NeuroGlasses: A Neural Sensing HealthCare System for 3D Vision Technology

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***Abstract*—3D vision technologies are extensively used in a wide variety of applications. Particularly, glasses-based 3D technology facilities are increasingly becoming affordable to our daily lives. Considering health issues raised by 3D video technologies, to the best of our knowledge, most of the pilot studies are practiced in a highly-controlled laboratory environment only. In this paper, we present NeuroGlasses, a non-intrusive wearable physiological signal monitoring system to facilitate health analysis and diagnosis of 3D video watchers. The NeuroGlasses system acquires health related signals by physiological sensors and provides feedbacks of health related features. Moreover, the NeuroGlasses system employs signal-specific reconstruction and feature extraction to compensate the distortion of signals caused by variation of the placement of the sensors. We also propose a server-based NeuroGlasses infrastructure where physiological features can be extracted for real-time response or collected on the server side for long term analysis and diagnosis. Through an on-campus pilot study, the experimental results show that NeuroGlasses system can effectively provide physiological information for health-care purpose. Furthermore, it approves that 3D vision technology has a significant impact on the physiological signals, such as EEG, which potentially leads to neural diseases.**

***Index Terms*—HealthCare System, Signal Processing, Patten Recognition.**

I. INTRODUCTION

SINCE David Brewer invented “Stereoscope” in 1844, which is the first device taking 3D photographic picture, there has been huge amount of researches and developments in 3D vision. Existing stereoscopic technology [1] includes 3D glasses, augmented reality, autostereograms, lenticular prints, Piku-Piku and much more. Eventually the only commercialized technology is 3D glasses due to reliability, stability and cost. Nowadays 3D glasses has become a popular and indispensable element in consumer electronics and entertainment. On January 31th 2010, James Cameron’s 3D movie “Avatar” became the first film to earn more than 2 billion. On April 3rd 2010, Sky launched the first 3D broadcasts in UK, and 3D televisions (with glasses) are out-of-stock in all the markets in London. These days all the giant TV manufacturers jump into the competition of this hot market, and the 3D television set becomes affordable to most of the family.

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However, as every emerging technology is criticized in its early stage, 3D technology has to face the similar situation. Unlike some products struggle with the marketing or pollution, health and safety issues, including physical and mental strain, accompany 3D technology with its birth. One of the major TV manufacturers “Samsung” issued a warning about possible health effects with the formal product release. It describes a long list of hazards potentially associated with technology and mentions a number of strict use rules. Actually the side-effects are far beyond people’s expectation. A lot of viewers complained about dizziness in front of 3D TV or movies for a slightly long time. Moreover, the report from one Taiwan public media said that one cinemagoer with chronic high blood pressure died from sudden death when watching “Avatar”.

Now it is time for us to pay more attention on corresponding health researches. However, the investigation of these possible effects is difficult. No watcher accepts to suffer a medical examination before they enjoy the visual feast; spreading inspective health meters on the watcher’s body is not a wise idea, in the sense that, it will diminish the users’ entertainment. Accordingly, to take a proper action, a comprehensive and noninvasive sensing technology is needed.

Wireless health technology is a feasible way to address this issue. It rooted in the World Health Organization established project for the environment in 1996. With the popular health concern continually growing in the past decade, wireless health becomes a new undependable branch both in industry and academia. Different from traditional human computer interface[2], wireless health technology has an invisible interface and play context-aware computing in the background.

Our research sought to develop a system to provide wireless health monitoring for 3D video watcher. The service can be provided in daily life outside of traditional highly-controlled scientific laboratories. In this paper, we presented the design, implementation and evaluation of NeuroGlasses, a mobile healthcare monitoring system. This system could provide a non-invasive realtime monitor and feedback of physiological status for 3D video watchers. Furthermore, we proposed a signal-specific physiological signal process algorithm to improve SNR to get more accurate features. There are two main contribution in this paper: the infrastructure of the monitoring system and signal-specific reconstruction algorithm.

The structure of the remaining part is as follows. In Section II we discuss 3D side-effects and related physiological features. The system architecture and implementation are introduced in Section III. Afterwards, physiological signal processing algorithm is described in Section IV. We presented

TABLE I
COMPARISON OF CHARACTERISTICS OF THE PHYSIOLOGICAL SIGNALS

Type		Origin	Frequency	Location	Pathology
ECG		Heart	1-40 Hz	arm, leg, head, chest	inverted T waves, hyperacute T waves
EOG		Eye	1-20 Hz	head	ophthalmology
EMG		Muscle	7-20 Hz	arm, leg, head, chest	neuromuscular diseases
EEG	Theta Waves	Brain	4-7 Hz	head	memory tasks
	Alpha Waves		8-12 Hz		sleep disorder
	Beta Waves		12-30 Hz		Parkinson's disease

the experimentation in Section V. Conclusion and future work are summarized in Section VI.

II. BACKGROUND

A. Physiological Signals

Physiological signals denote chemical and electrical signals generated by the tissue activity inside human bodies, which can provide some clues about vital health signs of human beings. For example, EEG is emitted by the brain, and EMG is emitted by the muscles. Normally the physiological signal can be measured by the bio-potential electrodes, enabling the people to explore and explain the biological problems with electronic technology. Here we listed the characteristics of classical physiological signals in Table I. Each signal originates from the specific organs and is linked to the featured disease. According to the signal distribution, the head is the largest concentration of the physiological signals required for our research. Additionally, some physiological signals overlaps with each other, and the same frequency interference will be a practical challenge.

B. Related Work

Pervasive sensing[3], [4], [5], [6] is a popular research topic in the last decade. Currently, deployment of bio-potential or inertial sensors attached on carry-on devices for health applications [7], [8], [9], [10], [11], [12] receives more attention. However, there are only limited study on the safety evaluation of 3D vision technology. Scientists from University of California Berkeley [13] built a stereo machine to investigate the unhealthiness. They claim that the physical strain, such as eye fatigue, root in abnormal eye movements; researchers at University of Central Florida [14] claim unknown disparities will cause mental strain, vertigo and nausea. Recently, Entertainment Technology Center [15] at University of Southern California began to collect the users' experience in order to dig out the pathogen and improve 3D technology. All these above-mentioned works require high-controlled environments, therefore, their needed professional assistance and device cost are very expensive. To address this problem, portable and low-cost physiological signal monitoring platforms are on demands.

III. NEUROGLASSES SYSTEM

A. System Architecture Overview

Figure (1) shows the system architecture. Here we use an application scenario to explain the flow of the data acquisition, data transmission, data mining, data archiving and data management in the Neuroglasses system. In this case, a watcher with Neuroglasses sits in front of 3D display. While he or she watches the movies, the neural sensors on Neuroglasses non-invasively collect his/her physiological data and send them to the smart phone device through the near-field body channels. Meanwhile, smart phone will also upload these received data to remote servers. The health-related computing could be launched on either mobile device or remote server.

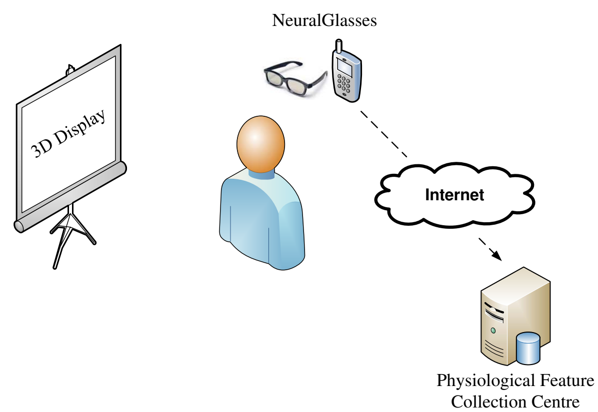


Fig. 1. Overview of NeuroGlasses System Architecture

B. Hardware

1) Neural Sensor Sets: Based on the analysis in Section II, the Neuroglasses system should be capable of sensing different kinds of physiological signals that characterize the health status. We do not take research-grade neural sensor sets into account. It is because that deploying research-grade neural acquisition system needs professional assistance. The sensors have to be put in the accurate location. Moreover, some of them, such as EEG electrodes, need conductive cream, which is unacceptable in daily use. So we vote for cheaper sensor solutions although the interference will make the signal processing more challenging. Some cheaper neural headsets are available in the form of off-the-shelf products. Table II shows a comparison of selected popular neural headsets, where "-" means the item is unknown. Neurosky cannot measure EOG and ECG signal; Emotiv EPOC is a powerful EEG headset and performs a comprehensive sensing. However, its driver is difficult to use. [16] uses this headset, and they have to use a laptop for relaying the signal between smartphone and sensor, which is not suitable in our application scenario. Therefore, we choose OCZ NIA as the front-end sensor. NIA

TABLE II
THE COMPARISON AMONG OFF-THE-SHELF NEURAL HEADSETS

Properties	Mindset[17]	Emotiv[18]	NIA [19]
Sensor Numbers	5	16	1
Sensor Weight	165g	200g	125g
Retail Price	$199	$299	$70
System requirements	Low	High	Low
EMG measurability	Yes	Yes	-
EOG measurability	No	Yes	Yes
ECG measurability	No	-	-
EEG measurability	Yes	Yes	Yes

is a headband with one neurosensor. Whenever the user wears it, the sensor will be attached to the skin at the forehead part. Different from typical two-pin neurosensor, NIA has three electrodes: the middle one is the the ground pin, and the side ones measure the differential signal value. The sensing signal will be amplified with gain of 50. After filtering, it will be quantified with 24-bit ADC with and sampling rate is 3.90625 KHz.

2) System Setup: We use PC phone BenQ S6 with 3G and WiFi as the data acquisition device and central control unit. The entire system is shown in Figure (2). The PC phone receives the signal from the sensor and perform some customized lightweight computation, display the results and provide the feedback. Then, the raw data or processed data will be uploaded to the remote server through 3G or WiFi wireless connection. On the server side, a comprehensive data mining procedure will be conducted for feature analysis.

Fig. 2. NeuroGlasses System consisting of PC phone and Sensors

C. Software Architecture

NIA sensor received the comprehensive physiological data and transferred them to PC phone. The software architecture consists of three layers which are shown in Figure (3): the sensor layer, the signal layer and the application layer. The sensor layer abstracts from the low-level details and generalizes the sensor API; The signal layer uses the cognition algorithm of retrieving the feature of the physiological signals. Based on the analytic results from the recognition layer, the application layer will make an analysis, perform the feedback and archive the data.

1) Sensor Layer: The software of the sensor layer is implemented in C++. In this layer, several physical-level data processing are performed. The driver here has two main functions: flow control and error detection. With 24-bit ADC and 3.90625 KHz sampling frequency, the data rate from the sensor is 93750 bps. In term of real-time consideration and computation limitation, the driver will empty the buffer every 10 samples.

2) Signal Layer: The signal layer is built on the sensor layer and extract the features of the bio-signal. As shown in the Figure (3), it has three phases: classification, preprocessing and feature extraction.

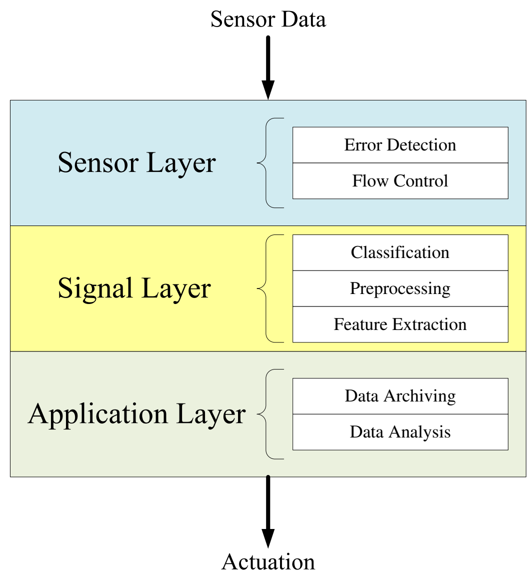


Fig. 3. Software Architecture

- **Classification** The phase "Classification" will separate the different kinds of physiological signals from the comprehensive data. Filter design is the main content in this phase. Due to the complexity of the filter, the tradeoff between the quality and the computation cost is the key issue in this phase.
- **Preprocessing** The phase "Preprocessing" is a context-aware algorithm for the information loss of the data. It will reduce the interference based after the classification. The lightweight action will be performed in the mobile device BenQ S6, and the server will run the computationally expensive task.
- **Feature Extraction** In this phase, we will extract the features describing the characteristics of the physiological signals. The extraction algorithm is dependent on the mark of the features in the time domain or the frequency domain.

3) Application Layer: The application layer is implemented on both PCphone and server. The partitioning depends on the requirement of the task. Basically there are two kinds of action here. One is the data storage, and it is implemented in servers. The other is the signal analysis. If the criteria of analysis is real-time, the computation should be executed on the phone side; if the key factor is accuracy or long-run trend, server will take over the task.

IV. Physiological Signal Processing

In this section, we introduce the structure of physiological signal processing. Figure (4) shows the process of data flow in the NeuroGlasses system. In our system, physiological signal processing consists of filtering and data reconstruction.

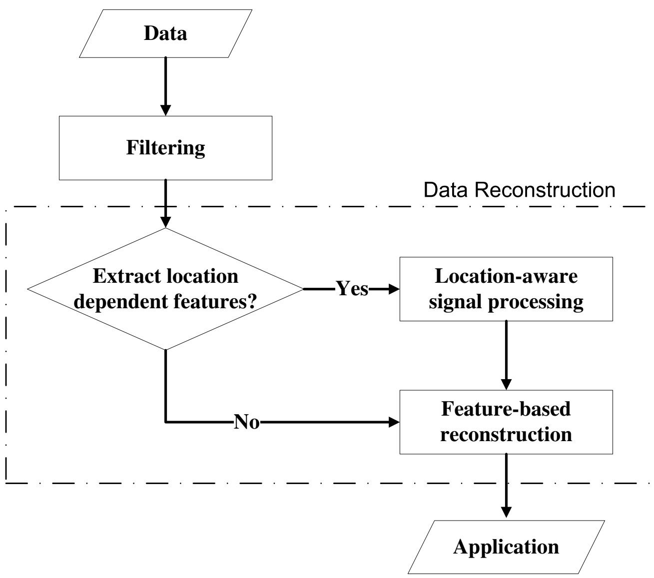


Fig. 4. Physiological Signal Processing Flow

A. Filtering

1) Filter Design: The raw data from the sensor layer has a low signal to noise ratio (SNR) and it is necessary to improve SNR by filtering before further analysis. There are two basic filter structures: Finite Impulse Response (FIR) filter and Infinite Impulse Response (IIR) Filter. Under the same pass band requirement, IIR is low cost and requires less computation in the filter realization. However, IIR is nonlinear and will distort the signal, which will weaken or even remove the features of physiological signals. Thus, we choose FIR filter in our implementation. The filter design for each physiological signal is referred to Table I.

In fact, the behaviors of the filter are not ideal, such as: the gain-to-attenuation band is significant; the in-band gain is not smooth. These non-ideal characteristics will introduce interference and make the feature extraction challenging.

2) Interference Analysis: Basically there are three types of un-removable interference in the filtered signal:

- Co-Channel Noise (CCN): CCN is the noise with the same frequency band of the desired signal. This kind of noise cannot be removed even with ideal filters.
- Adjacent Channel Noise (ACN): The gain-to-attenuation throughout in the real filter is not zero. The noise in this transition zone will not be attenuated completely, which will affect SNR.
- In-Band Distortion (IBD): Different from CCN, IBD is generated by that the signal within the pass-band will become distorted because the gain is not uniform.

Figure (5) shows the signal distortion after filtering. It is obvious that there is still significant fluctuation coupling with the signal wave. Moreover, the interference with large magnitude will change the profile of the signal. Therefore, we need a signal-specific methodology to restore the physiological features.

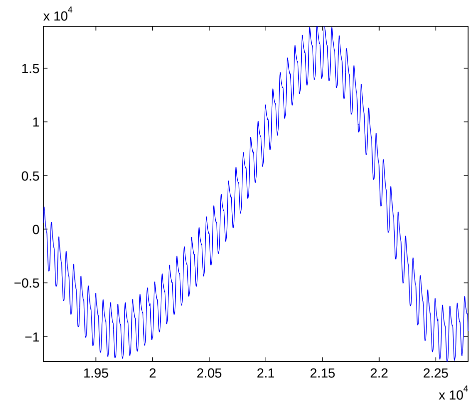


Fig. 5. Noise in Neural Signals(x-axis is time, y-axis is magnitude)

B. Data Reconstruction

As shown in the algorithm flow in Figure (4), the filtered data needs to be reconstructed before feature extraction due to significant signal distortion.

1) Location-aware Correction: The sensor location depends on how the user wears Neuroglasses individually. The variation of the sensor location greatly affects the sensing data. In the reality, Neuroglasses restrict the position of the sensor and the location variation will be within some range. For simplicity, we model that there are three different locations on the forehead: left, center, right.

Specific signal processing tools, such as Principal Component Analysis [20] and Local Discriminant Analysis [21], can explore more accurate location-dependent features. Considering the whole algorithm implementing in the carry-on device, we employ featured-based reconstruction to correct other distortions.

2) Feature-based Reconstruction: In order to extract the physiological features accurately, we propose a moving-window algorithm to detect and further correct the signal distortions. Our algorithm has been outlined as below:

With the filtered physiological signal as input, our algorithm can build a moving-window and move it along the time axis. In this process, we define an segmentation factor as $s_\gamma = \partial f(t)/\partial t$ to detect the noise interference, where $f(t)$ is the amplitude of physiological signal under studied. Also, s_γ^k can be approximated with $(f_k - f_{k-1})/\Delta t$ at each time-step. When the segmentation factor reaches certain threshold value, one concave can be identified and thus two spikes can be separated.

Next, we can reconstruct the shape of distortion-free physiological signal according to different interference impact: the noise peak should be removed for positive interference impact, while all the peaks within the moving-window should

Algorithm 1 Forward Windowing-Based Algorithm for Feature-Based Reconstruction

/* Setup */
Input the physiological signal after filtering;

/* Reconstruct the Interference Impact */
while Not reach the end of physiological signal **do**
  Move the search window along the time axis, and recognize the interference within the window;
  if Found Positive Interference Impact **then**
    Remove the noise spike;
  else
    if Found Positive Interference Impact **then**
      Merge the spikes within the window;
    end if
  end if
end while

be combined for negative interference impact. As such, the interference can be eliminated from the physiological signals and the accuracy of feature extraction can be improved significantly.

V. Evaluation

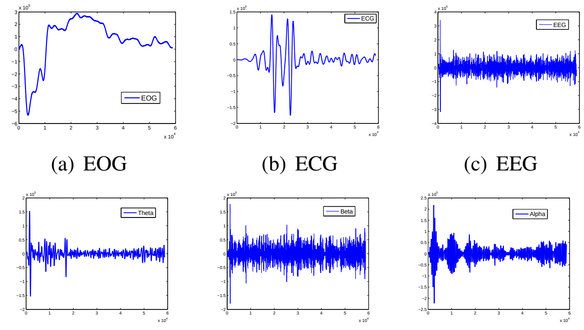
To verify the correctness and effectiveness of our proposed algorithm, we run an on-campus pilot with 20 subjects, including 10 male volunteers and 10 female volunteers. There are two sets experiments. The first one is to examine the performance of our algorithm, including location-aware correction, physiological feature extraction and etc. The second one is to validate the influence of 3D technology from the change of the physiological features.

A. Signal Reconstruction and Feature Extraction

1) Experiment Setup: We implemented the algorithm described in Section IV. In the experiment, the measured objects watch 3D videos when Neuroglasses can record their physiological signal and perform the analysis. The experimental purpose is to examine whether Neuroglasses could perform an accurate analysis in terms of physiological features.

2) Physiological Signal Classification: We collect a 16-second clip of the field data when the objects watch 3D videos, which contain different physiological signals. To analyze these signals, the first step is to remove the noise and increase SNR. Then, we will do signal classification to analyze the physiological spectrum, including EOG, ECG and EEG signals (including alpha, beta, theta waves) as shown in Figure (6). The processing result show that our algorithm could effectively classify different physiological signals from raw sensing data.

3) Signal Correction and Reconstruction: We further test the location-correction algorithm on EOG signals as illustrated in Figure (7), where Position 2 is the correct senor location (i.e. center of forehead). The remaining two positions denotes left and right location, respectively. It can be observed that our algorithm can efficiently eliminate the distortion due to different locations.



(a) EOG (b) ECG (c) EEG

(d) Theta Waves (e) Beta Waves (f) Alpha Waves

Fig. 6. Context-aware Classification for Raw Data (x-axis is time, y-axis is magnitude)

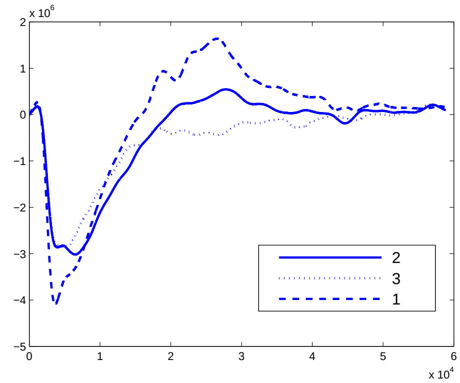


Fig. 7. EOG Location-aware Correction(x-axis is time, y-axis is magnitude)

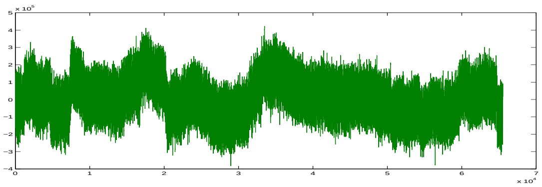
4) Physiological Feature Extraction: We also examined our algorithm in terms of physiological feature extraction. We use ECG as an example which is one of the three most important vital signs at a clinic and its significant features are ECG heart rate. In fact, ECG heart rate is the number of the heart beat per minute (hpm) and can vary dramatically according to the different physical states, such as exercise, sitting and sleeping. Also it will be effected by mood, such as anger, happiness and peace. It has been extensively used in clinical study for the basic guideline of the health status.

As shown in Figure (8(a)), ECG signal is interfered by the noise and heart rate cannot be calculated directly, which calls for the data reconstruction operation. Ideally, the reconstruction operation should remove the undesired noises and remain the significant features in the signal. Figure (8(b)) illustrates the reconstructed ECG signal from our proposed algorithm.

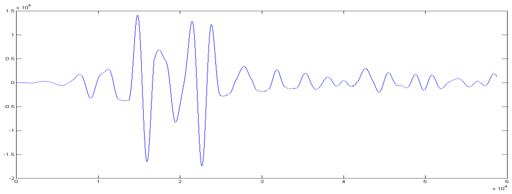
In details, there are 18 pulse with 16 seconds so that we could calculate heart rate of this person is around 67. In the same while, we used off-the-shelf heart rate meter to measure the ECG signal of the subjects. It shows that the calculated result from NeuroGlasses has the comparable accuracy with the ground truth and could offer reliable guidance for medical examination.

B. The Evaluation of 3D Vision Impact on Subjects

The second part is to investigate the 3D technology influence on human beings. We performed a pilot test on campus:



(a) ECG signal without filtering



(b) Reconstructed ECG Signal after filtering

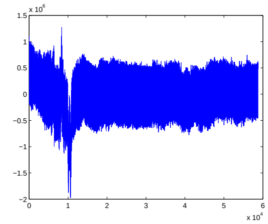
Fig. 8. Signal processing on ECG signal (x-axis is time, y-axis is magnitude)

there are twenty objects, including ten males and ten females. Each participant is required to put on the Neuroglasses system and watch the same videos with different formats, including 2D and 3D version. Note that these two videos have the same content and displayed within the same enviroments, and the only difference is the vision technology. During the experiments, Neuroglasses system will record the neural signals. After that, the user experiments will be surveyed as the reference. For simplicity of presentation, the analyzed data from one of the subjects is illustrated in Figure 9.

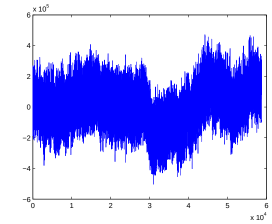
This case study demonstrates that the object shows evident abnormality on the physiological signal while watching the 3D video. For example, it can be observed that 2D raw data shows small fluctuation and constant mean value along the time. In contrary, 3D raw data has large variations (fluctuation) compared with the data in 2D case, which means the brain status of the object is much more active within the 3D case. It could be potentially associated with some neural disease. Accordingly, the extracted 3D ECG signals have larger amplitude and more peaks. The similar phenomenon can be observed in other subjects.

VI. Conclusion and Future Work

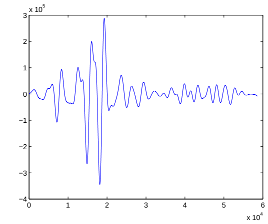
In this paper, we propose the Neuroglasses and a physiological feature acquisition system for 3D video goers. We also propose a lightweight location-aware signal correction and a feature-based reconstruction approach to compensate signal distortion due to the variation of sensor location or other noises. By a prototyping of Neuroglasses system, we show that physiological features can be extracted and corrected effectively, where features can be processed on a mobile device, such as a PC-phone, for on-line monitoring or stored on a server for long term analysis through wireless internet connection. Furthermore, we show a significant difference on physiological features between 2D video watchers and 3D video watchers. In the future, a comprehensive study of physiological feature extractions that are related to health issues for 3D technology will be involved. Then, we will develop an effective feature correction and extraction algorithm for these



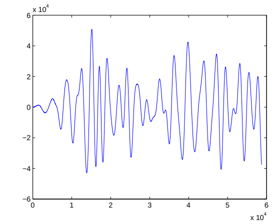
(a) 2D Raw Data



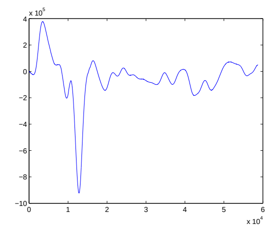
(b) 3D Raw Data



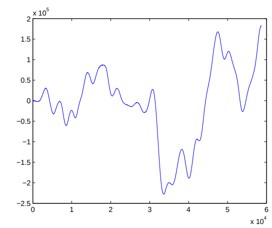
(c) 2D ECG



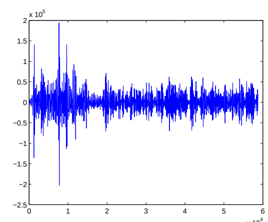
(d) 3D ECG



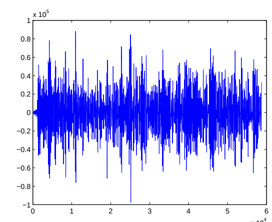
(e) 2D EOG



(f) 3D EOG



(g) 2D Beta Waves



(h) 3D Beta Waves

Fig. 9. Physiological Response: 2D V.S. 3D (x-axis is time, y-axis is magnitude)

physiological features that a more reliable health monitoring can be provided.

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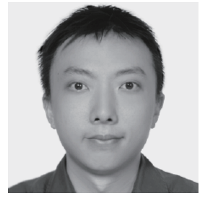

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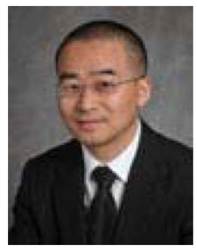

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