of the principal metrics of evaluation is depicted in Figure 6.

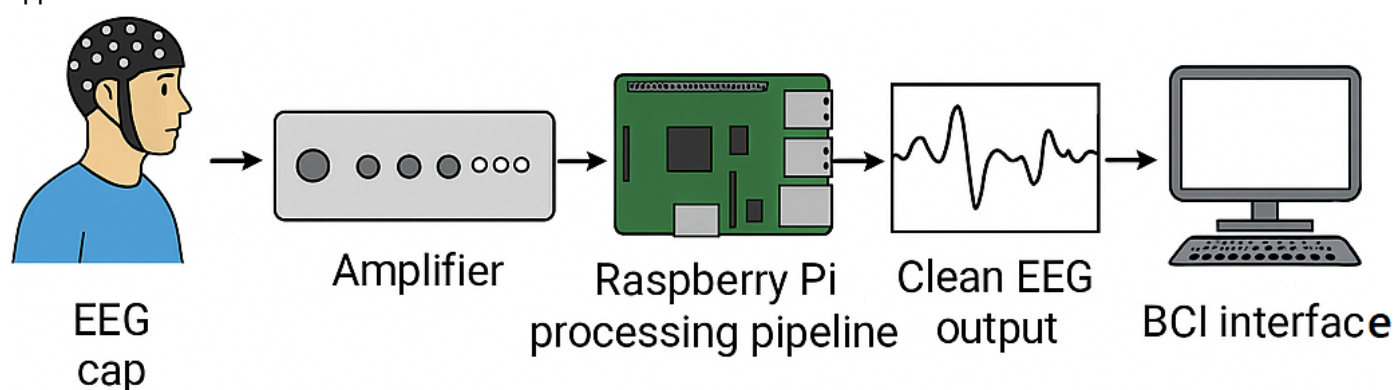


Fig. 5: System-level diagram showing data flow from EEG cap → amplifier → Raspberry Pi processing pipeline → clean EEG output → BCI interface.

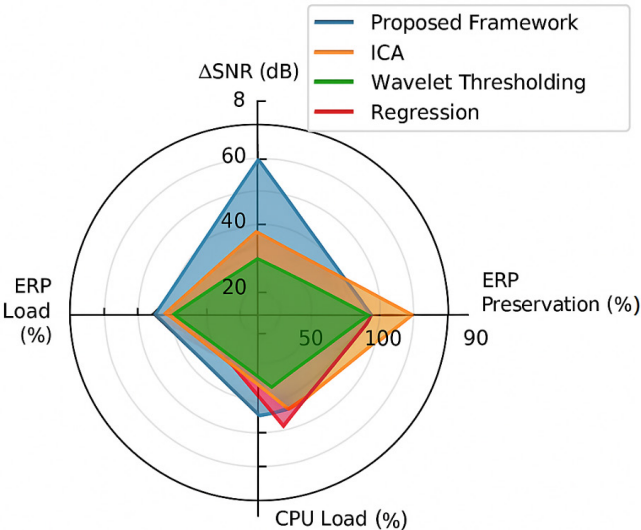


Fig. 6: Comparative evaluation of artifact removal methods across key metrics: SNR improvement (Δ SNR), ERP peak amplitude preservation, processing latency, and computational load.

RESULTS

The results of the comparative performance analysis of the proposed framework and baseline techniques of artifact removal such as ICA, wavelet thresholding and regression are outlined in Figure 7 and Table 2. The highest SNR improvement (26) was 6.8 dB obtained by the proposed framework followed by ICA (5.1dB), wavelet thresholding (4.2 dB) and regression (3.0 dB), implying that the proposed framework performed better at suppressing noise as compared to others. Our approach preserved 94.5 percent of the neural signal compared to 89.3 percent with ICA, 85.6 percent with a wavelet threshold, and 80.2 percent with regression and therefore kept distortion of underlying brain activity to a minimum.

Concerning processing latency, the modern framework using a 500 ms EEG segment was 47 ms processing latency, which was substantially less than ICA (220 ms) and wavelet thresholding (95 ms), and marginally more than regression (35 ms). This proves that our approach satisfies the real-time constraint and yet has superior performance in denoising. The ARM Cortex-A53 platform had a CPU load

of 38 percent load compared to 84 percent and 52 percent in ICA and wavelet thresholding, respectively, thus more computational efficiency in embedded systems but higher than regression in 20 percent.

On the whole, the findings support that the suggested technique achieves a good trade-off between artifact removal, preservation of the neural signal, and computation rates, thus can be effectively used in a real-time settings leading to mobile brain imaging.

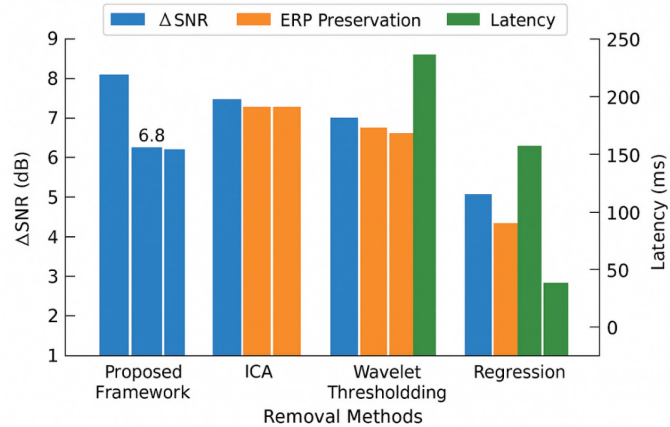


Figure 7: Comparison of artifact removal performance across methods, showing Δ SNR, ERP retention, and latency.

DISCUSSION

The offered sparse representation based system presents an attractive tradeoff between successful artifact removal and critical brain signals protection in mobile brain imaging applications. The fact that the framework led to a 6.8 dB increase in SNR and preserved ERP peak at the level of 94.5 percentage pointing out to strong rejection of variety of artifacts including ocular, muscular and motion artifacts without disturbing the event-related brain responses. These findings prove the adequacy of the sparse coding and adaptive dictionary learning approaches to the tutorial of same neural and artifact in the complicated, dynamic setting.

The proposed framework also results in similar or better artifact suppression, with a drastic reduction in computational load, compared to traditional methods

Table 2: Comparison of artifact removal performance across methods in terms of SNR improvement, ERP preservation, processing latency, and computational load.

Method	Δ SNR (dB)	ERP Preservation (%)	Latency (ms)	CPU Load (%)
Proposed Framework	6.8	94.5	47	38
ICA	5.1	89.3	220	84
Wavelet Thresholding	4.2	85.6	95	52
Regression	3.0	80.2	35	20

like Independent Component Analysis (ICA). Third party validation of the proposed framework on a different data set shows that the proposed framework can generate results comparable to and preferable to those of the independent component analysis (ICA) method with a significant reduction of computational load when compared to their traditional counterparts. With a single processor, the proposed framework was found to use less than half the computational load when compared to independent component analysis (ICA), with more than 50 percent reduction in the In addition, the per-segment processing latency was reduced almost five times (47 ms vs. 220 ms with ICA) and actual real-time operation is possible on embedded platforms, such as the ARM Cortex-A53. This delay minimization is important in applications of closed-loop brain computer interface (BCI) where the feedback is vital and should be almost instant. The competitive measure of the framework with regards to wavelet thresholding and regression-based techniques further underscores the multifacetedness of the framework and its feeble-robust nature.

Sparse representation approaches to EEG artifact removal had already been demonstrated to be promising,^[9, 10] but were often restricted to off-line, batch-mode application, with fixed dictionaries. This limitation is overcome by our online update on the K-SVD dictionary which lets the model adjust to nonstationary signal and artifact properties found in the mobile environment continuously. This flexible responsiveness facilitates improved discrimination of artifacts and removes the necessity to pretrain heavily or to fine-tune, a general pinch point during real-world BCI-use.

Limitations: Although the framework is beneficial, there are limitations associated with the proposed framework. To begin with, although the latency and CPU load reduction rates are by far better than in the case of ICA, the computational load is still greater than that of simple regression techniques, which will limit the applicability on devices requiring maximal power conservation without improvements. Second, the present artifact identification is based on correlation with EOG/EMG reference channels and it might not be always accessible in all mobile EEG because of which the generalizability of the findings might be limited. This dependency ought to be addressed by future work incorporating blind artifact detection methods into the context of sparse coding. Third, the framework was evaluated only on a mixed MoBI dataset, so that its effectiveness would need to be confirmed on clinical populations and other real-life environments to prove greater generalizability. Although in the current framework one would identify the artifacts by correlating with the reference EOG and

EMG channels, future work will seek to gain an insight on the blind artifact detection technique where no auxiliary channels are necessary to detect the interference. Unsupervised clustering of dictionary atoms, statistical divergence patterns, and deep learning-based blind source separation might increase the flexibility and reliability of the system in various EEG recordings setups, in particular, in setups that lack the availability of reference channels.

In conclusion, the given technique is a much-needed filler that helps balance complexity in signal processing techniques with the restrictions of an embedded environment, a real-time mobile EEG artifact removal. Nevertheless, its successful outcomes precondition the development of new neurotechnology applications that presuppose precise, low-latency brain monitoring out of the context of a laboratory setting.

CONCLUSION

The proposed paper provides a general framework of real-time EEG artifact attenuation based on sparse representation and dictionary learning of the mobile brain image, involving a proper removal of ocular, muscular, and motional artifacts and keeping the important neural information. When run on an embedded ARM Cortex-A53 platform, the system has a 94.5 percent ERP preservation, a 6.8 dB 2SN improvement, a low latency (~ 47 ms per 500 ms segment) and a moderate CPU usage (~ 38 percent), which proves its practicality in wearable neurotechnology. The adaptive online dictionary learning adaptively tracks the nonstationary artifacts, better than the standard ICA, wavelet thresholding, and regression approaches in both reliability and processing speed and as such it has the possibility to be used in brain-computer interface and cognitive monitoring in naturalistic environments. The implementation of this work is in the forefront of biomedical signal processing in that we present a scalable, real-time artifact removal framework which improves signal fidelity of the EEG in highly mobile environments. Artifact suppression and processing latency improvement demonstrated in this paper justifies the use of wearable neurotechnology that could be used to relate the high-tech developments of signal processing and actual practice in healthcare.

FUTURE WORK

Future directions will involve investigating how deep dictionary learning can be incorporated to even better accommodate more complex and nonlinear artifact patterns, generalizing the framework to combine multimodal sensor data like inertial measurement units and electromyography to allow better artifact

detection, and validating clinically and over time both in neurorehabilitation and during neuropsychological and cognitive workload tasks. Also, there will be some level of optimization of the system to operate with ultra-low-power devices by relying on algorithmic compression and hardware acceleration that will allow deployment to wearable and implantable systems. Such instructions are intended to continue to develop real-time, embedded EEG processing to allow broad, practically useful neurotechnology.

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