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Analysis of Hypertension using Fusion of EEG and fNIRS Features

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***Abstract*—Brain-computer interface (BCI) or brain–machine interface (BMI) is a way to communicate between the brain and hardware without the use of muscles or the peripheral nervous system. Simultaneous EEG+fNIRS metric have recently been developed. Until now, few researchers have analysed the possibilities of incorporating hemodynamic responses to their electrophysiologic counterparts in a hybrid way to increase overall performance of the system and accuracy. The combination of fNIRS and EEG signals provide a hybrid sensory motor rhythm based on a brain computer interface (BCI) paradigm. A meta-classifier has been designed to integrate the output probability of each classifier modality. The study found that the simultaneous EEG+fNIRS measurement can substantially improve classification precision.**

***Index Terms*— Hypertension, EEG, BCI, fNIRS.**

I. INTRODUCTION

Hypertension is on the rise and becoming more widespread in our culture. It is possible to test and assess hypertension based on a variety of reactions including psychological, physiological, and behavioural. Questionnaires and psychological evaluations of hypertension can be used to get data from patients about their own levels of hypertension or by having a psychologist evaluate the patient. However, surveys like this only provide information about Hypertension levels of a patient and do not include any information on the stressors or how the Hypertension levels change over time. Informative tests may be conducted from time to time, but they're unlikely to be ideal for identifying the more subtle alterations that might signify the development of a more significant problem in its earlier stages.

Even when you give your complete attention to the questionnaire, it's subjective, and this might affect your results. The statement "People can endure lapses in memory about emotional tone of a week in as little as 24 hours" asserts that we may not always be aware of our true Hypertension levels, which suggests that questionnaires that request an assessment of emotional tone, such as the one included in the SPSS Hypertension Profile, may be inaccurate at measuring actual Hypertension levels [1, 2]. It is more reliable to use a non-subjective, objective metric such as cortisol and alpha amylase. Estimating cortisol levels may be done from four other substances, all of which are found in the aforementioned bodily fluids [i.e. urine, hair, sweat, and blood/saliva]. Blood and saliva readings indicate the actual flow of cortisol in the circulatory system while others provide the storey of how cortisol is produced in the body over time. The cortisol levels in saliva have been proven t o be an accurate biomarker to diagnose and measure Hypertension in both clinical and behavioral

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investigations [3]. An increasing cortisol level has been noted in previous investigations, with the result that it is assumed that stressful situations and negative emotions might lead to stress [4]. According to studies, there is a substantial increase in the salivary alpha amylase level when doing stressful given task such as, playing video games, before and after examinations, and under general stress. On the other hand, cortisol has a slow response time (in minutes) and is strongly affected by circadian rhythms [5]. Cortisol concentrations measured in the early morning apparently are greater than those measured in the afternoon. While it is beyond the scope of this course to teach one how to continuously check their Hypertension levels, this approach does have some relevance, since it is related to psychological surveys. One of the researchers (the same one who developed the continuous sampling method) has argued that the continuous monitoring of these biomarkers is not possible. In reality, given the previous procedure, this sort of measurement is only performed when the affected person or the people surrounding him notice or assume the severity of symptoms.

In addition to using traditional means of measuring blood pressure, bio-signals may also be used. For many patients with hypertension, the most often employed bio-signals for assessing BP are heart rate and skin conductivity [6, 7]. The autonomous nervous system (ANS) activity as detected by heart rate variability (HRV) has also been demonstrated to provide an immediate, quantitative measurement of hypertension-related autonomic nervous system (ANS) activity [8]. High blood pressure (hypertension) may produce a drop in the high-to-low frequency components of the heartbeat interval signals as well as an increase in the low-to-high frequency components. The opposite is true in regard to skin conductivity. Changes in skin moisture level correlate with the sympathetic nervous system, but skin conductivity is significantly affected by changes in the sympathetic nervous system. However, the approaches may also be sensitive to other biological changes, including hypertension, cardiovascular illness, and skin illnesses. Without determining the levels of all risk factors, an in-depth analysis of Hypertension would be nearly impossible.

High blood pressure also influences individual behaviour. Notably, becoming more irritable or furious is easier to measure, whereas other types of induced changes, such as ones that are more known, are far more difficult to pinpoint. Researchers have attempted to understand the behavioural changes that may be caused by electronic devices. To test their connection to Hypertension, they have analysed people interacting with those devices to discover patterns. The pattern that they found has aided in the development of a reliable measurement [9].

A. EEG features

Numerous factors must be considered when selecting an EEG feature to be used for classification. To begin, EEG signals contain information that is both spatially and temporally oriented. A feature that ignores patterns that occur across electrodes or over time may miss significant patterns in the signal. The EEG features can be time- or frequency-domain in nature. Mean amplitude, mean amplitudes of Event Related Potential (ERP) components, variance, skewness, kurtosis, and peak values are frequently calculated in the time domain. Due to the fact that EEG signals frequently contain oscillatory patterns, features that utilise frequency spectra are frequently used, as is the case with BCI systems.

B. Functional near infrared spectroscopy (fNIRS)

fNIRS is a non-invasive brain imaging technique based on hemodynamic responses to cortical activation. fNIRS measures blood flow in the brain by measuring haemoglobin concentrations and tissue oxygenation [10]. The technique works by sending near-infrared light (with a wavelength of 650-850 nm) into the head via a light source. The oxygenated and deoxygenated haemoglobin concentrations can be calculated using a modified Beer-Lambert law by measuring light sent at two different wavelengths [11]. Since the 1990s, the fNIRS has been used in neuroimaging studies to assess cortical activity in response to cognitive and motor tasks [12]. The application of fNIRS to functional neuroimaging has been extensively studied by groups led by Britton Chance (Pennsylvania State University), David Boas (Massachusetts General Hospital), Theodore Huppert (University of Pittsburgh), Scott Bunce (Drexel University), and Enrique Gratton (University of Illinois at Urbana-Champaign). With additional research, such as the current study, fNIRS may develop into a valuable complement to EEG and other psychophysiological measures for monitoring and predicting cognitive states.

The fNIRS technique examines only the cortex's outer surface and quantifies changes in the oxygenated and deoxygenated haemoglobin concentrations ($[O_2Hb]$ and $[HH_b]$, respectively). It is lightweight, inexpensive, non-constricting, non-invasive, and safe for long-term monitoring. The spatial resolution is on the order of 1cm2 at best [13]. The temporal resolution is sub-second. The measurements were found to be consistent with those obtained using fMRI [14] and electroencephalography [15]. Optical absorption increases with increasing haemoglobin concentrations, which are determined by local neural activity [16]. This is analogous to how BOLD signals are generated in fMRI by changes in deoxygenated haemoglobin. Both techniques indirectly quantify

neural activity via neurovascular coupling. fNIRS and fMRI both detect hemodynamic responses [17], in contrast to Event Related Optical Signal (EROS) and Electroencephalogram (EEG) measurements, which detect neuronal activity (through cellular changes which affect optical scattering, or through electrical activity, respectively). A critical comparison of the most frequently used neuroimaging modalities is depicted in Figure 1.

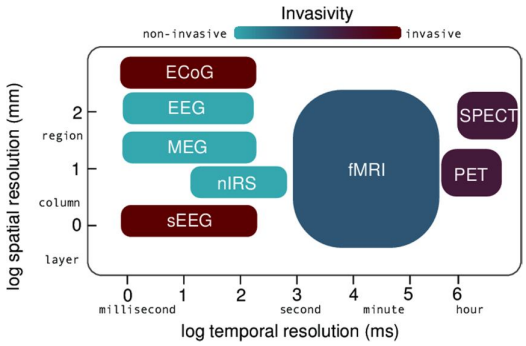

Figure : Comparing functional neuroimaging modalities spatially and temporally [17]

The operation of a near infrared imaging system is depicted in Figure 2 When a stimulus (e.g., finger tapping) occurs, related areas of the brain (motor cortex) activate, resulting in changes in local cerebral blood flow and volume. This results in changes in the concentrations of bloodborne cells and molecules in the capillaries surrounding the neurons, as well as in the level of blood oxygenation (hemodynamic response), which the fNIRS can detect.

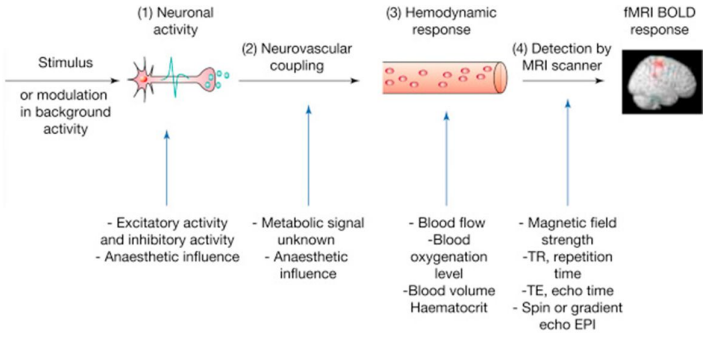

Figure 2: Neuronal activity alters blood flow, volume, and oxygenation level [13]

II. Hypertension Assessment using Fusion of EEG And FNIRS Features

The techniques that are introduced in this chapter include inter- and intra-hemisphere data pre-processing, feature extraction, statistical analysis, EEG and fNIRS data fusion, classification, and cortical connectivity. After the noise and artefacts were removed from the EEG data, ICA was used to identify independent components. Then a band-pass filter, which has a frequency range of 0.5 to 30 Hz, was used to separate features, and features were extracted using wavelet transformation. Classifier support vector machines were then used to sort and classify the features. Moving around in a magnetic scanner causes artefacts, such as heartbeats, breath noises, and blood pressure fluctuations. Linear regression, data moving average, block averaging, and feature extraction and classification all brought baseline correction to the table. The inter- and intra-hemispheric average squared coherence was studied based on control and stress conditions in which seven frequency intervals were considered. It explains the two feature-level fusion approaches, where joint independent component analysis (or canonical correlation analysis) is used to pair feature data and hidden data together. Figure 3 illustrates the overall process of this study.

A. Objective measurements and data processing

The objective measurements presented in this thesis are based on electroencephalogram (EEG) and near-infrared spectroscopy (fNIRS) signals. Th e acquisition method is discussed and reprocessing methods are discussed in

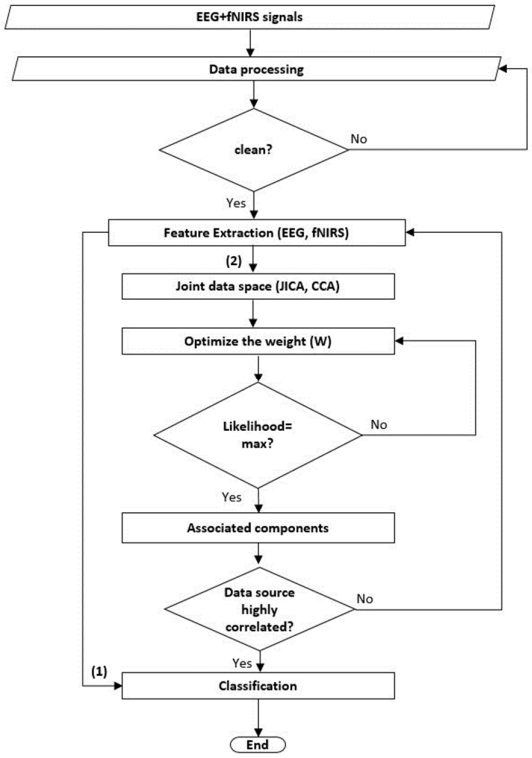

Figure 3: overall flow chart of the proposed study

coming sections in order to remove systemic noise and artefacts from the acquired data. Each modality was pre-processed independently. The following subsections detail the overall signal pre-processing.

Data acquisition

This study also gained data by measuring the EEG signal using Discovery 24E (Brain Master Technologies Inc., Bedford, OH) and by using a multi-channel fNIRS system to measure hemodynamic response (OT-R40, Hitachi Medical Corporation, Japan). The electrodes and canals of the modalities have been combined in one cap custom. Seven active electrodes and two different electrodes were attached to the lobes of the EEG system. Similarly, 16 optical fibers were fitted for the fNIRS system; eight sources (two wavelengths, 695nm and 830nm together in one source) and eight detectors. The EEG sampling frequency was set to 256 Hz and a 10 Hz sample of the fNIRS system.

EEG data processing

The MATLAB programming system was used to prepare the raw EEG data for offline processing. Third-order Butterworth band pass filtering was used to reduce the range of the raw EEG data from 0.5 Hz to 30 Hz. The Butterworth filter hypothesised here due its capabilities to smooth monotonically decreasing frequency response in the transition region. To remove eye blink and movements artefacts, the method of independent component analysis (ICA) was applied. each component was divided into individual channels (by default the number of components is equal to the number of recorded channels). Artefacts were no longer included. Further analysis of the signals using wavelet transform (WT) was performed. The WT technique can be used for time-frequency analysis at several resolutions. The process of decomposing the EEG signals into functions was done in order to calculate the approximate coefficients and the functions associated with them at various levels. To decompose the EEG signals into four frequency bands, the wavelet family of Dubechies-8 (db8) was employed (delta, theta, alpha, and beta). The coefficient from that section were then used to calculate the mean power values.

B. EEG Feature extraction

Wavelet coefficients mean absolute values of wavelet coefficients, while over the time period of the activation period, sub-band mean absolute values of wavelet coefficients, along with the average power and energy, were obtained (task condition). The initiation period was defined as beginning when the task started, and continuing

until the task was finished throughout each block. To smooth out the acquired signals, the five active blocks were averaged into a single block of 30s. The features of the EEG signals were calculated by moving the 500ms window. Eq. 1 was used to calculate the power spectral density values.

$$P_j = \frac{1}{N}\sum_{n--1}^{N} |x_j(n)|^2, j = 1,2 \qquad (1)$$

Where P_j is the mean absolute value of the EEG signals, $x_j(n)$ which is defined as the mean of the EEG signals segments in the alpha band at $j = 1$ and the beta band at $j = 2$,, and where is the length of the segmented EEG signal in the alpha band at and the beta band at. The frequency bands of the EEG were determined and calculated with the equation 2:

$$E_j = \frac{1}{N}\sum_{-\infty}^{\infty} |x_j(n)|^2, j = 1,2. \qquad (2)$$

Before normalisation, each feature set was standardised on the scale of "0" and "1." Then the standardised features were fed into the classifier using the formula (Equation 3).

$$Feature_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (3)$$

The feature set x features everything, the $\min(x)$ minimum value in the feature set is represented by the letter "m" and the maximum value $\max(x)$ in the feature set is defined by the letter "h". In this study, since the mean of the spectra l power was very significant, only the mean power features were analysed. Figure 4 depicts the entire process flow for EEG data processing and feature extraction. To determine the dominant region and the most significant electrode, a statistical analysis was conducted. The assumption in this study is that, significant differences can only be found if they exist $p < 0.05$. After applying the Support Vector Machine classifier to classify the data, control and stress classifications were made.

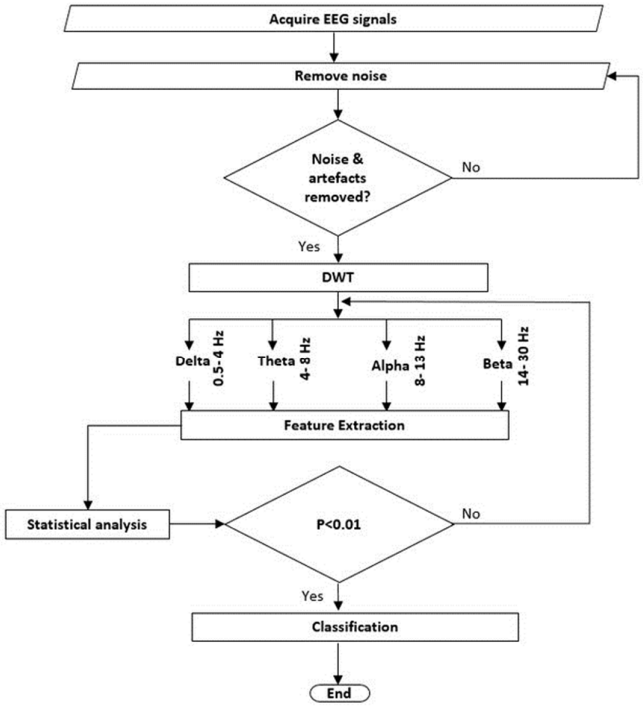

Figure 4: Flowchart of EEG data processing and features extraction

C. fNIRS data processing

Using the modified Beer-Lambert law, the fNIRS signals were transformed into the concentration changes of O_2Hb, HHb, and total haemoglobin Ht. Pre-processing steps were performed on the fNIRS signals, which

reduced noise and artefacts, to help improve accuracy by using MATLAB (R2013a, The Math Works, Inc., Massachusetts, USA) with custom scripts and the plug-in analysis software Platform for Optical Topography Analysis Tool (PUL), which includes custom scripts and the analysis software. Using a fifth order Butterworth filter, moving average, baseline correction, and epoch extraction, the signal was filtered between and using a range of fifth-order Butterworth filters. Due to its high strength in smoothing the overall signal at lower frequencies, the Butterworth was selected. A moving average was used to filter out high frequency artefacts in the signal, using a time window of 5. One analysis block was defined as the beginning of the task condition and the end of each task condition. Next, least-mean-squares regression was used to identify the linear trend of the baselines' regression. The treatment in this experiment was conducted solely to take into account the hemodynamic response to arithmetic activities, under either a controllable or uncontrollable environment. In order to decrease computation time and help overall process accuracy, the data were further averaged within all the analysis blocks. The analysis in this study was restricted to the signals, since responses were more pronounced.

D. fNIRS features extraction

To calculate the mean concentration, variance, skewness, kurtosis, and peak, feature extraction O_2Hb was performed using a moving time window of 500ms for each analysis block. The signal mean was calculated as:

$$O_2Hb = \frac{1}{N}\sum_{n=1}^{N}(\Delta O_2Hb)_n \qquad (4)$$

The variance, or variance ratio, O_2Hb is equal to the mean value of the variable divided by the standard deviation.

$$VAR(O_2Hb) = \frac{\sum_{n=1}^{N}(O_2Hb-\mu)^2}{N} \qquad (5)$$

where var is the variance, μ is the mean value of O_2Hb .
To calculate the skewness, the formula is:

$$Skew(O_2Hb) = E\left[\left(\frac{O_2Hb-\mu}{\sigma}\right)^3\right] \qquad (6)$$

Where *skew* is the skewness, σ is the standard deviation, and is the expected value of over a certain time window. In order to compute the kurtosis, the following calculation was used:

$$Kurt(O_2Hb) = E\left[\left(\frac{O_2Hb-\mu}{\sigma}\right)^4\right] \qquad (7)$$

Matlab's built□in function is used to determine the signal peak, and the function, The signal slope has been determined by fitting a section to all the data points and during mental arithmetic and rest using the built□in function, the polyfit function in Matlab. All channels from all subjects were used to compute these results, with the rest state, mental arithmetic at control, and mental arithmetic at stress. All feature values were distributed between a minimum value of zero and a maximum value of one before feeding them into the classifier using the equation:

$$O_2Hb' = \frac{O_2Hb-\min(O_2Hb)}{\max(O_2Hb)-\min(O_2Hb)} \qquad (8)$$

Where $O_2Hb \in R^n$ denotes the feature vectors vales, O_2Hb' denotes the value rescaled between 0 and 1 and the value $\min(O_2Hb)$ is the lowest of any signal set. However, in order to simplify the implementation of this research, the review was restricted to the mean feature of the O_2Hb signals because of their greatest reactions to stress stimuli. Figure 5 shows the overall flow of fNIRS data treatment and extraction features.

III. fNIRS AND EEG FUSION

Fusion of multimodality data presents a difficult problem because of the very different types of imaging data, which results in an almost endless number of assumptions. It is unrealistic to believe that data is anything other than what it is. Data fusion techniques in this study are distinctly different from data integration methods, which more commonly use information from one modality to improve the other. As a result, combining the analyses allows for the full interaction between EEG and fNIRS data types. The authors in this study chose to reduce the amount of data for each modality (EEG and fNIRS) by using an alternate method that provides a feature (a

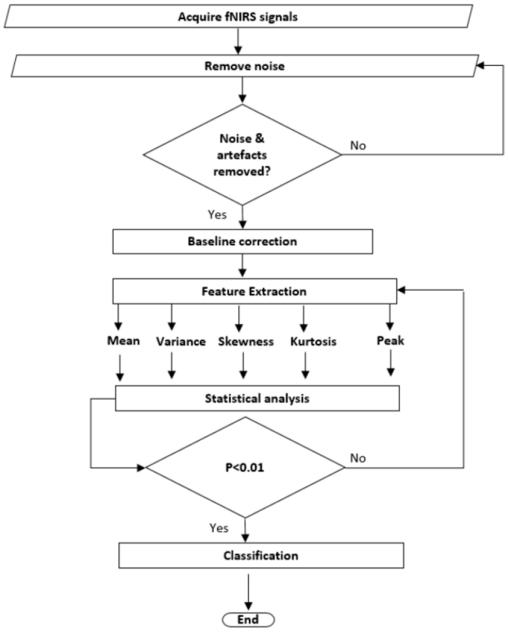

Figure 5: Flowchart of fNIRS data processing and features extraction

lower-dimensional representation of selected brain activity). A fusion of these two sets of feature data was then used to explore relationships between these two sets of feature data for each individual, in this study.

To overcome this issue, the technique can be used to conduct investigations on the variations in subjects or between stressed people and non-stressed people on a feature-level. This provides a natural route to discover multimodality associations and also eases the problem of fusing data types of different dimensionality and nature. Data-driven fusion techniques such as joint ICA [18] have successfully utilised feature-level analysis. The jICA methodology uses the concatenation of two feature data sets of X, and then ICA is applied to the concatenated data set. This is the first EEG and FNIRS study to use a joint component analysis technique to develop feature fusion. The assumption behind the Joint-ICA is that sources have a similar modulation profile for the subjects [18]. Even with that in mind, this is a fairly strong constraint because the data is sourced from two different modalities.

It has recently been found that CCA can support a more adaptive fusion approach [19]. This study makes this claim for the first time by proposing that we fuse the EEG and fNIRS features. An ingredient-based approach as well as a feature-based approach are both applied in the fusion method, which models the feature data set from each modality as a linear mixture of components, where each component's degree of activation varies depending on which subject it is for. As a result, modality relationships are dependent on intersubjectcovariations. Following the implementation of the proposed fusion technique, this section demonstrates its usage.

A. Fusion Based on Joint Independent Components Analysis $(jICA)$

The EEG and fNIRS data have been merged in this manner utilising two consecutive methods. First, the advantages of fNIRS spatial resolution have been employed to determine the geographical places of interest (regions of interest). The choice of EEG electrodes then was based on the importance of their neighbouring fNIRS canal response to mental stress. T□test statistical analysis was done to evaluate the significant brain responses from control to stress. The greater the t-value, the bigger the disparities between brain responses in the two circumstances. Only high-value channels have been selected for fusion and the surrounding electrodes. Secondly, each modality has examined its spatial and temporal advantages. EEG and fNIRS sources have been transformed by ICA into time tICA and space sICA components. This was done in order to extract good qualities with their strength to be complementary. The following generational model was used for joint Independent Component Analysis (jICA) to calculate the Mixing Matrix A, between the tICA components of the EEG as well as the sICA components from the fNIRS:

$$X^{EEG} = AS^{EEG}, X^{fNIRS} = AS^{fNIRS} \qquad (9)$$

While there are several significant advantages of jICA, its most significant advantage is that it maximises the likelihood between the two modalities' data features. The two data feature sets were combined using joint independent component analysis, and then just applied for maximum likelihood. Assumed there are two sources for each modality (EEG and fNIRS) and two subjects, and using the combined data for EEG and fNIRS, we can deduce that the total combined data for the EEG is $X^{EEG} = [X_1^{EEG}, X_2^{EEG}]^T$or that the total combined data for fNIRS is

$$S^{EEG} = [S_1^{EEG}, S_2^{EEG}]^T, \quad (10)$$

Each electrode of an EEG is specifically assigned to one part of the brain. $X^{fNIRS} = \left[X_1^{fNIRS}, X_2^{fNIRS}\right]^T$and the fNIRS sICA components of the two subjects are:

$$S^{fNIRS} = [S_1^f NIRSS_2 NIRS]^\tau, \quad (11)$$

and A is a shared linear mixing matrix whose individual mixing matrixes are A.:

$$A = \begin{bmatrix} a_{11} a_{12} \\ a_{21} a_{22} \end{bmatrix}, \quad (12)$$

Concatenation of the two sets of data and sources yields a single data and source vector for each subject. Here, I show you how to form a single equation that's linked between the two modalities, and it's called Equation 13..

$$\begin{bmatrix} X_1^{EEG} X_1^{fNIRS} \\ X_2^{EEG} X_2^{fNIRS} \end{bmatrix} = \begin{bmatrix} a_{11} a_{12} \\ a_{21} a_{22} \end{bmatrix} \begin{bmatrix} S_1^{EEG} S_1^{fNIRS} \\ S_2^{EEG} S_2^{fNIRS} \end{bmatrix}, \quad (13)$$

Additionally, this study used the infomax algorithm to determine the mixing matrix[20]. This model follows a linear progression. Time invariance in the mixing matrix indicates that The time invariant assumption no longer holds true for long-term acquisition. Using this method, the long time sequence is divided into several short segments. Then, batch by batch, the algorithm was applied to these segments. Using a natural gradient ascent technique, the infomax algorithm maximises the output entropy of a neural network in this study. Entropy is the state of being independent among the components. The weight matrix of the neural network, called the inverse matrix of the shared mixing matrix, A, describes the mixing behaviour of the neural network. Weight updating rule for the weight matrix uses the neural network and as given:

$$\Delta W = \eta\{I - 2y^{EEG}(S^{EEG})^\tau - 2y^{fNIRS}(S'^{fNIRS})^T\}W, \quad (14)$$

$$S'^{EEG} = WX^{EEG},$$

$$S'^{fNIRS} = WX^{fNIRS},$$

$$y^{EEG} = g(S^{EEG})$$

$$y^{fNIRS} = g(S'^{fNIRS}),$$

$$g(x) = \frac{1}{1+e^{-x}}, \quad (15)$$

The estimated independent EEG and fNIRS sources where *I* is the identity material matrix, S'^{EEG}, $S'^{fNIRS}$are regenerated EEG and fNIRS data. $y^{EEG}$and$y^{fNIRS}$are regenerated EEG and data fNIRS respectively. In Eq. 15, g(x) is the nonlinear neural network transfer function. The initial W, W (0) value is a random vector matrix. The study assumed in this fusion approach that the EEG sources as well as the fNIRS data modulated equally across all subjects. In both modalities, a normalisation method is applied to normalise feature data from 0 to 1. The assumption of common linear covariation both for modes is a parsimonious way of connecting multiple data

types and has led to better results in FMRI studies[18]. This property is an emerging approach and essential for future studies in a new type of imaging modality. Moreover, contrary to the Calhoun model[18], this fusion technique is carried out in a feature level wherein features were extracted using a small shared time-moving window of 500ms from each of the EEG and fNIRS data components.
Notably, optimising weights across data sources in both methods contributes to reducing attribute redundancy within each modality and increasing probability in both modes by minimising variance within each data set and increasing it between them. This process helps estimate the data type in the classification process at a later stage. A matrix consists of recreated extracted features of the associated components, which maximise their probability. It can be concluded that the task in this particular area is very local if the associated components/sources are significantly linked. Exploring the source correlation map of all people can help to diagnose mental stress. As shown in figure 6, the fusion aspect is shown in the flow chart. Observe that it only highly correlated sources were used to categorise data fusion performance.

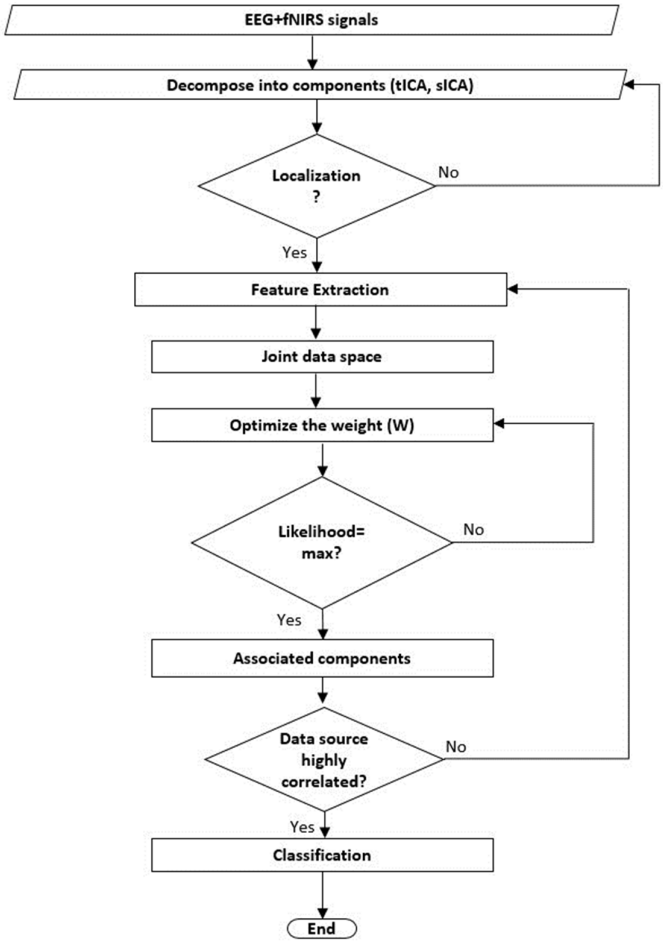

Figure 6: Flow chart of fusion based on jICA

IV. Experimental Data and Conditions

Figure 7 shows the placing of probes. Figure 8 shows raw data. The elements of Data Preprocessing (useful for eliminating random experimental errors and improving data quality) include deleting, filtering, and excluding data with random deviations (e.g., “steps” and “spikes”) that might bias the finding as shown in Figure 9.
We calculate the time series of hemodynamic states (i.e., oxy-Hb, deoxy-Hb, tissue blood volume, HbO2 saturation) by applying the elements seen in Figure 9 to the filtered data that the preprocessing utility provides.

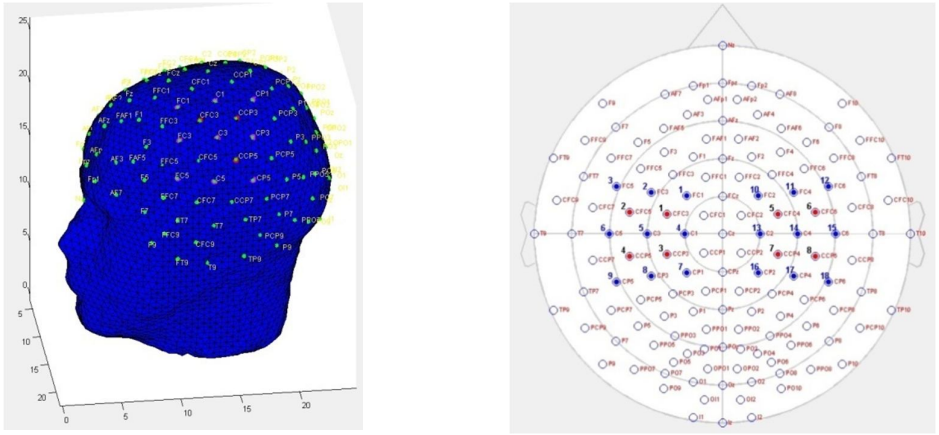

Figure 7: Sample figure placing the probes

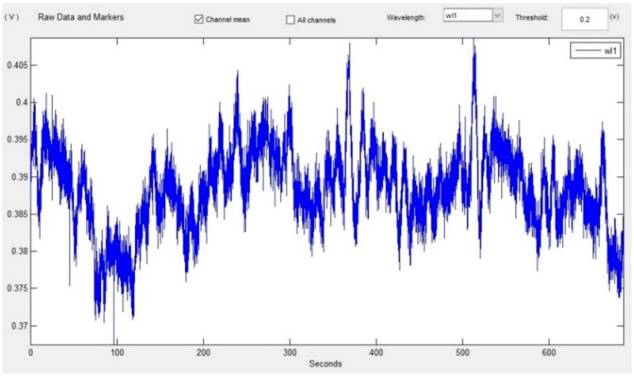

Figure 8: Raw data

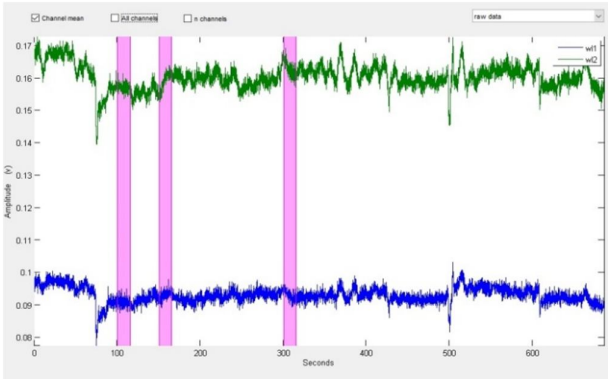

Figure 9: Data after applying filter

V. CONCLUSION

This paper details the experimental setup, the stress induction procedure, control of simultaneous EEG and fNIRS systems measurements, data processing, extraction of functions, statistical analysis, and classification processes. It also outlines the conceptual fusion technique which combines EEG and fNIRS signals to increase mental stress detection. In addition, it provides a new perspective in assessing connectivity-based stress in inter- and intra-hemispheric PFC regions.

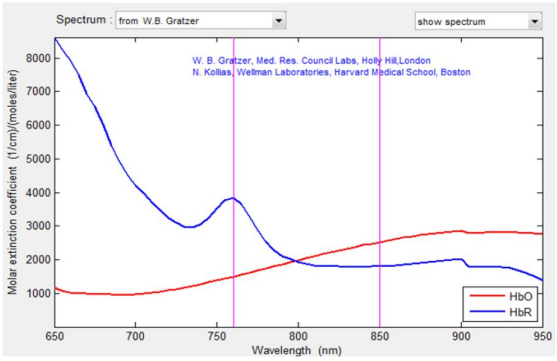

Figure 10: Parameter settings for Beer-Lambert Law

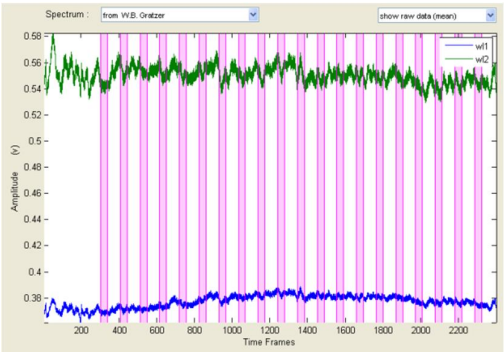

Figure 11: Spatial mean display with event markers

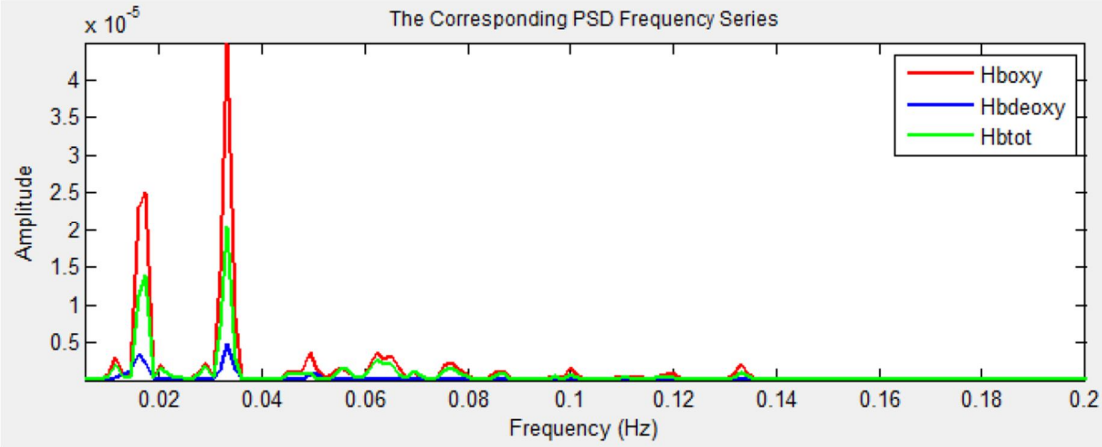

Figure 12: Detail view of the PSD plot window

REFERENCES

[1] T. H. Holmes and R. H. Rahe, "The social readjustment rating scale," Journal of psychosomatic research, vol. 11, pp. 213-218, 1967.

[2] T.-K. Liu, Y.-P. Chen, Z.-Y. Hou, C.-C. Wang, and J.-H. Chou, "Noninvasive evaluation of mental stress using by a refined rough set technique based on biomedical signals," Artificial intelligence in medicine, vol. 61, pp. 97-103, 2014.

[3] D. H. Hellhammer, S. Wüst, and B. M. Kudielka, "Salivary cortisol as a biomarker in stress research," Psychoneuroendocrinology, vol. 34, pp. 163-171, 2009.

[4] N. M. Stephens, S. S. Townsend, H. R. Markus, and L. T. Phillips, "A cultural mismatch: Independent cultural norms produce greater increases in cortisol and more negative emotions among first-generation college students," Journal of Experimental Social Psychology, vol. 48, pp. 1389-1393, 2012.
[5] R. Den, M. Toda, S. Nagasawa, K. Kitamura, and K. Morimoto, "Circadian rhythm of human salivary chromogranin A," Biomedical Research, vol. 28, pp. 57-60, 2007.
[6] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," IEEE Transactions on intelligent transportation systems, vol. 6, pp. 156-166, 2005.
[7] G. K. Verma and U. S. Tiwary, "Multimodal fusion framework: A multiresolution approach for emotion classification and recognition from physiological signals," NeuroImage, vol. 102, pp. 162-172, 2014.
[8] J. F. Thayer, F. Åhs, M. Fredrikson, J. J. Sollers, and T. D. Wager, "A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health," Neuroscience &Biobehavioral Reviews, vol. 36, pp. 747-756, 2012.
[9] B. H. Eijckelhof, M. A. Huysmans, B. M. Blatter, P. C. Leider, P. W. Johnson, J. H. van Dieën, et al., "Office workers' computer use patterns are associated with workplace stressors," Applied ergonomics, vol. 45, pp. 1660-1667, 2014.
[10] M. I. Ismail and T. Teck-Hong, "Identifying work-related stress among employees in the Malaysian financial sector," World, vol. 3, pp. 229-243, 2011.
[11] A. Sassaroli and S. Fantini, "Comment on the modified Beer-Lambert law for scattering media," Physics in Medicine and Biology, vol. 49, pp. N255-N257, 2004.
[12] F. Scholkmann, S. Kleiser, A. J. Metz, R. Zimmermann, J. M. Pavia, U. Wolf, et al., "A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology," Neuroimage, vol. 85, pp. 6-27, 2014.
[13] R. C. Bendall and C. Thompson, "Functional near-infrared spectroscopy: An emerging neuroimaging technique successful in studying the interaction between emotion and cognition," PsyPAG Quarterly, vol. 96, pp. 14-17.
[14] M. L. Schroeter, T. Kupka, T. Mildner, K. Uludağ, and D. Y. von Cramon, "Investigating the post-stimulus undershoot of the BOLD signal—a simultaneous fMRI and fNIRS study," Neuroimage, vol. 30, pp. 349-358, 2006.
[15] L. Li, P. Du, T. Li, Q. Luo, and H. Gong, "Design and evaluation of a simultaneous fNIRS/ERP instrument," in Biomedical Optics (BiOS) 2007, 2007, pp. 643429-643429-6.
[16] D. A. Boas, A. M. Dale, and M. A. Franceschini, "Diffuse optical imaging of brain activation: approaches to optimizing image sensitivity, resolution, and accuracy," Neuroimage, vol. 23, pp. S275-S288, 2004.
[17] T. J. Huppert, R. D. Hoge, A. M. Dale, M. A. Franceschini, and D. A. Boas, "Quantitative spatial comparison of diffuse optical imaging with blood oxygen level-dependent and arterial spin labeling-based functional magnetic resonance imaging," Journal of biomedical optics, vol. 11, pp. 064018-064018-16, 2006.
[18] V. D. Calhoun, J. Liu, and T. Adalı, "A review of group ICA for fMRI data and ICA for joint inference of imaging, genetic, and ERP data," Neuroimage, vol. 45, pp. S163-S172, 2009.
[19] N. M. Correa, Y.-O. Li, T. Adali, and V. D. Calhoun, "Canonical correlation analysis for feature-based fusion of biomedical imaging modalities and its application to detection of associative networks in schizophrenia," IEEE journal of selected topics in signal processing, vol. 2, pp. 998-1007, 2008.
[20] T. W. Lee, M. Girolami, and T. J. Sejnowski, "Independent component analysis using an extended infomax algorithm for mixed subgaussian and supergaussian sources," Neural Computation, vol. 11, pp. 417-441, 1999.