2012 IEEE 16th International Symposium 2012 ISCE 1569582413

INTEGRATION OF ELECTROENCEPHALOGRAPHY BASED SERVICES INTO CONSUMER ELECTRONICS

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Abstract—**Commercialized electroencephalography (EEG) sensors are available that one could extract EEG data more cheaply and more easily. As commercialized EEG sensors can be used commonly, the services that could be provided using EEG and interactions that can be achieved by EEG are needed to be studied. In this paper, we show the feasibility of integrating EEG based services and interactions into consumer electronics using commercialized EEG sensors. We use support vector machine (SVM) classifiers to classify the user's status using EEG data gathered from objects of interest and noise. The results show that EEG gathered from commercialized EEG sensors can be used to classify the user's status.**

I. INTRODUCTION

The electroencephalography (EEG) has been studied to extract and classify sentiments, intentions, and mobility. [1-3] These trials have shown the promising future for using EEG for next generation interaction. However these EEG data and measurements cannot be used in real world application, because they are measured and calculated with minimum noise. Movement of facial muscle, eye, blink of eye, and electronic power line can cause noises in EEG data [4], that we cannot apply EEG data analysis from publication to real world.

Currently EEG data are easy to gather with commercialized EEG sensors. Gel-type head caps are more accurate with high resolution EEG data. However, head caps are not preferable or applicable to use with everyday electronics. Two commercialized EEG sensors, NeuroSky mindwave with one dry EEG sensor [5] and Emotiv EPOC EEG headset with sixteen wet EEG sensors [6], were used in this study. Mindwave and EEG headset both use their own filtering algorithm, and detection algorithm for excitation values. [7] Also EEG headset sensors contain gyro sensor, and facial movement sensors that can be used to filter the head movement and facial movement.

Brain computer interaction has been growing field of study. There has been trial for interaction-oriented study such as to using EEG data patterns to move mouse in 2 dimensional movements [8], but there is little study on using EEG to use service-oriented study. In this paper, we try to observe the feasibility of integrating EEG based services into consumer electronics using commercialized EEG sensors with real world noise, and commercialized noise filtering algorithm.

This work was supported by the Global Frontier R&D Program on <Human-centered Interaction for Coexistence> funded by the National Research Foundation of Korea grant funded by the Korean Government(MEST) (NRF-M1AXA003-2011-0028371)

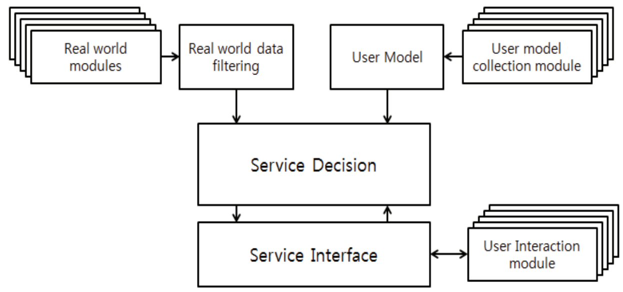

Fig 1. Flowchart of service algorithm

II. ALGORITHM

Service algorithm using EEG data is shown on Figure 1. User model collection module collects the user's interests. Also it includes trained EEG data and real world objects that include the user's interests. Real world modules, which include EEG and object recognition modules, collects the real world data in real time. Real world data filtering uses filtering algorithms to remove noises and unclassifiable objects. Using the filtered real world data, and the user model created with user model collection module, service decision process is executed. Currently we implemented the service to give more information about the object of interest to the user. Also by interacting with user, the service decision learns the preference of the user.

The service algorithm can be applied to many electronics with different services. User model can contain information from different sources including purchase information to social network service information, which can be used to provide various services, from sentiment extraction to shopping application.

III. EXPERIMENT

The purpose of experiment is to observe the classifiable patterns of EEG between noise and real world data that contains the object of interest. These EEG patterns can be used to decide the service to the user. First, we prepared survey about objects of interest from the participants. Secondly, with the objects interest, we've created viewing materials for participants. The viewing materials include the object of interest, and noise patterns. While viewing the materials, we measured EEG using commercialized EEG sensors. Figure 2. shows the picture of experimentation.

The results of the experiments were gathered from 4 participants (3 men, 1 woman, age 25-39) that did not have history of head injury, mental illness, visual impairment and hearing impairment. Participants were not asked to hold their eye blinking or hold their head still to gather EEG data with noises to be used for classification. Mindwave data were gathered with single channel from the forehead, and filtered eye movement and blink with NeuroSky's filtering algorithm. EEG headset data were gathered from 16 wet sensors (position : AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, including two reference CMS, DRL). From both dataset data with low signal values were removed.

After the first experiment we wanted to see if there exist different EEG pattern for gathering information and EEG pattern gathered from concentrating without object of interest in the viewing area. We used the same data from the first experiment for EEG pattern gathered with object of interest in the viewing area. For EEG pattern for mild concentration, we asked the participants to perform mental arithmetic while viewing noise patterns.

Fig 2. Experimenting with commercialized EEG sensors Neurosky mindwave (Left), and Emotiv EPOC EEG headset (Right)

IV. CONCLUSION

Using support vector machine (SVM) classifier, with radial kernel, we have modeled each participants EEG to three classes; information, mild concentration and noise. "Meditation" and "Attention" value from NeuroSky sample data from one of the participant is shown in scatter graph on Figure 3. Classifier accuracy of each participant and average accuracy is shown on table 1. As shown on the graph, classifying the information from noise or mild concentration has high accuracy, while classifying the noise to mild concentration shows lower accuracy.

This result shows that EEG gathered with visual information has different EEG pattern that is classifiable to be serviced. Data gathered with the noise and filtered using commercial EEG sensors can be used in EEG based service.

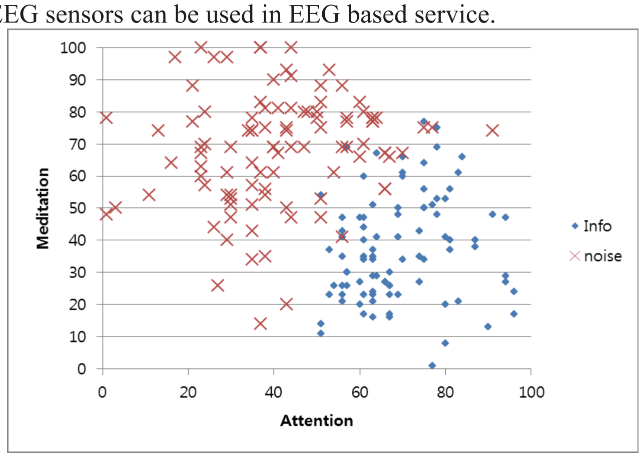

Fig 3. Scatter chart of result from one of the participant.

TABLE I. Accuracy of SVM classifier using 10-fold cross validation

	Information vs. Noise	Noise vs. mild concentration	Information vs. mild concentration
Participant 1	85.08065	68.12081	**89.58333**
Participant 2	**92.10526**	69.78022	86.04651
Participant 3	83.72093	78.74396	**86.70213**
Participant 4	**86.12717**	68.10811	76.19048
Average	**86.7585025**	71.188275	84.6306125

V. DISCUSSION

The main problem we face with implementing EEG data into consumer electronics is that every user has a unique EEG data patterns. Every user must train their EEG data to model a classifier, making it difficult to implement zero-configuration EEG-based services. Therefore EEG should be used as a subsidiary to support better main interaction.

Second problem of implementing the EEG to consumer electronics is the object recognition implementation. Currently we implemented the service algorithm to the known objects. The object recognition part must be improved to service EEG pattern based services in real time.

In this paper, we have shown the possibility of using commercialized EEG sensors to be used for services, and there exist limits to using EEG alone for interaction, but it shows the possibility of serving as one of subsidiary modules to support main interaction classification.

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