Using Novel MEMS EEG Sensors in Detecting Drowsiness Application

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***Abstract*—Electroencephalographic (EEG) analysis has been widely adopted for the monitoring of cognitive state changes and sleep stages because abundant information in EEG recording reflects changes in drowsiness, arousal, sleep, and attention, etc. In this study, Micro-Electro-Mechanical Systems (MEMS) based silicon spiked electrode array, namely dry electrodes, are fabricated and characterized to bring EEG monitoring to the operational workplaces without requiring conductive paste or scalp preparation. An isotropic/anisotropic reactive ion etching with inductive coupled plasma (RIE-ICP) micromachining fabrication process was developed to manufacture the needle-like micro probes to pierce the stratum corneum of skin and obtain superior electrically conducting characteristics. This article reports a series of prosperity testing and evaluations of continuous EEG recordings. Our results suggest that the dry electrodes have advantages in electrode-skin interface impedance, signal intensity and size over the conventional (wet) electrodes. In addition, we also developed an EEG-based drowsiness estimation system that consists of the dry-electrode array, power spectrum estimation, Principal Component Analysis (PCA)-based EEG signal analysis, and multivariate linear regression to estimate driver's drowsiness level in a virtual-reality-based dynamic driving simulator to demonstrate the potential applications of the MEMS electrodes in operational environments.**

Index Terms: Drowsiness Estimation, Dry Electrode, Electroencephalogram, Micro-electro-mechanical Systems, and Principle Component Analysis.

I. INTRODUCTION

Electroencephalographic (EEG) signals are the differences of electrical potentials caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between soma (body of neuron) and apical dendrites (neural branches) [1]. Biopotential electrodes for EEG-measurement transform the bio-signals from skin tissue to the amplifier circuit. Therefore, the most important characteristic of a biopotential electrode is low electrode-skin interface impedance to propagate signals without attenuation or production of noise [2]. When electrodes are placed on the skin of the forehead, an electrode-skin interface is constructed. Skin anatomy can simply be divided into three layers: epidermis, dermis and subcutaneous layer. The epidermis contains two layers: *stratum corneum (SC)* and *stratum germinativum (SG)*. *SC* consists of dead cells, thus, has electrical isolation characteristics. *SG* is composed of living cells, therefore, is electrically conductive. The *dermis* is the place where blood vessels and nerve exist [3]. To overcome the electrical isolation property of the *SC*, standard wet electrodes always need skin preparation (abrasion of *SC*) and the use of electrolytic. Improper skin preparation might cause skin irritation, pain, or even infection. Using electrolytic gel is uncomfortable and inconvenience; it can cause itchy feeling, and sometimes make skin red and swollen during long-term EEG-measurement. Furthermore, the conductivity of electrolytic gel will decrease gradually due to the hardened of the electrolytic gel, resulting in the degradation in the quality of data acquisition.

In this paper, the fabricated dry electrode is designed to pierce the *SC* into the electrically conducting tissue layer *SG*, but not reach the dermis layer so as to avoid pain or bleeding. Since the dry electrode is expected to circumvent the high impedance characteristics of the *SC*, thus, skin preparation and electrolytic gel application are not required. Note that the thickness of epidermis varies from 0.05 mm to 1.5 mm for different human race and different part of skin, and the thickness of *SC* and *SG* are approximately 10-15μm and 50-100μm, respectively [3]. Thus, in order to pierce the *SC* and penetrate the *SG*, the length of the probe must be longer than 20 μm with a sharp tip to avoid damage during the penetration. To reduce the noise in the electrode-electrolyte interface, the probes are coated with Titanium/Platinum for high conductivity and biomedical capability. The types of 20 × 20 probes dry electrode array with the size of 4 mm × 4 mm in detecting drowsiness application. Due to the limitation of our current MEMS technology, the heights of these probes are approximately

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250 μm, not sufficient to penetrate human hairs to contact stratum germinativum or even stratum corneum. The hair elasticity also makes it difficult to fix the dry electrode on the scalp. Therefore, in the current study, the dry electrodes are placed at non-hairy sites, such as *Fp1* and *Fp2*. In order to evaluate the performance of the developed dry electrodes for realistic applications, we designed an attention-demanding experiment in which we continuously estimate subject drowsiness level (task performance) based on the EEG signals measured by the dry electrodes.

II. FABRICATION OF DRY ELECTRODES

To fabricate needle-like probes on a silicon wafer with high aspect ratio, a microfabrication process that consisted of isotropic and anisotropic reactive ion etching with inductive coupled plasma (RIE-ICP) etching process and electroplating technology were developed and illustrated in Fig. 1. In this process, a thick photoresist film was patterned with circular dots to provide etching hard mask for the cylindrical probes. Since the etching selectivity between silicon and photoresist is approximately 1 to 60, thus, a 6 μm thick photoresist was chosen as a protection hard mask for the two-stage isotropic/anisotropic etching processes. Upon completing the isotropic etching process for the probe tip, we proceeded with the anisotropic etching process so that high aspect ratio probe shaft can be obtained. A wet-etching process is then used to release the hard mask at the probe tip. For electric conductivity, the probes were coated with Ti/Pt using DC-sputtering technique. The diced dry electrodes were then mounted on flexible printed circuit board by using silver glue. Fig. 2 shows the scanning electron micrographs of the fabrication results of the dry electrode. Etch dry electrode consists of a 20×20 micro probe array, etch probe is approximately 250 μm in height and 35 μm in diameter. The block bulge is observed at the base of the probe with an altitude about 50 μm, which is caused by the isotropic etching shape in the second fabrication process. Thus the effective penetration length of the probe is about 200 μm.

III. TESTING OF DRY ELECTRODES

We divided the testing of dry electrodes into two parts: the first part is dry electrodes in-vivo test and the second part is testing their applicability in realistic workplace.

A. Prosperity Test

To characterize the electrode-skin interface impedance effect, two electrodes were lined up on the forehead with a distance of 4 cm apart to perform the electrode-skin-electrode impedance interface experiments. A circuit proposed by Griss et al. was used to determine electrode-skin-electrode impedance (ESEI) and reduce the risk of harming the test person during biopotential recordings [4-5]. A total of 19 tests as shown in Table I were performed involving 5 different test patterns to evaluate the performance of 5 different types of electrodes.

These electrodes consisted of two standard wet electrodes coated with AgCl and Au of the size 1 cm in diameter, and three fabricated dry electrodes with the size of 4 mm × 4 mm, 3 mm × 3 mm, 2 mm × 2 mm, respectively.The impedance spectra between 4 mm × 4 mm dry electrode with no skin preparation and AgCl electrode with electrolytic gel or without skin preparation were put into comparison.

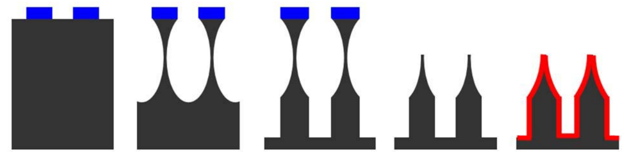


Fig. 1. Fabrication Process: (a) Pattern photoresist to provide etching masks. (b) Perform isotropic etching for probe tip. (c) Perform anisotropic etching for probe shaft. (d) Release the hard mask on the probe tip. (e) Coat the probes with Ti/Pt using DC-sputtering technique.

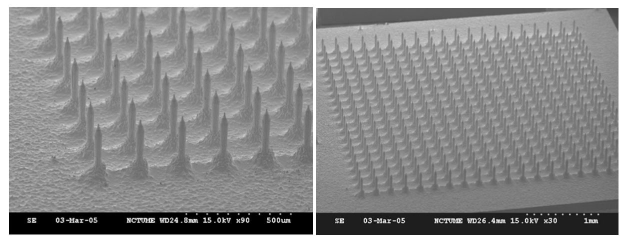


Fig. 2. SEM of the Fabricated Dry Electrodes

Table I. Test patterns for ESEI measurement

Measurement Series	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Subject	1	1	1	2	2	2	3	3	3	4	4	4	4	4	5	5	5	5	5
Type	a	c	b	a	c	b	f	a	c	f	a	c	d	e	f	a	c	d	e

a = AgCl without skin preparation
b = AgCl with skin preparation
c = $4mm^2$ without skin preparation
d = $3mm^2$ without skin preparation
e = $2mm^2$ without skin preparation
f = Au without skin preparation

B. Dry Electrodes Used for Acquiring EEG Data in a Realistic Driving Task

The growing number of traffic accidents has become a serious concern to the society in recent years. Accidents caused by driver's drowsiness behind the steering wheel have a high fatality rate because of the marked decline in the driver's abilities of perception, recognition and vehicle control abilities while sleepy. Preventing these accidents caused by drowsiness is highly desirable but requires techniques for continuously detecting, estimating, and predicting the level of alertness of drivers and delivering effective feedbacks to maintain their maximum performance [6-7]. Recently, we [8-9] proposed an EEG-based drowsiness estimation system that continuously estimates driver's drowsiness level in a virtual-reality-based driving simulator. Here, we use the same method to estimate subject drowsiness level, except we employ MEMS dry electrodes rather than conventional wet ones to acquire continuous EEG data. EEG power spectrum estimation, PCA-based EEG signal analysis and multivariate linear regression are applied to estimate driver's drowsiness level in a virtual-reality-based dynamic driving simulator to demonstrate the potential uses of the dry electrodes during long and routine recordings in operational environments.

1). Virtual-Reality (VR)-based Driving Environment:

A VR-based dynamic driving simulation environment is designed and built for interactive driving experiments. It includes four major parts as shown in Fig. 3: (1) the 3D highway driving scene based on the virtual reality technology, (2) the driving cabin simulator mounted on a 6-DOF dynamic Stewart motion platform, (3) the EEG measurement system with 13-channel sensors, and (4) the PCA-based EEG signal analysis approach, power spectral density analysis, and linear regression model. The main purpose of this environment is to make a lifelike driving simulation in real situation. The detailed development of the VR-based scene was shown in [8-9].

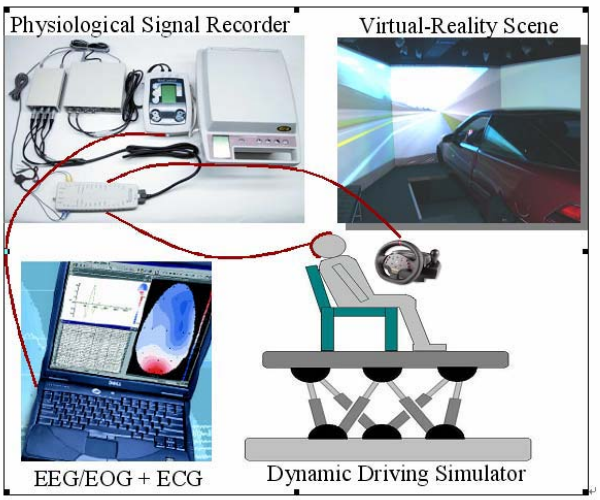


Fig. 3. The dynamic VR-based driving simulation environment integrated with the EEG-based physiological measurement system.

2). Comparison of EEG signals obtained by dry and wet electrodes

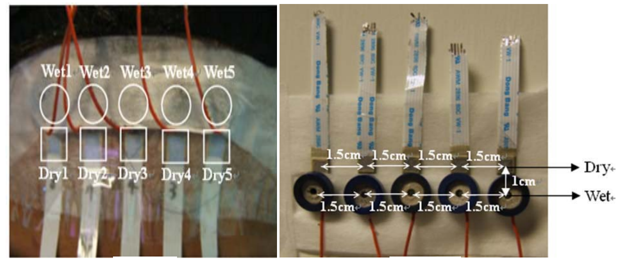
Figure 4(a) shows the placements of five dry/wet electrode pairs at the frontal locations. The dry electrodes 1 and 5 are placed at *Fp1* and *Fp2* according to the international 10-20 electrode placement system [10]. Corresponding wet electrodes were placed 1cm above the dry electrodes (cf. Fig. 4(b)). All experimental setups are followed the standard of procedures (SOP) that were described in detail in [8-9].

Figure 5 plots the raw EEG data obtained by dry and wet electrode pairs, wet/dry 1 and 5. The detailed description of the EEG-based drowsiness level estimation system will introduce in the next section. As can be seen in Fig. 7, the EEG signals recorded by dry sensors are extremely comparable to those obtained by corresponding wet electrodes.

Figure 6 plots the EEG power spectra of dry1/wet1 and dry5/wet5 electrode pair. As can been seen, they are extremely similar, indicating that the signals obtained by dry sensors can match the quality of the EEG recorded by conventional electrodes.

3). Drowsiness Estimation Performance

In order to demonstrate the potential applications of the MEMS electrodes during long and routine recording in operational environments, we investigate the quality of the EEG signals recorded by the dry electrodes placed at *Fp1* and *Fp2* for estimating subjects' drowsiness in an attention-demanding driving experiment. The EEG signals were



(a) (b)

Fig. 4. (a) Positions of Wet electrodes and dry ones. (b) Distance between wet electrodes and dry ones.

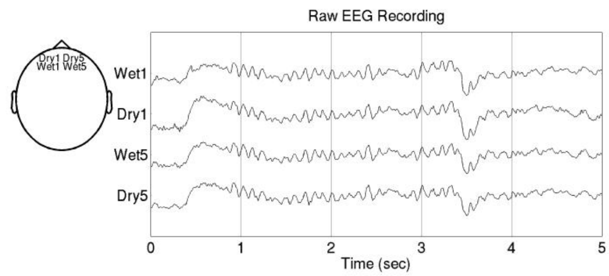
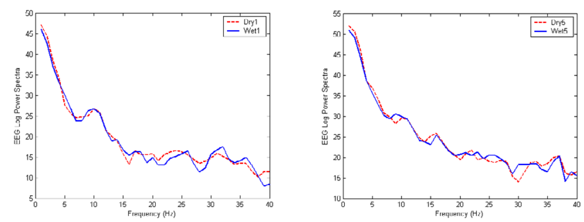


Fig. 5. Raw EEG Data Recording of Dry and Wet Electrodes



(a) (b)

Fig. 6. The EEG power spectra of dry1/wet1 (a) and dry5/wet5 (b) electrode pairs

recorded by 5 dry electrodes and processed by an EEG-based drowsiness estimation system [8] as shown in Fig. 7. The EEG data recorded by 5 dry (or wet) electrode pairs were first preprocessed using a simple low-pass filter with a cut-off frequency of 50 Hz to remove the line noise and other high-frequency noise [11]. After moving-average power spectral analysis, we obtained EEG log power spectrum time series of the 5 dry (or wet) electrode pairs and the frequency range is from 1 to 40 Hz. Then, we applied Karhunen-Loeve Principal Component Analysis (PCA) to the resultant EEG log spectrum to extract the directions of largest variance for each session. Projections (PCA components) of the EEG log spectral data on the subspace formed by the eigenvectors corresponding to the largest 50 eigenvalues were used as inputs to a multiple linear regression model [12] for each individual subject to estimate the time course of his/her driving error [13]. Each model was trained using the features only extracted from the training session and tested on a separate testing session.

Figs. 8 (a) and (b) show the estimated driving error of subject 1 in session 1 estimate session 2 and session 2 estimate session 1, respectively.

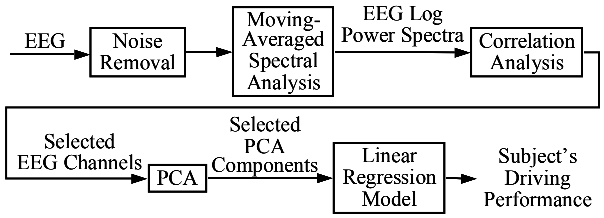


Fig. 7. Flowchart for processing the EEG signals.

The estimators were trained with the EEG signals from former session (red lines) to estimate the driving error of latter session (blue lines). Similarly, Figs. 9 (a) and (b) show estimated and actual errors made by subject 2. Table II shows the comparison of correlation coefficient between the actual and estimated driving error time series. As can be seen, the estimated driving errors matched well with the actual errors, consistent with our recent report in the same driving tasks using whole-head 32-channel EEG [8-9]. The results demonstrate the feasibility of accurately estimating subject drowsiness level based on EEG signals collected from the frontal non-hairy sites. Furthermore, the estimation accuracy based on the EEG collected by dry electrodes is comparable to that based on the signals collected by conventional wet electrodes, indicating the feasibility of using dry electrodes to acquire quality EEG signals without requiring skin preparation or conductive pastes in operational environments.

Table II. Test patterns for ESEI measurement

	Session 1 estimates Session 2		Session 2 estimates Session 1	
	Using Features	Dry electrode	Using Features	Dry electrode
Subject 1	14	0.86	27	0.74
Subject 2	6	0.83	34	0.69

IV. Conclusions

In this paper, MEMS dry electrodes are fabricated and characterized to bring EEG monitoring to the operational environment without requiring scalp gel or other scalp preparation. Our results demonstrated that the dry electrodes have advantages in electrode-skin interface impedance, signal intensity and size over the conventional (wet) electrodes. Furthermore, we employed the dry electrodes to collect continuous EEG signals in realistic 1-hour attention-demanding experiments to test the feasibility in VR-based dynamic driving simulator environments. The subject drowsiness level (task performance) based on the EEG signals measured by the dry electrodes and parameters derived from the pilot data from the same subject. Our results showed that the dry electrodes perform comparably to conventional electrodes placed adjacently, suggesting the practical uses of MEMS dry electrodes in operational environments where skin preparation and messy conductive paste are not feasible or undesirable.

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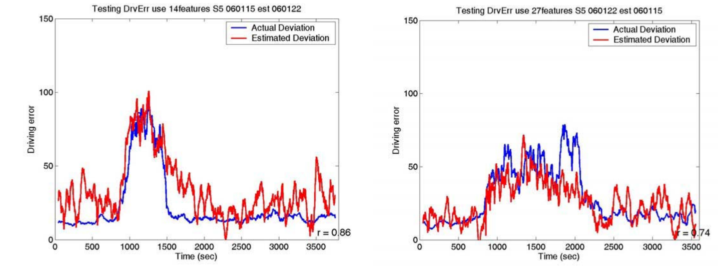
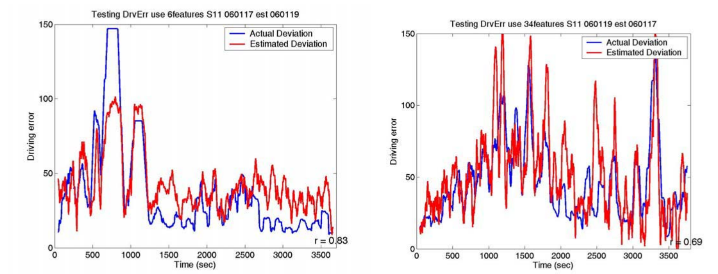


(a) (b)

Fig. 8. Estimated (red traces) and actual driving error (blue traces) of subject 1 using the EEG signals (a) session 1 estimate session 2 and (b) session 2 estimate session 1



(a) (b)

Fig. 9. Estimated (red traces) and actual driving error (blue traces) of subject 2 using the EEG signals (a) session 1 estimate session 2 and (b) session 2 estimate session 1

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