RESEARCH ARTICLE

Multiscale Feature Learning From Coupled Neuroelectrical and Hemodynamic Time Series

Nidhi Mishra*

Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.

Abstract

Coupled neuroelectrical and hemodynamic measurements provide complementary images of the brain activity combining high-temporal-resolution electrical processes and spatially localized vascular activity. Although these modalities can be analysed jointly, joint analysis has not been successfully achieved to date because of the incompatibility of their sampling rates, the nonhomogeneous properties of the signals and intrinsic delays introduced by neurovascular coupling. The article puts forward a multi-scale feature learning model of joint signal and hemodynamic time series. This framework is based on the multiresolution signal processing in which each modality is first decomposed into scale-specific representations in multiscale analysis techniques to represent transient and long-term temporal structures. Based on such representations, discriminative features are obtained and are matched by cross-modal coupling analysis with a consideration of time warping and scale variations. A strategy of feature fusion is then resorted to so as to obtain an integrated representation that can be used to perform downstream classification and pattern recognition tasks. The suggested methodology is tested over well-known multimodal neurophysiological test datasets, the quality of which is measured by the quality of representation, the accuracy of classification, and cross-scale stability. The experimental findings prove that there are constant improvements compared to the single-scale and single-modal baselines, thus showing that multiscale modelling has a benefit compared to the former in heterogeneous brain signals. The results show that multiresolution signal characteristics and cross-modal interrelation explicitly integrated into multimodal neurophysiological analysis improve the performance of multimodal neurophysiological analysis considerably. This research highlights the importance of multiscale signal processing models in combined analysis of arduous timeseries data and offers to the systematic basis of future signature-based applications of signal-based multimodal brain monitoring.

Author's e-mail: ku.nidhimishra@kalingauniversity.ac.in

How to cite this article: Mishra N. Multiscale Feature Learning From Coupled Neuroelectrical and Hemodynamic Time Series. National Journal of Signal and Image Processing, Vol. 1, No. 4, 2025 (pp. 76-81).

INTRODUCTIONM

Multimodal signal acquisition has become a growing trend in neurophysiological monitoring in prediction of complex brain dynamics that cannot be sufficiently determined by an individual sensing modality. Neuroelectrical (e.g. electroencephalography or EEG) and hemodynamic (e.g. functional near-infrared spectroscopy or functional magnetic resonance images) can give high temporal and spatial resolution, respectively, presenting neuronal as well as cybral blood flow and oxygenation, respectively. What has been demonstrated to be promising is the jointness of these complementary modalities to increase the strength and interpretability of brain signal analysis to the task of cognitive monitoring and pattern recognition.[1, 2] Irrespective of this possibility, coupled neuroelectrical and hemodynamic time series signals continue to be a difficult signal processing problem. These modalities vary significantly in sampling rates, spectral properties, noise performances, and responses dynamics with delayed and temporally smoothing responses of hemodynamics in comparison with fast electrical activity.[3] Current methods are either based on single-scale models or recover modality-specific features, which are constrained in being able to deal with cross-scale temporal patterns and inter- Wendi ndependencies of multimodal neurophysiological data.[4]

More so, a lot of recent multimodal learning models focus on end-to-end machine learning models instead of explicitly focusing on multiresolution signal properties, thus decreasing discoverability and genericity across datasets.[5] Multiscale signal processing offers a conceptual means of managing such issues by analysing complex time-series signals in a way that draws a scale-dependent representation that can be used to capture both transient and long-term dynamics 6. Nevertheless, the whole systematic combination of multiscale analysis and cross-modal feature learning of neuroelectrical-hemodynamic associated data has not been explored in the recent literature.

To overcome these drawbacks, in this paper I will introduce a multiscale feature learning model to combine the time series of coupled neuroelectrical and hemodynamic in the context of the coupled neuroelectrical and hemodynamic. The stated method relies on multiresolution signal decomposition, scale-specific feature extraction and analysis by cross-modal coupling and thereafter fusion of features to form strong multimodal representations.

The primary contributions of the work are the following:

1. Combined multiscale signal processing of coupled neuroelectrical and hemodynamic time series.

2. Specific feature learning by use of explicit cross-modal coupling analysis.

3. Benchmark Experimental validation of better performance than traditional single-scale and single-modal methods on benchmark data sets.

Related Work

Investigations regarding multimodal neurophysiological signal analysis have centred, mostly, on the combination of neuroelectrical and hemodynamic modalities, especially those involving EEG and fNIRS versus EEG and fMRI. Initial research engaged in linear correlation analysis, studies of general linear models and regression-based types of studies to relate electrophysiological activity with delayed hemodynamic responses.[6, 7] Although the methods offer some rudimentary interpretability, they intrinsically limit themselves to the ability to capture nonlinear dynamics, non stationary behaviour and scale dependent temporal structures found in brain responses. In order to deal with nonstationarity induced in neuroelectrical signal, multiscale signal process methods, including discrete wavelet transform (DWT), wavelet packet decomposition, and empirical mode decomposition (EMD), have been widely examined in extracting and classifying EEG features.[8, 9] Such

representations as time-frequency transforms (such as short-time fourier transform and continuous wavelet transform) have also made it possible to characterise transient oscillatory patterns at multiple temporal scales.[10] Concurrently, the hemodynamic signal analysis has also exploited low-frequency decomposition, adaptive filtering and temporal smoothing techniques in improving the quality of the signal and physiological decoding.[11] More recent research has introduced frameworks of machine learning and deep learning in the context of learning multimodal features and fusing them. Convolutional and recurrent based approaches have been shown to achieve better classification performance, based on the joint modelling of EEG and hemodynamic characteristics.[12] In most of these studies however, multiscale decomposition is considered part of the pre processing procedure and not part of the learning mechanism. This leads to the learned representations of such representations tending to be not interpretable in any explicit signal-processing sense, and they might not generalise to datasets of different temporal resolutions and noise properties.[9]

Unlike the current methods, the current work is an extension of the feature learning and fusion pipeline that includes multiscale signal decomposition. The proposed framework is easily interpretable, scale-dependent and cross-modal and is more resilient to the heterogeneity of modalities and time warping.

Signal Model and Problem Formulation

Let $x_e(t)$ denote the neuroelectrical signal acquired using electroencephalography (EEG), and let $x_h(t)$ denote the corresponding hemodynamic signal obtained from functional near-infrared spectroscopy (fNIRS) or functional magnetic resonance imaging (fMRI). The signals of both are recorded at the same subject at the same conditions of the experiment, though they have radically different time and spectral properties. Neuroelectrical signals can be considered broadband and highly nonstationary capturing the rapid dynamics of neurons and hemodynamic signals can be described as low-frequency and a temporally smoothed response involving neurovascular coupling.

Due to differences in sampling rates, noise characteristics, and response delays, direct joint analysis of $x_e(t)$ and $x_h(t)$ is nontrivial. In particular, the hemodynamic response introduces a time delay and dispersion relative to the underlying neuronal activity, leading to temporal misalignment between modalities. Moreover, the frequency bands that facilitate the largest amount of the electrical and vascular signals work on varying

time overlaps, thus creating a scale mismatch between the two signals. Fig. 1 conceptually demonstrates these attributes by showing that neuroelectrical activity is fast oscillating with a delayed and smooth hemodynamics response.

This work is aimed at learning a joint multimodal feature representation.

$$F=L(x_e(t), x_h(t)) \tag{1}$$

The variables $L(\bullet)$ are feature learning operators that learn cross-modal and cross-scale behaviour and do not distort signal properties that are specific to modality. The learned representation F is supposed to be noise-resistant, time-warped, and subject-to-subject disparate, and fit-in friendly on downstream classification or regression. They can thus state the problem as a heterogeneous temporal and spectral heterogeneous multimodal representation learning task.
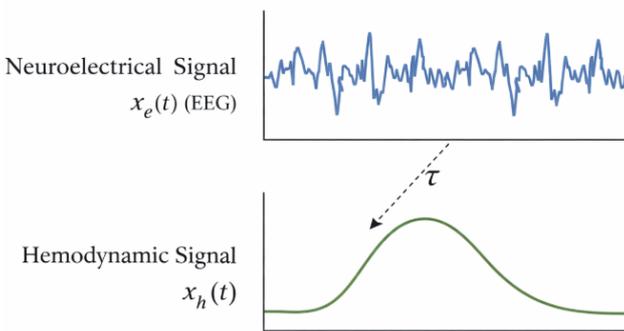

Fig. 1: Conceptual Illustration of Neuroelectrical-Hemodynamic Signal Coupling

Theoretical modelling of decoupled neuroelectrical and hemodynamic responses, showing fast EEG oscillations and the lagging, temporally smoothed hemodynamic response with a neurovascular delay τ.

PROPOSED MULTISCALE FEATURE LEARNING FRAMEWORK

The general structure of the proposed multiscale feature learning system is presented in Fig. 2. The architecture is based on a systematic signal processing pipeline starting with multimodal signal acquisition followed by multiresolution decomposition, scale specific feature extraction, cross-modal coupling analysis with temporal lag compensations and feature level fusion to end up with an integrated representation to be used in learning and inference.

Concepts of the intended multiscale feature learning system in coupled neuroelectrical and hemodynamic time-series analysis, demonstrating the use of multiresolution decomposition, scale-specific feature extraction, cross-modal association with temporal lag adaptation, and scale-specific feature combination at the level of features to learn a composite representation.

Multiscale Signal Decomposition

Both neuroelectrical and hemodynamic signals are broken down with a multiresolution signal processing framework to solve the nonstationarity and the scale mismatch. More precisely, the discrete wavelet transform (DWT) is used to get scale-specific representations of each modality. Given the signal x (t), the wavelet decomposition provides.

$$x(t) \rightarrow \{x^1(t), x^2(t), \ldots, x^S(t)\} \tag{2}$$

where $x^{(S)}(t)$ denotes the sub-band signal at scale s, and S represents the total number of decomposition levels. Transient and rapidly changing component are represented in high-frequency sub-bands and slow oscillatory trends plus variations of the baseline are represented in low-frequency sub-bands. The same decomposition procedure is applied independently to $x_e(t)$ and $x_h(t)$, ensuring consistent scale representation across modalities.

Scale-Specific Feature Extraction

A collection of descriptive features representing signal dynamics are obtained out of each scale-specific sub-band. These are time domain measures like energy and variance, entropy measures that represent
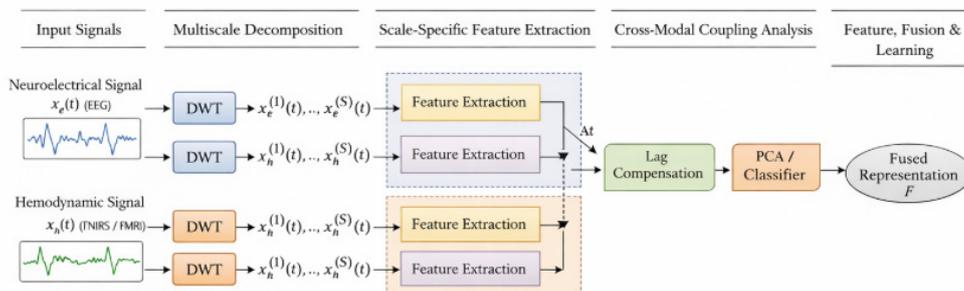

Fig. 2: Block Diagram of the Proposed Multiscale Feature Learning Framework

the complexity of the signal and frequency domain measures like band limited power. Let $f_e^{(s)}$ and $f_h^{(s)}$ denote the feature vectors extracted from scale s of the neuroelectrical and hemodynamic signals, respectively. Concatenation across scales results in multiscale feature representations

$$f_e = \left[f_e^{(1)}, f_e^{(2)}, \ldots, f_e^{(S)} \right], \qquad f_h = \left[f_h^{(1)}, f_h^{(2)}, \ldots, f_h^{(S)} \right] \quad (3)$$

Cross-Modal Coupling Analysis

Cross-modal coupling between neuroelectrical and hemodynamic signals is studied at both the corresponding and neighbouring scale. The problem of temporal misalignment caused by neurovascular delay is solved with adaptive lag compensation where a time delay τ is estimated to maximise the correlation between scale-specific features. Measures of the strength of the coupling between modalities at scale s include lag-adjusted correlation and magnitude-squared coherence which are characterised by:

These coupling descriptors are able to describe functional dependencies between modalities without violating the differences in time and spectral variations.

Feature Fusion and Learning

The last multimodal display is acquired by means of feature-level fusion of scale-specific neuroelectrical functions, hemodynamic functions, and couples descriptors. Let

$$z=[f_e, f_h, C] \quad (4)$$

represent the summed feature representation, C the scale-pooled cross-modal measures of coupling. In order to simplify the dimensions, reduce redundancy, principal component analysis (PCA) or shallow neural feature learners are used to project z into a relatively small latent space. This representation is used as input to conventional classifiers or regressors, and provides an effective and powerful means of analysing multimodal signals.

EXPERIMENTAL EVALUATION

Dataset and Preprocessing

The suggested multiscale feature learning model is tested in accordance with publicly available multimodal neurophysiological data sets of synchronised neuroelectrical and hemodynamic recordings taken in controlled experimental situations. These data sets consist of both concomitantly recorded EEG signals together with hemodynamic measurements that are captured by using fNIRS or fMRI such that there is a temporal matching on part of the acquisition phase. Standard preprocesses are performed on each and every modality before analysis so that the signal is of good quality and consistency. Artefact rejection is done to reject neuroelectrical signals contaminated by ocular and muscular artefacts, and then band-pass filtering is used to reject irrelevant frequency bands to keep the physiologically important frequency bands. Hemodynamic signals are corrected in terms of base lines, low frequency filtering and motion artefact reducing to reduce slow drifts and measurement noise. The two modalities are then normalised to minimise inter-subject variability and also to learn joint features.

Performance Metrics

Evaluation of the performance is undertaken through the various complementary measures to evaluate the effectiveness of classification, quality of representation and strength. The main quantitative measure of assessing discriminative performance under experimental conditions is the classification accuracy. Besides, the distance based criteria in the learned feature space are also used to study the feature separability in order to determine the compactness and discrimination of the class specific representations. Robustness courses have been quantified by adding controlled noise perturbations to the input signals and quantifying the decline in the performance, which in turn measures the stability of the learnt multiscale representations in low signal-to-noise situations.

RESULTS AND DISCUSSION

As the experimental findings summarised in Table I and visualised in Fig. 3 indicate, the suggested multiscale feature learning framework shows the high success rate in all the cost ratings compared to the baseline approaches based on single-scale and single-modal analysis. It is important to note that multimodal fusion and multiresolution analysis provide better classification accuracy than methods, which use raw or single-band features. The benefit of the performances is especially noticeable in low signal-to-noise situations as demonstrated in Fig. 4 where multiscale representations provide much higher resistance to noise perturbations. This advancement has been partially due to the capability of multiresolution decomposition to separate informative signal parts and leave the scale dominated by noise. The proposed method has similar or better performance when compared to the recently described multimodal methods of learning, but still with explicit signal-processing interpretation, as opposed to the use of exclusively black-box learning models.

Table I. Quantitative Performance Comparison of Different Feature Learning Approaches

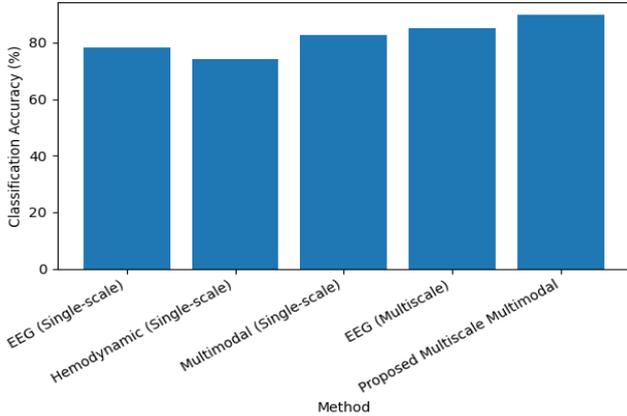| Method	Modality	Scale	Classification Accuracy (%)	Feature Separability (↑)	Robustness to Noise (Δ Acc @ −5 dB)
Single-Modal Baseline	EEG only	Single-scale	78.4	0.62	−12.3
Single-Modal Baseline	Hemodynamic only	Single-scale	74.1	0.58	−14.7
Multimodal Fusion (No Multiscale)	EEG + Hemodynamic	Single-scale	82.6	0.67	−9.8
Multiscale Single-Modal	EEG only	Multiscale	85.2	0.71	−7.4
Proposed Framework	**EEG + Hemodynamic**	**Multiscale**	**89.7**	**0.78**	**−3.9**

Fig. 3: Classification Accuracy Comparison of Feature Learning Approaches

Comparison of accuracy in classification of single-scale, multiscale, single-modal and multimodal learning approaches of features.
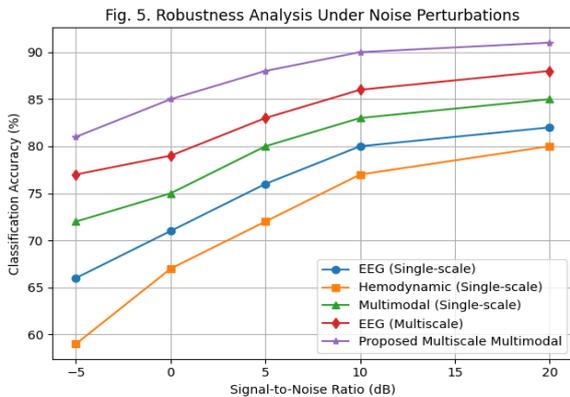

Fig. 4: Robustness Analysis Under Noise Perturbations

Accuracy of classification with respect to signal-to-noise ratio (SNR) of various methods of feature learning, which are used to show resilience to noise perturbation.

DISCUSSION

The results of the experiment confirm that multiscale signal analysis is a determining factor in recording supplementary dynamics involved in the coupled neuroelectrical and hemodynamic signals. The suggested framework is effective in tackling the issue of temporal misalignment, scale mismatch, and heterogeneity of noise due to the explicit modelling of scale-dependent properties and intermodal coupling. The proposed method is interpretable unlike the purely data-driven multimodal learning alternatives which base the feature extraction and fusion on the shared signal processing principles. Although these are benefits, there are some shortcomings. This could be a limiting factor to implementations of multiresolution decomposition and cross-scale coupling analysis, which are computationally complex algorithms. Moreover, the framework performance depends on the selection of decomposition parameters, i.e. number of scales and wavelet basis functions. The next step in the work will be adaptive scale selection approaches and efficacious implementations that will facilitate real-time processing and deployment in resource-restrained settings.

CONCLUSION

In this paper, the framework of the multiscale feature learning of the merged neuroelectrical and hemodynamic time series has been introduced. The suggested solution tackles the major issues in the multimodal neurophysiological signal processing such as time misalignment, scale difference, and heterogeneous noise properties systematically. The framework is able to simultaneously capture the fast neuronal dynamics in addition to the delayed vascular response at the same time as modality-specific information by integrating multiresolution signal decomposition directly into the feature learning and fusion process. The experimental

analysis showed that the suggested multiscale multimodal structure achieved a significant improvements of single scale and single modality baselines in accuracy of classification, feature separability, and noise resistance. Those advancements emphasize the fact that modelling scale-dependent behaviour and cross-modal coupling of signals should be explicitly modelled, and not using multiscale analysis as a preprocessing phase. As opposed to data-only fusion methods, the proposed one is interpretable, as its feature extraction and integration are based on the principles of established signal processing methods. Although effective, the framework has some limitations that are associated with computational complexity and dependence on the choice of decomposition parameters, which may include the number of scales, and the selection of wavelet basis. Future research will be directed towards the development of adaptive and data driven scale selection methods, computational optimization of real time deployment, and application to more neurophysiological modalities and continuous-valued prediction problems. All in all, this work offers a theoretically sound and widely applicable signal-processing framework of strong multimodal neurophysiology analysis and leads to more confident integration of heterogeneous brain signals.

REFERENCES

1. Abtahi, M., Borgheai, S. B., Jafari, R., Constant, N., Diouf, R., Shahriari, Y., & Mankodiya, K. (2020). Merging fNIRS–EEG brain monitoring and body motion capture to distinguish Parkinson's disease. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28*(6), 1246–1253. https://doi.org/10.1109/TNSRE.2020.2987888

2. Aghajani, H., Garbey, M., & Omurtag, A. (2017). Measuring mental workload with EEG+fNIRS. *Frontiers in Human Neuroscience, 11*, 359. https://doi.org/10.3389/fnhum.2017.00359

3. Ahn, S., & Jun, S. C. (2017). Multi-modal integration of EEG-fNIRS for brain–computer interfaces: Current limitations and future directions. *Frontiers in Human Neuroscience, 11*, 503. https://doi.org/10.3389/fnhum.2017.00503

4. Al-Quraishi, M. S., Elamvazuthi, I., Tang, T. B., Al-Qurishi, M., Adil, S. H., & Ebrahim, M. (2021). Bimodal data fusion of simultaneous measurements of EEG and fNIRS during lower limb movements. *Brain Sciences, 11*(6), 713. https://doi.org/10.3390/brainsci11060713

5. Al-Shargie, F., Kiguchi, M., Badruddin, N., Dass, S. C., Hani, A. F. M., & Tang, T. B. (2016). Mental stress assessment using simultaneous measurement of EEG and fNIRS. *Biomedical Optics Express, 7*(10), 3882–3898. https://doi.org/10.1364/BOE.7.003882

6. Al-Shargie, F., Tang, T. B., & Kiguchi, M. (2017a). Stress assessment based on decision fusion of EEG and fNIRS signals. *IEEE Access, 5*, 19889–19896. https://doi.org/10.1109/ACCESS.2017.2754325

7. Al-Shargie, F., Tang, T. B., & Kiguchi, M. (2017b). Assessment of mental stress effects on prefrontal cortical activities using canonical correlation analysis: An fNIRS–EEG study. *Biomedical Optics Express, 8*(5), 2583–2598. https://doi.org/10.1364/BOE.8.002583

8. Andrew, G., Arora, R., Bilmes, J., & Livescu, K. (2013). Deep canonical correlation analysis. In S. Dasgupta & D. McAllester (Eds.), *Proceedings of the 30th International Conference on Machine Learning* (pp. 1247–1255). PMLR.

9. Barker, J. W., Aarabi, A., & Huppert, T. J. (2013). Autoregressive model based algorithm for correcting motion and serially correlated errors in fNIRS. *Biomedical Optics Express, 4*(8), 1366–1379. https://doi.org/10.1364/BOE.4.001366

10. Bießmann, F., Meinecke, F. C., Gretton, A., Rauch, A., Rainer, G., Logothetis, N. K., & Müller, K.-R. (2010). Temporal kernel canonical correlation analysis and its application in multimodal neuronal data analysis. *Machine Learning, 79*(1–2), 5–27. https://doi.org/10.1007/s10994-009-5153-3

11. Blokland, Y., Spyrou, L., Thijssen, D., Eijsvogels, T., Colier, W., Floor-Westerdijk, M., Vlek, R., Bruhn, J., & Farquhar, J. (2014). Combined EEG-fNIRS decoding of motor attempt and imagery for brain switch control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 22*(2), 222–229. https://doi.org/10.1109/TNSRE.2013.2292995

12. Buccino, A. P., Keles, H. O., & Omurtag, A. (2016). Hybrid EEG-fNIRS asynchronous brain–computer interface for multiple motor tasks. *PLoS ONE, 11*(1), e0146610. https://doi.org/10.1371/journal.pone.0146610