Signal Quality Assessment Model for Wearable EEG Sensor on Prediction of Mental Stress

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***Abstract*—Electroencephalogram (EEG) plays an important role in E-healthcare systems, especially in the mental healthcare area, where constant and unobtrusive monitoring is desirable. In the context of OPTIMI project, a novel, low cost, and light weight wearable EEG sensor has been designed and produced. In order to improve the performance and reliability of EEG sensors in real-life settings, we propose a method to evaluate the quality of EEG signals, based on which users can easily adjust the connection between electrodes and their skin. Our method helps to filter invalid EEG data from personal trials in both domestic and office settings. We then apply an algorithm based on Discrete Wavelet Transformation (DWT) and Adaptive Noise Cancellation (ANC) which has been designed to remove ocular artifacts (OA) from the EEG signal. DWT is applied to obtain a reconstructed OA signal as a reference while ANC, based on recursive least squares, is used to remove the OA from the original EEG data. The newly produced sensors were tested and deployed within the OPTIMI framework for chronic stress detection. EEG nonlinear dynamics features and frontal asymmetry of theta, alpha, and beta bands have been selected as biological indicators for chronic stress, showing relative greater right anterior EEG data activity in stressful individuals. Evaluation results demonstrate that our EEG sensor and data processing algorithms have successfully addressed the requirements and challenges of a portable system for patient monitoring, as envisioned by the EU OPTIMI project.**

***Index Terms*—ANC, DWT, EEG, features extration, mental stress, ocular artifacts, signal quality assessment.**

I. Introduction

ELECTROENCEPHALOGRAPHY (EEG) is frequently used in the diagnosis of brain related diseases such as epilepsy, sleep disorders, mental disorders, and so on. EEG signals are relatively weak and prone to noise. The quality of EEG data, therefore, presents a common challenge for accurate and in time diagnosis of brain related diseases. Currently, the measurement of EEG requires sophisticated and expensive medical instruments operated by professionally trained domain experts. In hospitals and clinical centers, in order to ensure data quality, EEG is normally taken in dedicated soundproofed facilities, involving the use of electromagnetic shielding (RF shielding).

EEG is an electronic record of the oscillations in the human brain, recorded from multiple electrodes attached to the scalp. Depending on the individual's state of relaxation [1], EEG can vary in shapes. EEG data are generally labeled according to the frequency ranges, namely delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–20 Hz), and gamma (roughly >20 Hz). Typically, the scalp electric potential amplitude is between 20 and 100 μV.

EEG has also demonstrated potential values in sports-training, mind-control technologies and personalized E-health care. Increasingly, in recent years, wearable EEG sensors for E-mental healthcare have emerged to be a key research and development direction. Research institutes and commercial organizations around the world are designing and rolling out prototypes or products targeting at E-mental health monitoring and management. Prominent examples of such work include *Trimbos Institute* in Netherlands, *Psychmed Group* in USA, *e-Mental Health* in Central Massachusetts which is a project of the Lamar Soutter Library of the University of Massachusetts Medical School, as well as leading IT companies such as Google, Apple, and so on.

The OPTIMI (Online Predictive Tools for Intervention in Mental Illness) project, funded by the Seventh Framework Programme (FP7) of European Union (EU), aims to exploit the latest sensor technologies in tackling mental disorders (in particular mild depression). OPTIMI is based on the hypothesis that the central issue and starting point of longer term mental illness depends on the individual's capacity and ability to cope with stress. The goal of OPTIMI is to develop tools to perform prediction through early identification of the onset of an illness by monitoring poor coping behavior. In order to identify the onset of a mental illness, an individual will use wearable and domestic appliances to collect data on EEG, ECG (electrocardiogram), and cortisol levels, which are combined with voice analysis, physical activity analysis, and a self-reporting electronic diary to provide comprehensive understanding of his/her mental status. Specific markers of depression will be checked using EEG, voice analysis, and physical activity. Therefore, it is clear that wearable EEG system is a key success factor of the OPTIMI project.

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The application domain of OPTIMI implies unique requirements of EEG sensors. Firstly embeddable EEG bio-sensors are desirable to offer, as much as possible, unobtrusive data collection. Such sensors should offer high portability, present ease of deployment and use, and be suitable for complex environments. Secondly, for EEG-based technologies to be widely adopted by people in the "real world," it is necessary for EEG bio-sensors to achieve high efficiency in signal processing. In this paper we present the concept of a "smart" wearable EEG sensor. It is our contention that in "real-world" applications, sensors must function effectively away from the traditional dedicated facilities used to capture EEG signal data. This broaches three key questions to be addressed in the rest of this paper: 1) the maintenance of EEG signal quality, 2) the removal of Ocular Artifacts, and 3) the extraction of features related to mental disorders (in this paper the focus is on depression). The remainder of this paper is structured as follows: we briefly present the background of E-Mental Healthcare in Section II. The design of wearable EEG sensors is discussed in Section III. Following the assessment methods of EEG signal quality in Section IV, we propose our approach to the removal of OA using a model combining Discrete Wavelet Transformation (DWT) and Adaptive Noise Cancellation (ANC) in Section V, where experiments and application in the OPTIMI project are also detailed. Section VI covers feature extraction for depression predication. Section VII concludes the paper with observations/discussions, conclusions, and directions for future work.

II. E-Mental Healthcare

Mental disorder is a leading disease burden estimated by World Health Organization (WHO). In the U.K. and major western European countries, mental illness is considered one of the biggest challenges of modern society. It is estimated that one in four residences in the U.K. is directly affected by mental illnesses while 27% of the total adult EU population experienced a certain type of mental disorder. Among others, depression is becoming increasingly prevalent. In China, every year around 1900 million adults are affected by depression of various severities. In fact, WHO has estimated that approximately 25% of the world's population will experience episodes of depression during their life time. Without help, this subpopulation is exposed to a significant risk of developing full-blown depression. Thus, the scope and need for the identification, prevention, and intervention of depression is expected to increase significantly in the near future.

E-Mental Healthcare is a branch of E-healthcare, with the aim of delivering mental health services via the internet through bio-electric information, diary, movement, voices, or internet applications. It makes use of a wide range of e-Interventions defined as "mental and behavioral health promotion, prevention, treatment and management-oriented interventions that are delivered via the internet or other electronic technologies, with or without human support" [2].

Unlike other types of mental disorders, depression lends itself as a perfect test-bed for emerging ICT technologies—it has been proved that depression can be evaluated and successfully intervened through online tools and digitized therapeutic methods. This gives rise to web-based and mobile-based solutions. When considering data collection, while the traditional methods with dedicated (generally hospital) facilities have been the predominant source of data, web-based services call for alternative gathering method: the contribution made by general users in a wide variety of "non-standard" settings. In such environments users "self-report" data about their physical and mental activities and "self-collect" a range of relevant health monitoring data that are considered important for depression and stress management.

III. The Design of Wearable EEG Sensors

As discussed previously, when away from purposely built facilities (generally in hospitals and clinic centers), wearable EEG sensors can facilitate continuous monitoring. We have identified three key requirements to direct the design and development of our EEG:

- Signal quality should meet certain criteria.
- OAs should be identified and removed for signal pre-processing.
- Suitable features should be selected for the depression use case.

EEG signal quality: Without the help of technical staff, how can users' know whether the EEG sensor is worn correctly and whether the test can start? If the sensor is not placed correctly on the scalp, the quality of the data may be compromised. It is, therefore, necessary to identify an effective and simple method by which the connection or signal quality can be determined. Traditional commercial EEG products in hospital, made by MindMedia, NeuroSky, Emotiv, BP, etc., rely on "electrode-to-skin" contact resistance as a key to judge the quality of the connection [3], [4]. However, for wearable EEG sensors, methods to estimate the quality of connection are extremely limited and impedance measurements will raise complexity and cost of wearable EEG sensors. In this paper, a novel quality measure of EEG signal is proposed, which are evaluated in the OPTIMI project. This method ignores the tradition skin-electrode contact impedance and focuses on the raw EEG data, thus it can be adapted to quantify the connection and data quality of all types of wearable EEG sensors.

Ocular Artifacts removal: In order to avoid user's resistance, the electrodes are set as Fp1, Fpz, and Fp2 which are just located on the forehead. This, however, means that the EEG signals are easily corrupted by noises, especially ocular artifacts. Eye movements can cause changes to the electric fields around the eyes and consequently affect those over the scalp, leading to low-frequency band noises. In order to clean EEG signal data, a algorithm based on discrete wavelet transformation (DWT) and adaptive noise cancellation (ANC) is designed to identify and remove ocular artifacts from EEG signal. Our evaluation results have proved that this proposed algorithm is a novel, effective approach even when the EEG signal has only one channel, making our algorithm particularly suitable for portable applications.

Depression features definition and extraction: The aim of OPTIMI is to characterize the stress level of the groups under great stresses by the use of EEG. In this paper, based on previous EEG research in other areas we identify and extract features from EEG to effectively distinguish high-stress and mod-

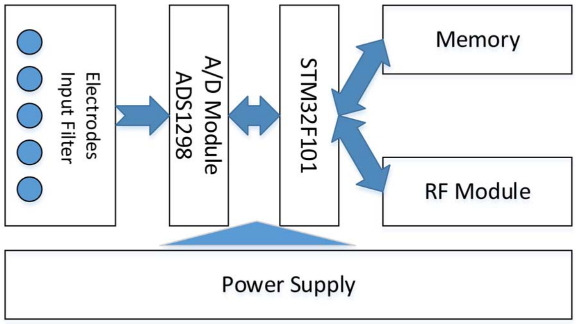

Fig. 1. EEG Sensor, primary hardware components.

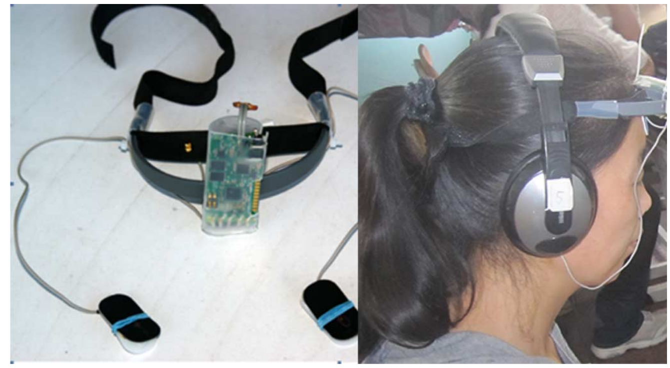

Fig. 2. EEG sensor, worn on the head of a volunteer.

erate-stress individuals. EEG features, including linear features, such as absolute and relative power, frequency, and asymmetry as well as nonlinear dynamic measures are taken into account to examine the difference between those with chronic stress and the normal control. Features of alpha asymmetry and C0 complexity are applied as main features to calculate the degree of mental disorder (depression).

In the OPTIMI project, a 5-electrode EEG sensor has been developed to provide data to the envisioned on-line predictive tools for early identification and intervention during the onset of depression due to inadequate coping with day-to-day stress.

The 5 electrodes are configured as follows: three location points on the forehead (FP1, FP2, and FPZ) and two ear lobes (A1 and A2). Users are expected to record their resting EEG signal twice (in the morning and evening) on a daily basis. In order to ensure that users comply with the daily testing schedule (required every day for 4 weeks), EEG should be performed as unobtrusive as possible: the deployment of electrodes should be simple and once electrodes are deployed, data recording should be carried out promptly. Therefore ergonomic design must be considered at each stage of the development process. As there are no suitable commercial sensors available, we have designed a novel, low cost, and light weight wearable EEG sensor. The main board of sensor (as illustrated in Fig. 1) consists of 6 modules: electrodes, A/D module (including amplifier), CPU, memory, RF module, and power supply [5].

On the left, five electrodes are connected to a signal conditioning circuit to clamp any voltage spikes that may arise due to electrostatic discharge. The five input leads are inter-connected in a manner so as to obtain the following channel combinations: FP1 relative to A1, FP0 relative to A1, FP2 relative to A1, FP1 relative to A2, FP2 relative to A2, and FP1 relative to FP2. In addition, passive filtering is performed to remove 100 Hz or higher input noise.

We selected ADS 1299 instrumentation amplifier ADC from Texas Instruments. This device is derived from a family of multichannel, simultaneous sampling, 24-bit, delta-sigma analogue-to-digital converters with built-in programmable gain amplifiers, internal reference, and an on-board oscillator. This component has an extremely low input bias current of 300 pA (typical) and an input-referred noise of 1.0 μVPP (typical). The common mode rejection ratio (CMRR) is about 110 dB, with 1000 Megohm input impedance. Its requirement is very low, in the order of 5.0 mW/Channel. ADS 1299's data rate is from 250SPS to 16 kSPS. The chip is 9 mm $\times$ 9 mm and requires few external components. ASD1299's specification allows us achieving a very compact design.

Our wearable EEG is equipped with STM32 F101CB (from ST Microelectronics) as CPU. F101CB is an ARM 32-bit Cortex-M3 CPU with a maximum 36 MHz clock, 1.25 DMIPS/MHz (Dhrystone 2.1) performance. The 32 MB of flash memory serves as the main storage for the sensor.

The RF frontend allows the CPU to accept commands from a computer. In order to maintain compatibility with other sensors in the OPTIMI project, the RF frontend is based on the nRF24L01+ low power 2.4 GHz ISM (Industrial, Scientific and Medical) band RF Transceiver from Nordic Semiconductor.

In our EEG sensor, the reference voltage is set at 2.4 V, and the sampling rate in test and project is currently 260 Hz which can also be easily set to other rates if necessary. The sensor incorporates a 470 mAh Lithium Polymer single cell battery. This allows the sensor to be used continuously for approximately 300 minutes. Since the trials are planned to include 24–56 sessions each lasting 5 minutes, a single full charge is sufficient for just recording during the whole trial period. But the communication between the EEG sensor and HomePC will occupy much power, especially when downloading the data, so the users will charge the battery 2–5 times during the trial. Final version of our EEG sensor is shown in Fig. 2. Users can easily put on the EEG sensor by securing it with a belt around head.

IV. Assessment Method of EEG Signal Quality

High EEG recording accuracy is necessary in experimental trials. If the sensor is not correctly placed on the head with electrodes properly attached or the environment presents strong electromagnetic noise, the quality of data may be compromised. In order to ensure the availability of EEG signal, research has been carried out in the environment using a variety of electrodes.

In a hospital or laboratory setting, the use of an electromagnetic shield can reduce noise. When such equipment is not available, there are generally two approaches to improve EEG data quality. A number of research projects have focused on novel wet or dry electrodes and have attempted to reduce the electrode-to-skin contact resistance [4]. Many expensive and delicate EEG products from MindMedia and BP take the electrode-to-skin contact resistance as a key to judge the quality of the connection. Other research has, however, focused on the final EEG signal quality [3], [6]. Thus far, existing study rarely considers the quality issue from the perspective of raw EEG data, which is the basis of final EEG signal processing. Essentially, quality of processed data ultimately depends on the quality of raw data. This is the rationale of our approach towards EEG quality validation.

In the context of OPTIMI, nearly all the personal users have no access to an electromagnetic shield room and cannot get help from others to test the electrode-to-skin contact resistance. As a result, when any EEG sensor is used to record very low voltage brain wave activities, extra care must be taken to ensure good electrode-skin contact. This imposes extra burden to the participants of OPTIMI trail. In order to address this issue, we propose a novel method to calculate the raw EEG signal quality. The calculation takes a 4-second period of EEG record to decide whether: 1) the signal is fine; if so the system can proceed to the next step or 2) the signal is bad; if so the user has to check the electrode connection (or even change the location) prior to beginning the trial. The program is very intelligent and is designed to run locally in a sensor embedded system.

A. Experimental Setup

For economic and ergonomic reasons the sensor developed here makes use of very low cost disposable skin friendly solid gel pads. Such pads provide all the electrical benefits of wet gel without the attendant mess in use. When the recording is completed, the pads are simply removed and discarded, providing an enhanced hygiene level.

The problem most frequently experienced is that the electrodes may not be correctly attached to the skin and/or the connection may be poor. The situation is aggravated when solid gel pads are used, as users may forget to clean their forehead with alcohol before attaching the pads. This can result in that the gel pads become dry or improperly positioned or connected. Our goal is, therefore, to collect sufficient data so as to recognize and differentiate two connection conditions: 1) a *good connection* where the trial can proceed: (the connection is correct and the electrode is moist), and 2) a *bad connection* where trial cannot proceed further before the focal user check and fix poor sensor-skin connections. We considered the various scenarios where the EEG sensors were most likely to be used. In the end, three typical scenarios were chosen: 1) in an outdoor setting where there is generally very weak and low frequency electromagnetic noise (e.g., in a public park with ambient noise), 2) in an office setting that typically has noise in the 50/60 Hz range (from electrical power lines and low frequency electromagnetic noise from machines and artefacts), and 3) in a domestic setting with noise generally similar to that one can experience in an office setting.

With the EEG sensor design as discussed in Section III, EEG signals were initially gathered using different environments and electrode-to-skin connections. We had collected data in all the three identified scenarios, i.e., offices, homes, and public parks over a time period of one month. The volunteers begin the data collection by pushing a button. It is expected that the volunteers should keep their eyes closed (to reduce the effect of OA) and remain quiet for a period of several seconds. The captured data are processed and go through several experiments to identify the optimal method to calculate a quality score of the EEG signal.

B. Assessment Methods of EEG Signal Quality

In total we have collected more than 4000 samples of EEG data for both good and bad connections in office and park settings. After applying a band pass filter from 0.5 Hz to 40 Hz, the time domain of EEG signals are illustrated in Fig. 3. It is impossible to get the quality score of EEG signal only from the time domain. We therefore processed EEG signals in the frequency domain too, the results of which are illustrated in Fig. 4.

Considering that when the eyes are closed, the power of Alpha rhythm will become dominant and can occupy a large percentage (%) of all EEG band [7], we take the ratio of Alpha power to the total EEG power (Alpha/Total EEG) as one feature in evaluating EEG signal quality. In the meantime, we calculate the variance (VAR) of each EEG data as the second feature. In the office and domestic settings, the most prevalent low frequency noise is at 50/60 Hz. Hence, the power of 50/60 Hz can be taken as another feature (50 Hz/Total EEG). Out of the aforementioned 4000 EEG data samples, we computed the values of each feature (listed in Table I). These provide a solid ground for us to make the following observations: the variance for good EEG signals is in the range 100 to 2500, while the variance tends to be in the range of 2500 to 5000 if the connection is poor. This leads to the conclusion that a very bad connection is likely to occur, when the VAR is over 5000.

The selection of a frequency at 50 Hz/Total EEG is based on the consideration that the rate will be extremely high with respect to the office noise, and very low when connected well or in public parks (for both good and bad connections). The rate of Alpha/Total EEG varies from 0.4 to 0.8 (or even higher when connection is good) and from 0.06 to 0.4 when not connected with only noise being registered.

Each of these features, when considered alone, cannot decide whether the signal is EEG data or noise. However, with the combination of VAR, 50 Hz/Total EEG, and Alpha/Total EEG, we can define 3 functions to calculate the overall final score.

The initial score is given by VAR which is from 0–100. The values of 50 Hz/EEG and Alpha/EEG are between 0 and 1 (taken separately). The overall signal quality is calculated as the multiplication of all these three scores.

We denote the VAR as x1, 50 Hz/Total EEG as x2, and Alpha/Total EEG as x3. We designate y1 to represent the initial score, y2 as the score after x2 is taken into account and y3 after x3 is applied.

The score of y1 is computed as (1) and is depicted in Fig. 5.

$$y1 = \begin{cases} 0.02 * x1 * x1 & x1 < 50 \\ 0.6 * x1 + 20 & x1 < 100 \\ 100 & x1 < 2000 \\ -0.013333 * x1 + 126.6 & x1 < 5000 \\ 0.006 * x1 + 90 & x1 < 10000 \\ \frac{15}{(x1-10000)*(x1-10000)} & x1 > 10000 \end{cases} \quad (1)$$

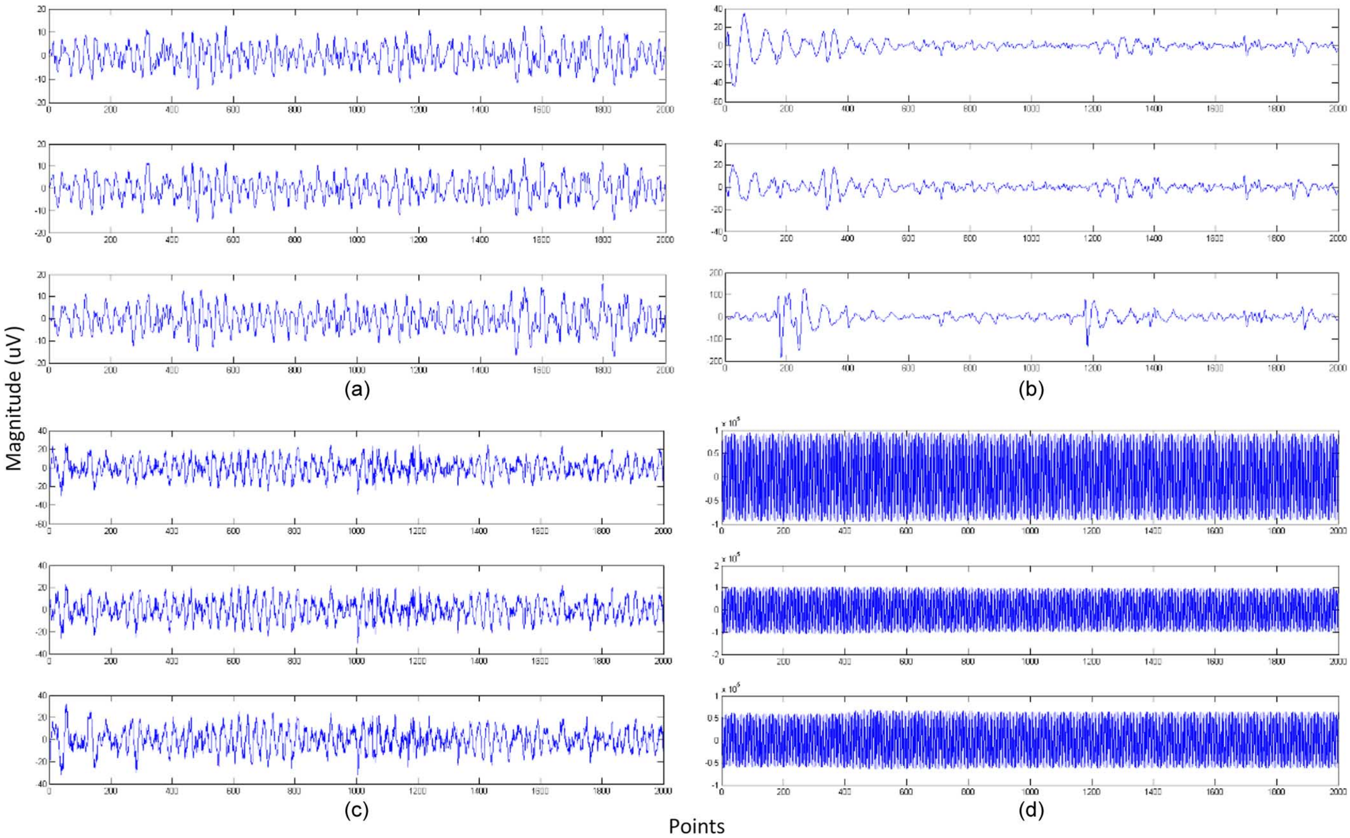

Fig. 3. Time domain of signal. First line is recorded in the park, (a) Good connection. (b) Bad connection. Second Line is recorded in the office. (c) Good connection. (d) Bad connection.

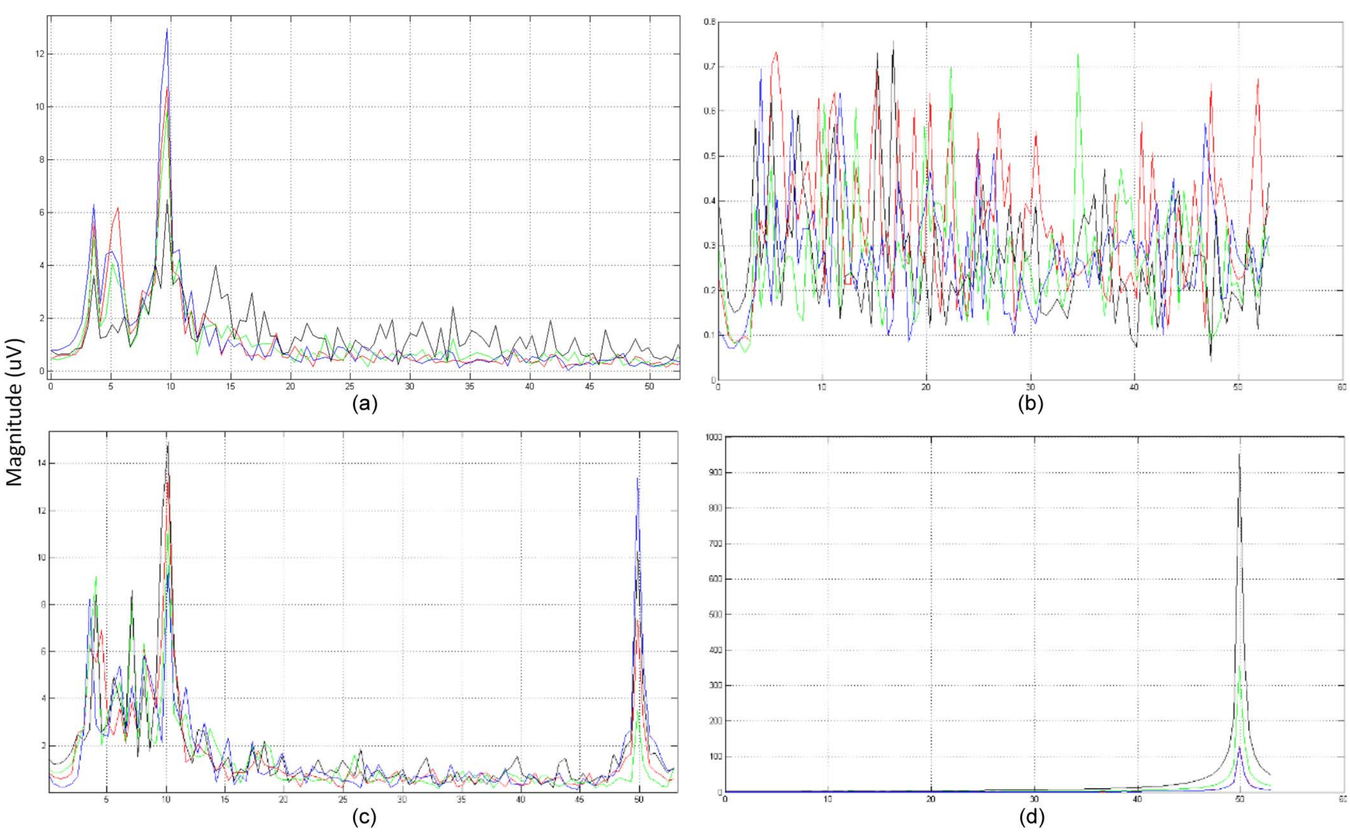

Fig. 4. Frequency domain of signals. First line is recorded in the park. (a) Good connection. (b) Bad connection. Second Line is recorded in the office. (c) Good connection. (d) Bad connection.

TABLE I
VALUES OF VARIANCE, 50/TOTAL EEG AND ALPHA/TOTAL EEG IN PARK AND OFFICE

Features	Good connection in Park	Bad connection in Park	Good connection in Office	Bad connection in office
Variance	100-1200	6-50	400-2500	5000-
50Hz/Total EEG	0.001-0.01	0.005-0.1	0.003-0.03	30-600
Alpha/Total EEG	0.4-0.8	0.06-0.5	0.5-0.8	0.1-0.2

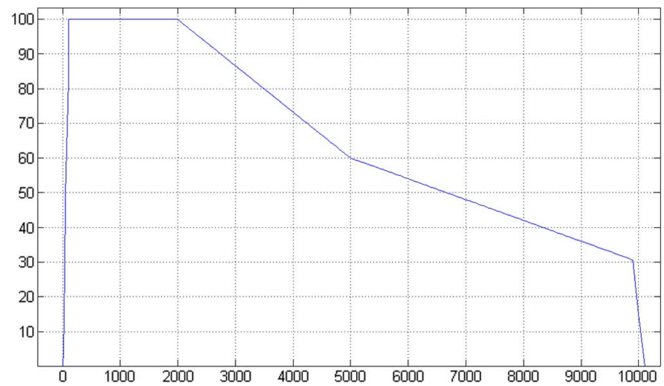

Fig. 5. Origin score of y1 relative to x1 = VAR (x: x1, y: y1).

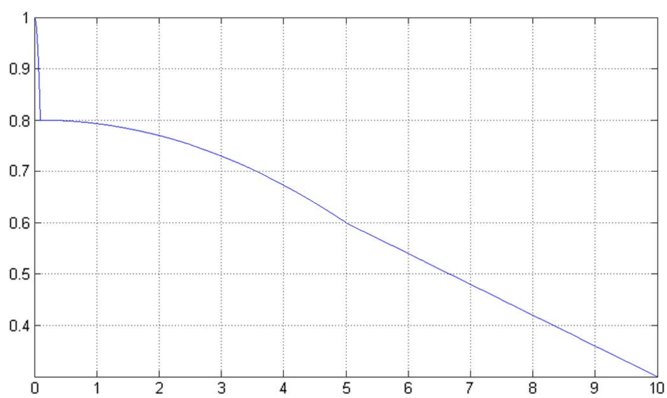

Fig. 6. Score of y2 relative to x2 = 50 Hz/Total EEG (x: x2, y: y2).

The score of y2 is computed using (2) and is shown in Fig. 6.

$$y2 = \begin{cases} 1 & x2 < 0.01 \\ 1 - 24.691 * (x2 - 0.01) * (x2 - 0.01) & x2 < 0.1 \\ 0.8 - 0.00833 * (x2 - 0.1) * (x2 - 0.1) & x2 < 5 \\ 0.9 - 0.06 * x2 & x2 < 10 \\ \frac{30}{x2 * x2} & x2 > 10 \end{cases} \qquad (2)$$

The score of y3 is calculated using (3) and is shown in Fig. 7.

$$y3 = \begin{cases} 2.8 * x3 * x3 & x3 < 0.5 \\ 1.2 * x3 * x3 + 2.4 * x3 - 0.2 & x3 > 0.5 \end{cases} \qquad (3)$$

The final quality score of EEG signal (y) is defined as in (4).

$$y = y1 * y2 * y3 \qquad (4)$$

C. EEG Quality Scores in OPTIMI

In OPTIMI, the experiment population was made up of a total of 90 volunteers, each using the EEG sensor presented in this paper. The population consists of volunteers with different backgrounds from three different countries. They are 30 students from Switzerland, 30 employed persons located in Spain, and 30 mothers with disabled children from China. Each volunteer gathered their EEG data twice every day for one month. This assessment method of EEG signal quality helped these non-professional volunteers to develop necessary skills of using EEG sensors to avoid errors in the capture of EEG data.

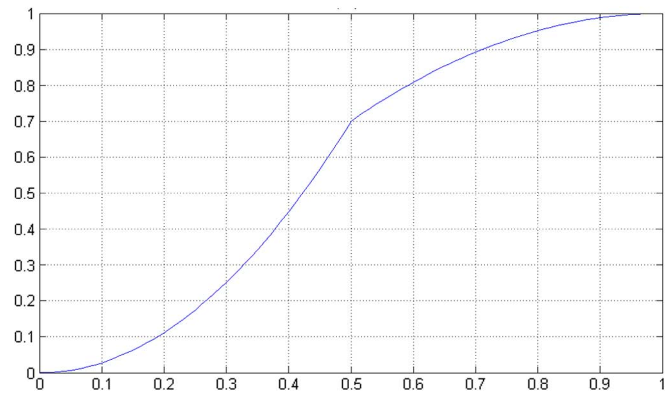

Fig. 7. Score of y3 relative to x3 = Alpha/Total EEG (x: x3, y: y3).

TABLE II
SCORE OF EEG SIGNAL QUALITY IN DIFFERENT CONDITIONS

Condition	Score
Good connection in park	90-99
Noise in park	0-44
Good connection in office	78-99
Noise in office	0-30
Half-dry electrodes in office	22-80

Table II lists the result of the signal quality scores. For those records with EEG signal quality score as 0, a further investigation into the frequency domains shows that these are just 50 Hz or low frequency noises.

The results also show that if the score is greater than 60, the connection and environment are considered good and the process can proceed to the next step which is the recording of EEG data. However, this algorithm depends on the type of EEG sensors and thus modification may be required where other types of EEG sensor are used.

V. REMOVAL OF OCULAR ARTEFACTS COMBINED WITH DISCRETE WAVELET TRANSFORMATION AND ADAPTIVE NOISE CANCELLATION

EEG signals are taken from electrodes positioned on the forehead. The scalp electric potential amplitude is typically 20 to 100 μV. Signal data can be contaminated by non-cerebral potential interference such as electromyography (EMG) from muscle activity or baseline drift and power line interference (50/60 Hz),

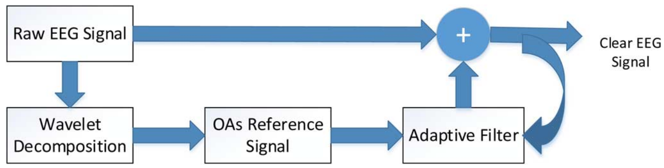

Fig. 8. OA removal model combining DWT and ANC.

etc. [8]. Also, since the electrode points of Fp1, Fpz, and Fp2 are so close to eyes, the recorded data are likely to be distorted seriously by eye movements and blinks. An eye blink produces signal amplitudes of more than 10 times that of the ambient EEG signal. Eye movements can also be recorded during the EEG collection trial, even when the subjects keep their eyes closed. It is necessary to develop an efficient method for removing the noise caused by eye movements.

Traditional approaches to attenuating ocular artifacts are based on time domain [9] or frequency domain [10] techniques. A number of investigations have applied Principal Component Analysis (PCA) [11], [12] or Independent Component Analysis (ICA) [12]–[14]. However, given that ICA needs a reference signal which requires tedious visual classification of the components [16]–[18], it is not suitable for short time trial employed in OPTIMI.

DWT is a method that neither relies upon the reference ocular artifacts nor requires visual inspection. In this paper, we have developed a new model based on DWT and ANC cancellation to remove the ocular artifacts. This is conducted as follows. First step is to construct a reference signal with DWT. With this reference signal, a new model is established based on ANC, hence a combination of DWT and ANC [19]. It is our contention that this is a novel and effective approach, particularly suitable for portable applications, even if the EEG signal has only one channel.

OA are mainly concentrated in the low frequency band, so DWT is used to construct the OA in the frequency domain. DWT is a multi-resolution representation of signals and images. It can be used to decompose signals into multi-scale representations. It is widely used for analyzing non-stationary signals. The wavelets used in DWT are effective in constructing both time and frequency domain information from time-varying and non-stabile EEG signals [20], [21]. An alternative method of estimating signals, corrupted by additive noise interference, is to apply an ANC adaptive filter [22]. In an ANC filter, the interference source is used as a reference when adjusting coefficients automatically to achieve optimal results. The combination of DWT and ANC in our new model is shown in Fig. 8 [19].

Derived from the contaminated EEG, the reference input has a strong correlation with OA that meets the conditions of employing ANC as a reference input. Choosing an adaptive algorithm is the key to achieve the result. An ANC based on RLS algorithm is adopted to remove OA [18]. This method works as follows. 1) Wavelet decomposition is applied to expand the contaminated EEG signal so as to get the wavelet coefficients. Daubechies 4 wavelet is selected as the mother wavelet function. 2) According to the minimum risk value, the soft threshold is applied to the three lowest level coefficients to obtain the new coefficients for those three levels. 3) Wavelet reconstruction is applied to the new wavelet coefficients for constructing the reference signal. 4) ANC is applied to the contaminated EEG with the constructed reference signal as an input to remove the OA.

In OPTIMI, a filter from 0.5 to 40 Hz frequencies has been adopted to avoid the influence of power line interference. The new model proposed in this paper removes the OA from recorded EEG data. The results are sufficiently good to facilitate feature extraction.

VI. Features Extraction

When EEG signal is collected, features relate to stress will be calculated in the user's notebook/PC and sent to a data server over the Internet. It is, therefore, important to identify the EEG features both from practical and effective perspectives. In this paper, EEG features, including linear features (such as absolute and relative power, frequency and asymmetry) as well as nonlinear dynamical measures, (e.g., namely C0 complexity (C0), LZ complexity (LZC), correlation dimension (D2), Renyi entropy (RE), and the first positive Lyapunov exponent (L1)) are calculated to examine the difference between those with chronic stress and those from normal control.

In the experiments, the recording task is 2 minutes for each participant in a relaxed state with their eyes closed. The scalp sites are located according to the international 10/20 system recommendation with EEG signals recorded from 3 electrodes-Fp1, Fp2 and Fpz-using earlobes as references at a sample rate of 260 Hz.

Among the experiment population, there are 3 groups of right-handed participants who volunteered to take part in the study. Eighteen unemployed men aged from 21 to 41 were recruited in group 1. Participants of group 2 were students aged from 20 to 35 at risk of chronic stress due to frequent examinations and graduation stress, while group 3 were mothers of disabled children aged 30–52. All the participants are free of prior history of psychopathology. Previous cardiovascular conditions or medications are also taken into account due to a potential negative impact on the heart and the fact that using medication can affect mood. Participants initially completed the Beck Depression Inventory (BDI) scale. Individuals with a BDI score below 10 belong to the control group, while individuals with a BDI score of 10 or higher are included in the stress group [24].

For both Group1 and Group2, D2, L1, and LZC can effectively distinguish stressful individuals from normal controls. The stress group presents a significantly higher LZC and D2 than the normal control group. Higher LZC and D2 values imply a greater chance of the occurrence of new sequence patterns and thus a more complex dynamical behavior. Stressful subjects show significantly lower L1 value compared to normal controls. As for Group3, mothers caring disabled children, the Renyi entropy of the stress group is significantly higher than the control group. These results are consistent with the finding given by Tang [25], showing that the alpha activity of depression patients is more complex during rest. There is a significant difference on power asymmetry of Alpha, Beta, and Theta bands between stressful individuals and normal controls in all the three groups faced with different kinds of stressors [26]. Stressful subjects have negative hemispheric asymmetry indices, while the controls are the opposite, implying greater relative right anterior EEG activity in the stressful subjects. It is in agreement with the outcomes of other researches addressing similar problems.

VII. Conclusion and Future Work

EEG signal processing is at the heart of the OPTIMI project. Considering a lack of suitable low cost and light weight EEG sensors, we have designed and produced a novel wearable EEG sensor that can be easily used by ordinary public in an everyday setting. In order to validate the sensor when used in normal/real-world conditions by a non-professional (i.e., not professionally trained and qualified) person, we have presented an algorithm to calculate EEG signal quality with which the users can adjust the connection of electrodes to correct any errors and to suit the prevailing environment. The reported results show that our proposed method functions well, meeting the design goals/requirements and helping to ensure the quality of the EEG signal. In addition, the wearable sensor can also be used as a low cost diagnostic tool to meet the needs of large e-health trials.

EEG signals collected from subject's forehead are very easily contaminated by noise. This is especially true for OA. The paper addresses this issue by proposing a new model combining DWT and ANC to remove OA in the low frequency band even when OA's frequency band is overlapping with that of the EEG signal. After DWT is applied to obtain wavelet coefficients, a threshold is selected and applied to the three lowest level coefficients to derive new wavelet coefficients. Thus the OA signal is reconstructed and used as a reference signal.

ANC based on an RLS algorithm is used to remove the OA from the original EEG data. The results from the OPTIMI project are very promising, with reduction levels of the OA being shown to be sufficient for use in practice. In further studies, we will use more statistical methods to prove our model with respect to efficiency and "real-time" constraints.

The results based on the selected features demonstrate that EEG nonlinear dynamics features are effective measures to detect chronic stress. EEG frontal asymmetry of theta, alpha, and beta bands can be biological indicators for chronic stress, showing relative greater right anterior EEG activity in stressful individuals. In addition, different stress factors in real life can lead to varying degrees of emotional, behavioral and physiological changes, reflecting in complexity of frontal EEG. Consequently, analysis of chronic stress according to the specific stressor is necessary.

The crux of our further work lies in sensor performance improvement. The proposed EEG sensor will be enhanced with a rule-based system to interpret the data and to provide a diagnostic foundation for both pharmacological and Cognitive Behavioral Therapies (CBT) based preventative and intervening treatments.

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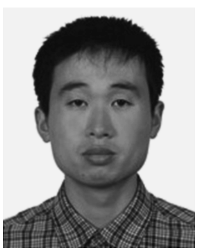

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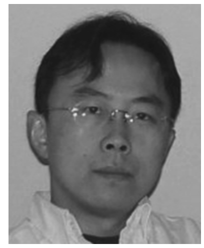

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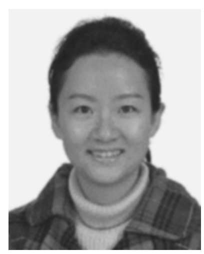

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