A Mobile TDR System for Smart Phones

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***Abstract*—In our previous work a multi-level slow intelligence system with multiple sensors, called the TDR system, was developed [1]. It consists of interacting super-components each with different computation cycles specified by an abstract machine model. The TDR system has three major super-components: Tian (Heaven), Di (Earth) and Ren (Human), which are the essential ingredients of a human-centric psycho-physical system following the Chinese philosophy. Each super-component further consists of interacting components supported by an SIS server. In this paper we further developed a mobile TDR system for smart phones, intended for practicing health exercises such as conducting meditation. The initial experimental results and further research topics are discussed.**

Keywords—slow intelligence system, component-based software engineering, sensor networks, mobile TDR system.

1. Introduction

Our goal is to develop a mobile TDR system for smart phones so that the user can carry this mobile TDR system anywhere. This experimental TDR system thus provides a platform for exploring and integrating different applications in personal health care, emergency management and social networks.

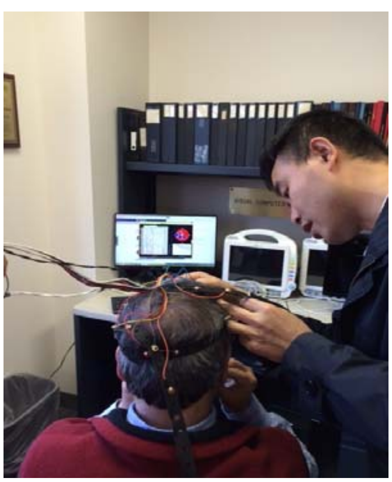

Figure 1. A brain wave headset.

To develop this experimental mobile TDR system, we need to port the TDR system to a smart phone. This mobile TDR system empowers the user so that he or she can have continuous access to the sensory devices and apps offered by the mobile TDR system. An example of such a sensory device is the brain wave headset. As shown in Figure 1, the user can wear the headset with sixteen OpenBCI brain wave sensors so that the time signals detected by the sensors can be continuously sent to the TDR system. The displayed time signals (left), positions of the sensors (upper right) and power spectrum (lower right) are illustrated in Figure 2.

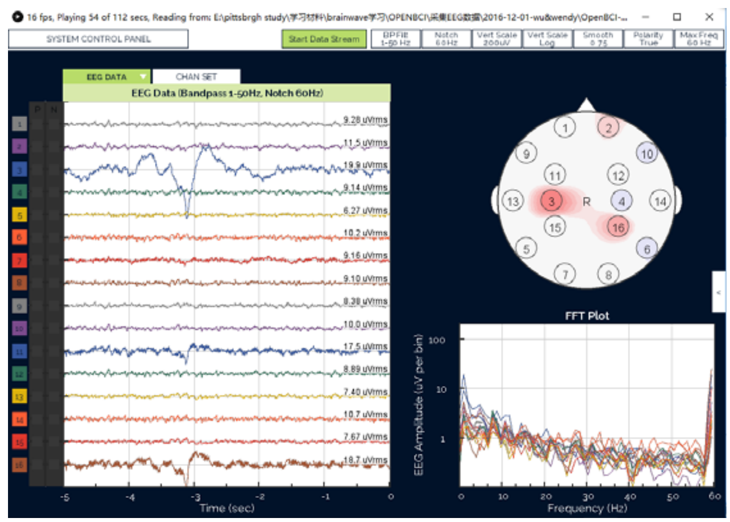

Figure 2. Time signals from OpenBCI brain wave sensors.

In addition to brain wave sensors, a smart phone has built-in sensors such as its camera, which can be used to analyze the gaze of the user (see Figure 3) to obtain certain measurements. The smart phone also has audio output. Thus the mobile TDK system provides multiple sensory input/output devices to continuously monitor user's state of health. In our initial experiment, the objective is to monitor user's meditation state.

Figure 3. Gaze analysis.

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We need to answer two basic questions: (1) Can a mobile TDR system for smart phone be developed? (2) Can the information from various sensors of the mobile TDR system be analyzed and combined to monitor user's meditation state?

The paper is organized as follows. To answer the first question, Section 2 presents the system architecture and development environment. The basic scenarios of the mobile TDR system are described in Section 3.

To answer the second question, the identification of meditation state from brain wave sensors is described in Section 4. Gaze analysis for the detection of meditation state is described in Section 5. Experimental results show the two approaches are consistent in detecting the meditation state.

The related work is reviewed in Section 6. Section 7 discusses further research topics.

2. System Architecture

To facilitate the design of complex slow intelligence systems such as human-centric psycho-physical systems, we introduced the concept of super-components [1]. A complex slow intelligence system basically consists of interacting super-components, which further consist of many interacting components supported by an SIS server. Communications are through the SIS server, and the messages are *layered*, i.e., each message type has its hierarchical *scope*. A super-component can be viewed as a collection of components interacting by messages within the same scope. From an architectural viewpoint the result is a multi-level slow intelligence system as illustrated by Figure 4.

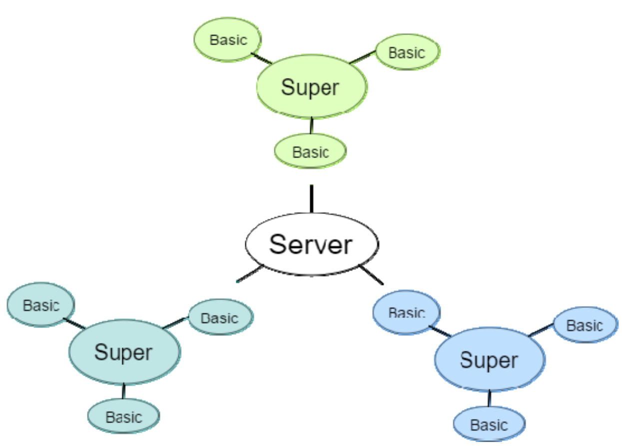


Figure 4. A multi-level slow intelligence system.

Figure 5 shows the structure of the TDR System. The seven components are the graphical user interface **PrjRemote**, **Audio** output, **Gaze** analyzer, internet **Uploader**, **OpenBCI** input processor and data **Filter**. These components communicate with each other via the Server. These seven components all reside in the smart phone and be running at the same time. For this reason a high-end smart phone, ASUS ZenFone 3 ZS570KL with 64GB storage, 6 GB RAM, micro-SDXC Memory Card Slot, USB Type-C and Android 6.0 was acquired.

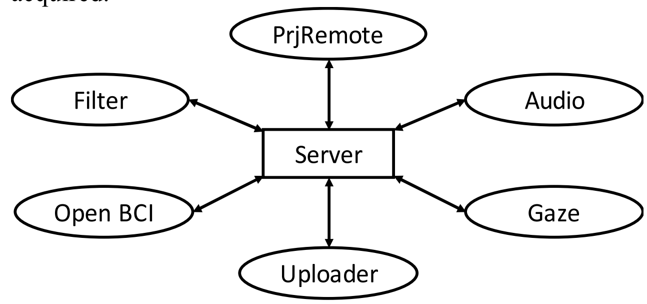


Figure 5. The structure of the mobile TDR system.

The development environment is illustrated by the UML development diagram shown in Figure 6. The Android components are first developed in Android Studio on a PC and then uploaded to the smart phone. The OpenBCI brain wave headset is the external device connected to the smart phone via Blue Tooth and a USB port. As shown in Figure 6 the headset can also be augmented for audio output such as rhythmic music (see Section 8).

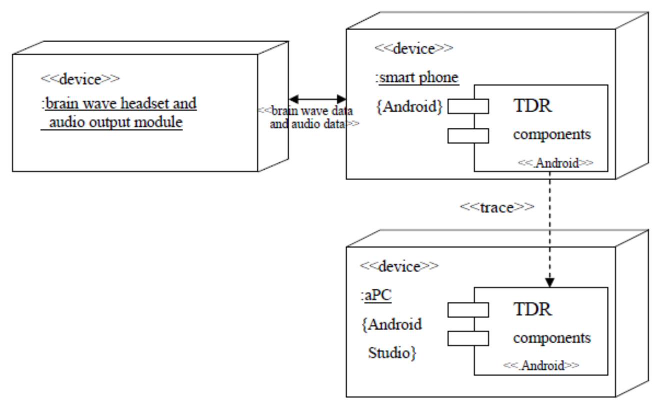


Figure 6. TDR Development environment.

3. Basic Scenarios of Mobile TDR System

The mobile TDR system initially provides the following apps: (1) The Audio app plays rhythmic music to help calm down the user. (2) The Gaze app analyzes a user's gaze to decide whether he/she is in meditation state. (3) The BrainWave app uploads the brain wave signals if the user is wearing a brain wave headset, to Internet for further processing. (4) The Analyzer to analyze data to detect meditation state, and verify whether the decisions made by the Gaze analyzer and the Brain wave analyzer are consistent. The first three apps are in the smart phone, and the analyzer may either be in the smart phone or runs on the Internet. The latter option allows the continuous improvement of the analyzer so that it can learn and improve its performance following slow intelligence principles.

3.1. The Audio App

This app requires three components: PrjRemote, Server and Audio. The Audio component can play a small piece of rhythmic music (e.g. raining) again and again at a certain frequency, helping user to relax. There are several pieces of music pre-stored in the Audio component. User can select or change the music by sending an ID number from PrjRemote. PrjRemote will send the ID number to the Server, Server will forward the ID number to Audio and finally Audio will play the music that user selected, as shown in Figure 7.

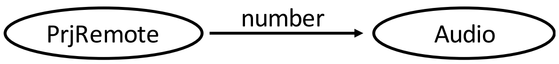


Figure 7. Information flow for Audio App.

For example, user wants to listen to the second piece of music. User types “2” in the PrjRemote and clicks the button “send” (Figure 8 (a)). Then, user hears the Audio component playing the number “2” music and Audio component displays the received message on its interface (Figure 8 (b)).

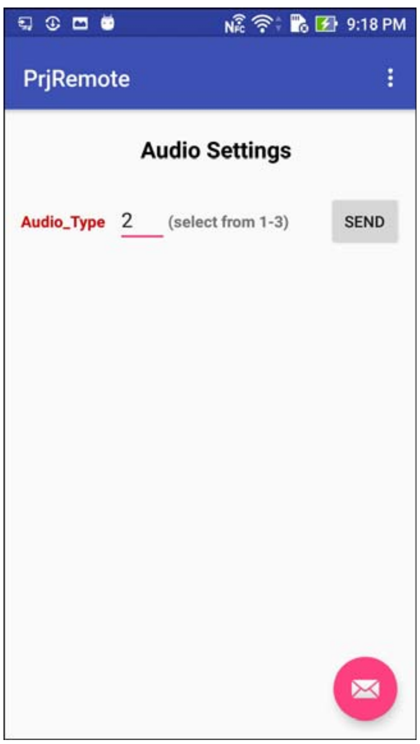


Figure 8(a). Audio_type “2” is selected.

3.2. The Gaze App

This app requires three components: PrjRemote, Server and Gaze, as shown in Figure 9. The Gaze component evaluates whether the user is relaxed or not by analyzing user’s gaze. After the analysis, Gaze will generate a parameter to reflect the degree of the user’s relaxation. When the Gaze component is activated, it will open the front camera of the smart phone and record a video clip of the user’s face. The duration of the recording is set by the user by sending a number from PrjRemote to Gaze.

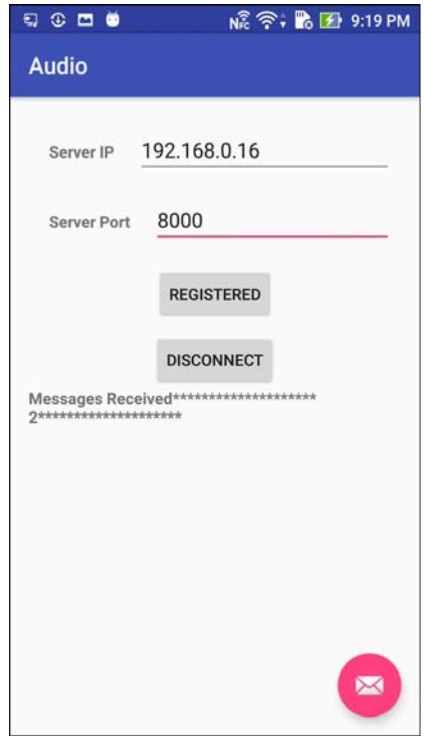


Figure8(b). Audio component received “2”.

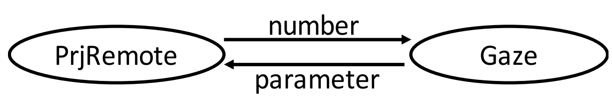


Figure 9. Information flow for the Gaze sub-system.

In Gaze Duration Setting view of PrjRemote user can choose standard setting or customized setting. For example, user wants to set the Gaze duration to be 10 seconds. He clicks the button “send” on the first line of Standard Setting (Figure 10 (a)).

When the Gaze component receives the message, it changes the duration time and displays the message on the bottom (Figure 10 (b)).

Next, user activates the Gaze component by clicking the ”Start Mental State Tracking” button. After the recording and the gaze analysis. the result parameter “0.75” is displayed on the bottom of the PrjRemote interface (Figure 10 (c)).

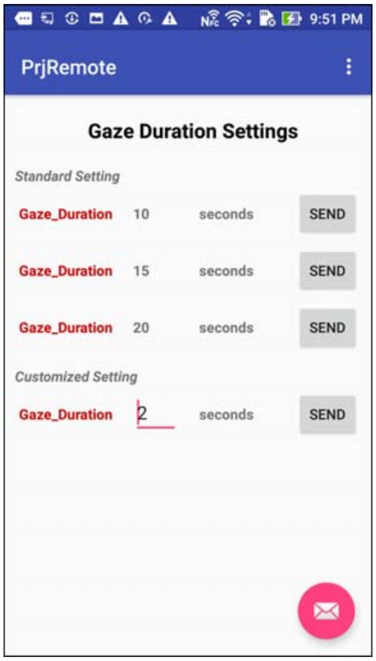


Figure 10(a). Gaze_duration “10” is selected.

Figure 10(b). Received message is displayed.

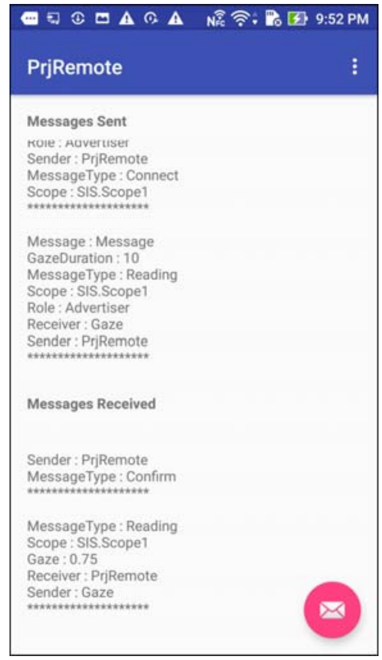


Figure 10(c). Gaze parameter “0.75” is displayed.

3.3. The Brain Wave App

This app requires five components: Filter, Open-BCI, Uploader, PrjRemote and Server. The Open-BCI input processor component receives the input data from a wearable brain wave headset. User can set the frequency and duration of the input data collected from the wearable headset by setting these two parameters.

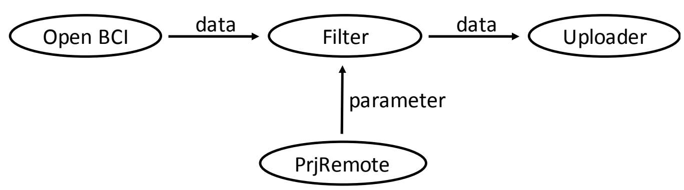


Figure 11. Information flow for Brain Wave App.

Suppose the user wants to collect the data every 5 seconds, and the total time period for collecting data is 20 seconds. He enters “5” on the first line of Customized Setting and enters “20” on the second line, and then clicks the “send” button (Figure 12(a)).

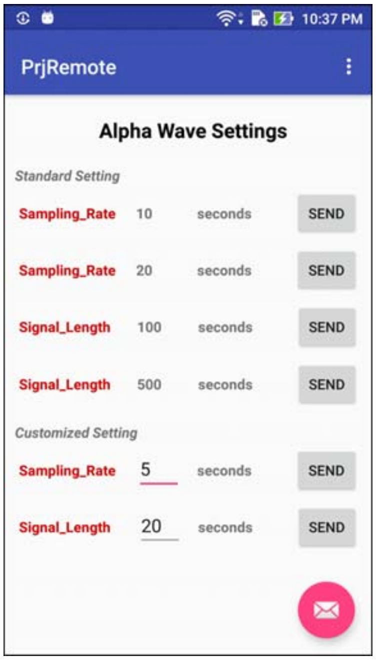


Figure 12(a). Frequency and time period are selected.

When the filter component receives the frequency and time period from PrjRemote, it displays them on its interface (Figure 12 (b)). Open-BCI input processor receives data that are filtered according to the parameters set by the user (Figure 12(c)).

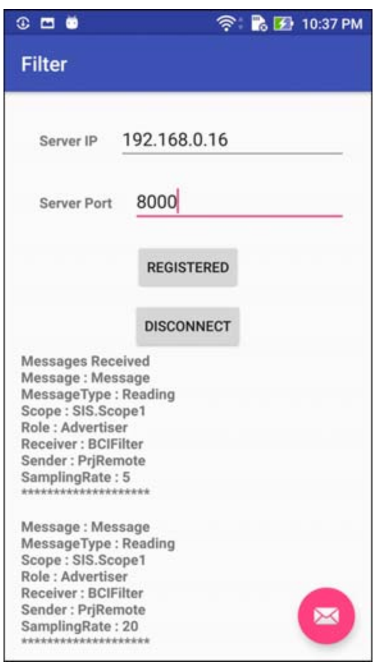


Figure 12(b). Filter is activated.

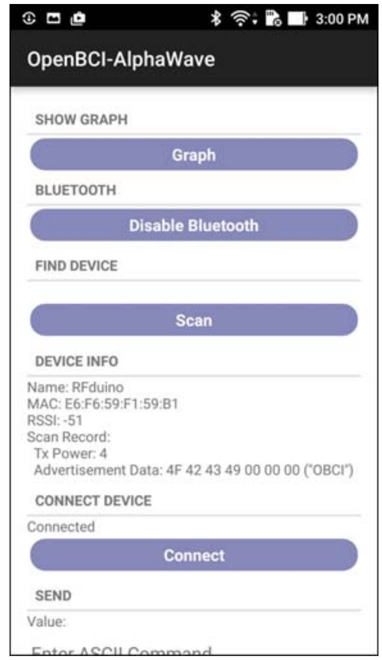


Figure 12(c). Data is received and filtered.

The OpenBCI input processor can process and plot the input Alpha brain wave data as shown in Figure 12(d). When the user is concentrating, the curve tends to move upward and the *alert probability* increases. In Figure 12(d) the alert probability is 0.8 (80%). When the user is not concentrating, the curves tends to move download and the alert probability decreases. Finally the uploader can upload the data to the Internet and store it in a database.

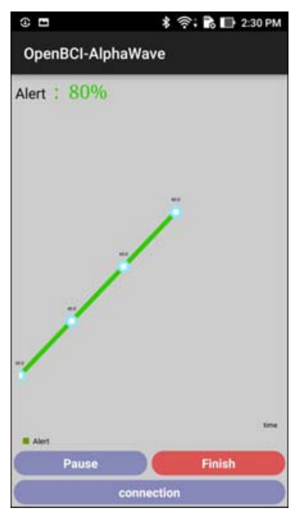


Figure 12(d). Alpha Brain Wave data is plotted.

3.4. The Meditation State Detection App

After the gaze data and brainwave data have been uploaded to the database in the Internet, they can be further analyzed to detect the meditation state, and whether the predictions are consistent. This will be further discussed in Section 5, and the results are illustrated in Figure 16. The green color prediction is when both EEG and eye-tracking predictions are consistent and correct. Blue colors are EEG predictions that are inconsistent with eye-tracking predictions. Red colors are eye-tracking predictions that are incorrectly predicted. 1 is meditation state, -1 is high cognitive workload.

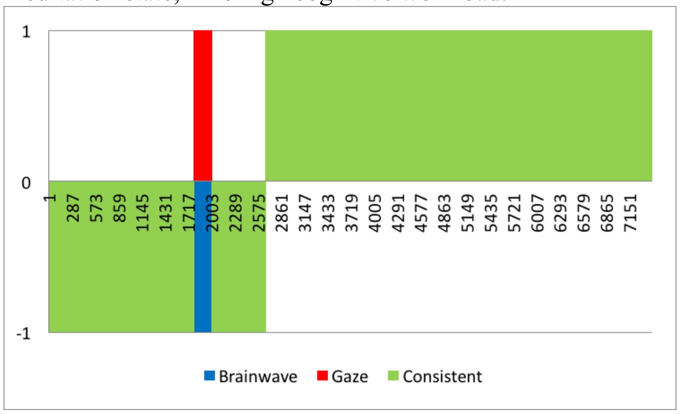


Figure 16. Comparison of meditation state predictions.

4. Meditation State Detection

Meditation, according to [2], is used to describe "practices that self-regulate the body and mind, thereby affecting mental events by engaging a specific attention set." In the Western tradition, meditation can be classified into *mindfulness meditation* and *concentrative meditation* [2]. Mindfulness meditation emphasizes the rise of all possible feelings in awareness, whereas concentrative meditation requires concentrating on a specific object or activity.

In our initial experiment we regard meditation as concentrative meditation. Our concentrative meditation system includes three major components: 1) State-Meditating: detecting concentrative meditation state via brainwave signals; 2) State-Meditating: detecting concentrative meditation state via eye tracking signals; 3) Trait-reading: detecting concentrative meditation traits via eye movement patterns.

State-Meditating: Brainwave

According to [2], the meditation state is the state when the user is more relaxed as exhibited by the brain wave patterns with little or no activity. Given the strong relationship reported between EEG signal and meditation state, we developed a technique to detect the meditation state, or more precisely, to predict the probability of the meditation state, from input brain wave data.

The alert probability described in the previous section can be regarded as a measurement of the meditation state probability from AlphaWave provided by OpenBCI software.
In our approach, The OpenBCI Monitor component makes such prediction based on pre-trained prediction model, and decides whether it is necessary to upload data into the database for further analysis.
For training the prediction model, a software tool called "Weka" is used. Weka provides a lot of flexible well-programmed machine learning algorithms. With its help, the module can train a prediction model easily using different machine learning algorithms. In addition, Weka is a package implemented in Java, so it is easy to integrate the package into the TDR system as a component.

After the 16 channel brain wave data is appropriately cleaned, 4 consecutive records of brain wave data, plus the mean, variance and standard deviation of these records, are used to train the predication model. Weka provides a lot of machine learning algorithms, from KNN or linear regression, to other high level machine learning algorithms, such as SVM. With the help of the package, the system can train any model by different classifiers. We implemented the program that, user can easily to change the classifier they need. To select a proper algorithm, we did a few experiments using different classifiers, such as Linear Regression, Logistic Regression, Bagging, Ada Boost, Naïve Bayes, J48, Random Forest, and SMV. We used 10-folds cross validate to select a better model. In our initial experiment, the two subjects are both experts in meditation, therefore no matter what classifier was used, the prediction accuracy is always 100%. Therefore we chose to use SMV as the model.

To summarize our initial experiment, we can train, test a model, and save the model into a file so that the BCI Monitor can load the model easily and make prediction dynamically in a live demo. We did a pilot study to test the workability of our system. In the pilot study, we recruited a concentrative meditating master, to meditate (s1) and stay calm (s2). The experimental results are shown in Figure 13.

```
train: 461
test: 51
=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall   F-Measure   ROC Area   Class
                 1         0          1          1         1           1         0
                 1         0          1          1         1           1         1
Weighted Avg.    1         0          1          1         1           1

=== Confusion Matrix ===

  a  b   <-- classified as
 22  0 |  a = 0
  0 29 |  b = 1
```

Figure 13. Experimental results of meditation state prediction.

We can see the predication accuracy is always 100%. Such results are of course too good to be true. We are curious whether the mastery of meditation induces the huge difference in the two states. Therefore we design another pilot study to evaluate it, which will be described in later section.

State-Meditating: Eye-Tracking

When a user is walking or exercising, it is inconvenient to wear a brain wave headset with many electrodes. Therefore, we would like to explore whether the meditation state can be detected through gaze analysis. If it can be done, then the user only needs his smart phone and nothing else.

We propose to use face-tracking and eye-tracking technique to monitor meditating on smart phone based on two hypothesis: 1) when a user is meditating, there is a potential that the mental and conscious change might affect the user's facial emotions slightly; 2) When a user is meditating, the conscious change might affect his eye-movements even if the eyes are closed. We are investigating the potential to observe meditating state via appearance changes. Our State-Meditating function is designed to be an application connected with SIS-server. We used a Google Nexus 5x smart phone running Android 6.0 to launch the SIS system applications. After the user settled the duration parameter on SIS-GUI, SIS-GUI will redirect the user to Gaze-component. The meditating state tracking will be started after user clicked the start button. During state tracking, each frame captured by the front facing camera will go through 2 steps: 1) Face landmarks tracking: we track the important landmarks of a face (e.g. left, right, and center point of eyebrows). In table 1, we listed the detail face landmarks being tracked; 3) Eye gaze estimation: we rely on the location of the pupil relative to the rest of the eye to estimate the direction of eye gaze. In our Gaze-Component, the Qualcomm Snapdragon SDK is being used to accelerate the tracking process. On 808 CPU in Nexus 5x, the per-frame image processing time is 17 ms.

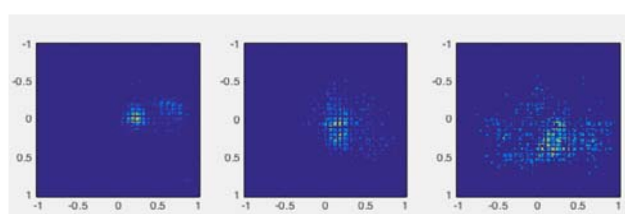
Region	Landmarks Detail
Brows	leftEyeBrowsPointTop
	leftEyeBrowsPointBot
	leftEyeBrowsPointLeft
	leftEyeBrowsPointRight
	rightEyeBrowsPointTop
	rightEyeBrowsPointBot
	rightEyeBrowsPointLeft
	rightEyeBrowsPointRight
Ear	leftEarPointTop
	leftEarPointBottom
	rightEarPointTop
	rightEarPointBottom
Eye	leftEyeBot
	leftEyeTop
	leftEyeCenter
	leftEyeLeft
	leftEyeRight
	rightEyeBot
	rightEyeTop
	rightEyeCenter
	rightEyeLeft
	rightEyeRight
Mouth	mouthULipBot
	mouthULipTop
	mouthLLipBot
	mouthLLipTop
	mouthLeft
	mouthRight
Nose	noseBridgePoint
	noseCenterPoint
	noseLLeft
	noseLRight
	noseMLeft
	noseMRight
	noseTipPoint
	noseULeft
	noseURight

Table 1. Details of face tracking landmarks.

Pilot study

We design another pilot study to 1) evaluate the accuracy of state prediction, 2) test whether our system is applicable to non-professional users (which are our targeted users), 3) compare the signals of brainwave and eye tracking in state prediction.

In this pilot study, we recruited a local college master student (male, age 24) to test the meditation state prediction accuracy. The subject performed 3 different state in front of a mobile phone front facing camera with EEG sensors on: concentrative meditation (s1), stay calm (s2) and high cognitive workload (s3). In s1, we followed concentrative meditation instruction to train the user to focus on his nose and try to arise any feeling on nose. In s2, the subject simply stayed calm and avoided thinking anything. In s3, we ask the subject to thinking a math problem (a four digit number plus a four digit number) to induce the cognitive workload.



(a) (b) (c)

Figure 14. Eye gaze heat map on different state: (a) s1, meditation state; (b) s2, staying calm state; (c) s3, high cognitive workload state. We observe a clear difference among different state, where s1 is the most concentrative state and s3 is the sparsest state.

We use OpenBCI to collect EEG data, and smart phone front facing camera to collect eye-tracking signals. We parallelize the two groups of data, and separate both EEG data and eye-tracking data into 2 parts: first 70% as training and later 30% as testing.

To train the EEG model, we followed the previous pilot study and used Weka in java, and SVM for creating the model. The features we extracted are 16 channel brain wave data and the mean, variance and standard deviation of these records within 4 step sliding window.

From the raw gaze data, we can observe a clear difference among different state, where s1 is the most concentrative state and s3 is the sparsest state (Figure 14). To quantify the difference, we also trained the eye-tracking model. We kept consistent with EEG model, using Weka in java to perform SVM, with gaze x and gaze y coordinate at each timestamp and the corresponding mean, variance and standard deviation within 2s sliding window.

When comparing concentrative meditation (s1) with calm state (s2), the EEG model for predicting meditation state is 100% accuracy and eye-tracking model is 82.86% accuracy. The corresponding parallel result is shown in Figure 15.

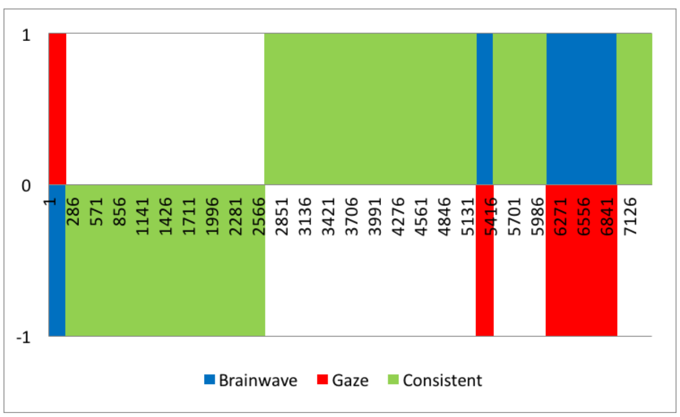


Figure 15. Meditation prediction from staying calm states. The green color prediction is when both EEG and eye-tracking predictions are consistent and correct. Other than green, blue colors are EEG predictions that are inconsistent with eye-tracking predictions. The red colors are eye-tracking predictions that are incorrectly predicted. 1 is meditation state, -1 is staying calm state.

When comparing concentrative meditation (s1) with high cognitive workload state (s3), the EEG model for predicting meditation state is 100% accuracy and eye-tracking model is 97.06% accuracy. The corresponding parallel result is shown in Figure 16.

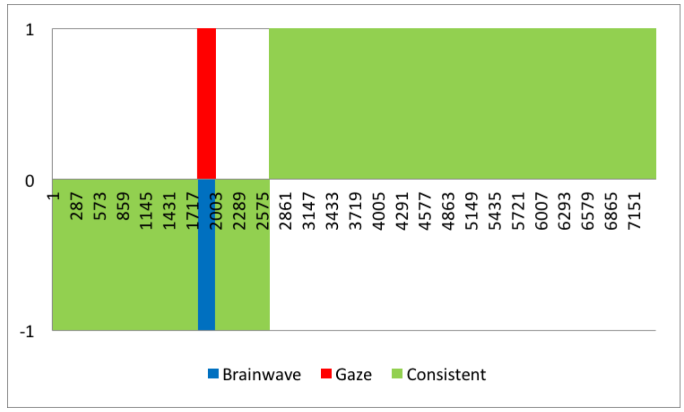


Figure 16. Meditation prediction from high cognitive workload states. The green color prediction is when both EEG and eye-tracking predictions are consistent and correct. Other than green, blue colors are EEG predictions that are inconsistent with eye-tracking predictions. The red colors are eye-tracking predictions that are incorrectly predicted. 1 is meditation state, -1 is high cognitive workload.

5. Detecting Reading Patterns by Gaze Analysis

In this section, we first explain how to apply gaze analysis to find out user's reading patterns. This will give some empirical justification that such technique may be applicable to track user's reading patterns to determine users' meditation trait. For initial design, we use the instruction manual to practice Chi as the reading material, and track users' gaze pattern to see whether the user understands the instruction. We believe the time a user takes to read and the user's gaze pattern reflect his (her) meditating trait.

To process the data in SIS database and visualize the processing workflow, we write our code in PHP, and the visualization can be easily observed on SIS GUI webpage.
The visual object consists of two levels. Using visual object definition, the two levels are:

Top level:
Y_m is: Binary Trait State (Have trait of meditation or not)
Y_i is: Different color on 'Reading' Tag (Red: don't have trait, Green: have trait)
Bottom Level:
X_m is: User's Gaze data within 1 second time period
X_i is: Gaze coordinates (points) and corresponding time
Our system controlled by two directions: bottom-up and top-down. The top down direction is on scope of TDR system in the whole.
In bottom up direction:
H_i represents the covariance value for each individual segment X_m calculated by function:

$$\operatorname{cov}(X,Y) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{2}(x_i - x_j)\cdot(y_i - y_j) = \frac{1}{n^2}\sum_{i}\sum_{j>i}(x_i - x_j)\cdot(y_i - y_j).$$

We set a fuzzy number (fuzz) R ranging from 0 to 1 with 5 levels. If Hi = 0-0.2, then the fuzzy number R=1, the level indicates the user has a strong trait; If Hi = 0.2-0.4, then the fuzzy number R=0.8, the level indicates the user has a trait; If Hi = 0.4-0.6, then the fuzzy number R=0.6, the level is medium; If Hi = 0.6-0.8, then the fuzzy number R=0.4, the level indicates the user might not have a trait; Otherwise Hi = 0.8-1, and the fuzzy number R=0.2, the level indicates the user don’t have trait. The pseudo code for the algorithm is presented below:

```
$lastTime = 0;
while($data!=null)
{
        $d = $data[0];
        $data = $data[1:end];
        if($d[‘time’]==lastTime){
                $Xm = $Xm+$d;//put current data into Xm
        }
        else{//current Xm is full and the new data should be add to a
new Xm
                $lastTime = %d[‘time’];
                        $uncert = 0.75;
                $assessScore = covariance of ($Xm)
if($assessScore>=0.8){//Fuzz level 5
                        Table-background-color:Red;
                }
                else if($assessScore>=0.6){//Fuzz level 4
                        Table-background-color:Orange;
                }
                else if($assessScore>=0.4){//Fuzz level 3
                        Table-background-color:Yellow;
                }
                else if($assessScore>=0.2){//Fuzz level 2
                        Table-background-color:Green;
                }
                else{//Fuzz level 1
                        Table-background-color:Blue;
                }
                $Xm = $newXm;
        }
}
```

In GUI, we display a ReadingBehaviorObservation table with each row as a segment (Figure 14). The background color shows the trait level when user is reading within this one-second segment.

Xm	# of Xi	Assessment Score1	Assessment Score2	Assessment Score Avg.	FuzzNum	Uncertainty
1	4	0.14890001959662	0.1318945367093	0.14039477915308	0.71821244266366	0.75
2	6	0.18819593164204	0.098078990144336	0.13713749589319	0.72572508621362	0.75
3	3	0.48658124640194	0.1960834260109	0.34133253620642	0.31733532756715	0.75
4	15	0.17364544144138	0.16327657731016	0.17946100937576	0.84307798124847	0.75
5	16	0.13328470339942	0.15567282003267	0.15946678181614	0.68106247636771	0.75
6	13	0.23334362963704	0.16885631531977	0.2011000724784	0.59779965504319	0.75
7	4	0.30436181811287	0.32599923572062	0.3151905269166	0.36963894616641	0.75
8	4	0.2904531206578	0.29647019596103	0.29346165831941	0.41307966336117	0.75
9	12	0.15899006760798	0.1271316996728	0.14356035384039	0.71287923231921	0.75
10	12	0.29930450196887	0.27424095117043	0.28679772656965	0.4264045468607	0.75
11	14	0.27443905582572	0.26715247419796	0.27079676501184	0.45840946697632	0.75
12	11	0.24169168262764	0.16968923226017	0.2056804574439	0.58863906011219	0.75
13	15	0.33456234136029	0.34472371990497	0.33964303063263	0.32071393873474	0.75
14	15	0.19984612353597	0.14173584194958	0.17079098274278	0.65841803451445	0.75
15	14	0.14937376083627	0.25707369096685	0.20322372090156	0.59355255619686	0.75
16	9	0.32754454469131	0.17768394879747	0.25261424674439	0.49477150651122	0.75

Figure 14. Reading Behavior Observation Table.

Besides fuzzy number, we also include uncertainty number in our System to indicate the capability of our prediction. The uncertainty number for random guess is 0.5. We initially set it as 0.75 for our system. This uncertainty number will be updated based on future user study prediction accuracy.

We include a HeatMap, which is a saliency map of user’s attention, as an overview (Figure 15).

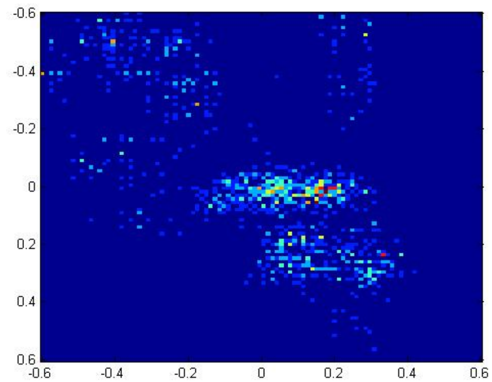


Figure 15. HeatMap of Reading Indicating High Meditation Trait in user’s reading of CHI manual.

6. Related Work

Mindfulness meditation along with relaxation and biofeedback are major self-regulatory strategies that are wildly explored in clinical used therapy [3]. Mindfulness meditation has been proven to have positive effects on social skills, feeling of compassion, self-management, somatic awareness [7] and mental flexibility [8]. Besides that, studies has been work on usage of mindfulness meditation in treatment of anxiety disorders, stress reduction [3], [5], chronic pain and persistent pain [5], [9], depression [5], autism spectrum disorders [5], traumatic experiences [10], acquired brain injury [11], and even disordered eating, psoriasis and substance abuse [12], [13] and so on. Concentrative meditation, based on its unlimited physical form, is being taught broadly for stress reduction. However, the traditional researches on mindfulness as well as concentrative meditation mostly relied on self-report and verbal comprehension as measurements [3], [4], [5].

Transcendental meditation is a technique that turns “the attention inwards towards the subtler levels of a thought until the mind transcends the experience of the subtlest state of the thought and arrives at the source of the thought” [15], which can be classified as concentrative meditation [2]. Because of the easiness and enjoyableness, large subject number, repetition of mantra [2], and immediately experience beneficial physiological changes [16], TM becomes a popular meditation technique that being measured via physiological signals [[2], [6], [14]. Metric of meditation measurement via physiological signals consists of two major parts: state and trait. State is “altered sensory, cognitive, and self-referential awareness that can arise during meditation practice" and trait is "the lasting changes in these dimensions that persist in the meditator irrespective of being actively engaged in meditation" [2].

Among all physiological signals being used to measure TM, brain signals via electroencephalography (EEG) have more than 60 years history and are most commonly used [2]. Hans Berger first recorded EEG signals in the 1920s [20]. After about 90 years development, EEG now can be divided into 6 bands by frequency: alpha, beta, gamma, theta, delta, and mu. Alpha and theta bands are highly related to meditation state [18], [21], [22], [23], [24], [25]. Although many researchers [21], [22], [23] found that alpha power increases during meditating, different results have been reported based on different location of EEG sensors (i.e. frontal, parietal, temporal, or occipital) [18]. Besides EEG, physiological signals of ERP [2], GSR [6], Oxygen consumption [6], HRV [6] and neuroimaging [2] have been applied to monitoring meditation.

Our TDR-CHI Gaze component was inspired by [17], which tracks the gaze duration of a subject in meditation, and control-subjects on different emotional face stimuli and found that meditators spent less time on angry and fear faces than control subjects. TDR-CHI Gaze component has two functions: 1) State-Meditating: measuring state during meditating via face-tracking and eye-tracking technique, 2) Trait-Reading: evaluating trait during reading. Gaze component is different from previous works in three aspects: A. We creatively use face tracking and eye tracking technique to monitor meditation state (State-Meditating). To our knowledge, we are the first one that attempts to use face tracking and eye-tracking technique to track appearance changes in order to understand the internal changes in meditating. B. We track users reading patterns to determine users' binary meditation trait. We are changing the simple stimuli task to complicated reading task. C. The state and trait are monitored via smart phone, without dedicated wearable sensors and eye tracking sensors.

7. Discussion

We proposed in Section 7 to determine medication state by analyzing gaze obtained from the smart phone's camera. The initial experimental results indicate the approach might be viable. More experiments are to be performed.

If the brain wave headset is to be used, we would like to use the least amount of data to train a model, so that users do not need to get a device to monitor 16 channels. A smaller and cheaper device that only monitor a few channels may be good enough for meditation status prediction. To select few channels, we used information gain for feature selection. Since the records are mostly plain data from each channel, thus, by using feature selection technique, it can select channels that can differentiate data most efficiently.

Another solution is through Principal Component Analysis (PCA). With help of PCA, the system can find out which feature (channel) contributes most to the data. Then we may use one or more most contributes channels to be our final channels. This will lead to the most efficient (fewest channel) headset.

Our long-term goal is to expand the TDR system for the estimation of Chi. The Chi super-component can be regarded as the super-component at the highest level. It has attributes including both objective measurements and subjective evaluations. Some researchers propose to employ electrical measurements to estimate Chi [26]. Other researchers propose to combine objective measurements with subjective evaluation into an evaluation matrix to estimate Chi [27]. This makes the Chi super-component both pro-active and adaptive at multiple levels.

Finally we also want to add audio output so that a person's health exercise can be further enhanced. Our grand hypothesis is the mobile TDR system with multiple sensors will facilitate the estimation of Chi, so that a person equipped with the mobile TDR system can practice meditation and continue to enhance his/her health. Further experimental research will hopefully confirm at least a portion of this grand hypothesis.

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References

[1] Shi-Kuo Chang, JunHui Chen, Wei Guo and Qui Zhang, "TDR System - A Multi-Level Slow Intelligence System for Personal Health Care", Proceedings of 2016 International Conference on Software Engineering and Knowledge Engineering (SEKE2016), Hotel Sofitel, Redwood City, San Francisco Bay, California, USA, July 1-3, 2016, 183-190.

[2] Cahn, B. Rael, and John Polich. "Meditation states and traits: EEG, ERP, and neuroimaging studies." Psychological bulletin 132.2 (2006): 180.

[3] Peterson, Linda Gay, and Lori Pbert. "Effectiveness of a meditation-based stress reduction program in the reatment of anxiety disorders." Am J Psychiatry 149.7 (1992): 936-943.

[4] Kabat-Zinn, Jon, Leslie Lipworth, and Robert Burney. "The clinical use of mindfulness meditation for the self-regulation of chronic pain." Journal of behavioral medicine 8.2 (1985): 163-190.

[5] Spek, Annelies A., Nadia C. Van Ham, and Ivan Nyklíček. "Mindfulness-based therapy in adults with an autism spectrum disorder: a randomized controlled trial." Research in developmental disabilities 34.1 (2013): 246-253.

[6] Wallace, Robert Keith. "Physiological effects of transcendental meditation." Science 167.3926 (1970): 1751-1754.
[7] Reid, Denise T. "Teaching mindfulness to occupational therapy students: Pilot evaluation of an online curriculum." Canadian journal of occupational therapy 80.1 (2013): 42-48.
[8] Thompson, Barbara. "Mindfulness-based stress reduction for people with chronic conditions." The British Journal of Occupational Therapy 72.9 (2009): 405-410.
[9] Stroh-Gingrich, Bethany. "Occupational therapy and mindfulness meditation: An intervention for persistent pain." Occupational Therapy Now 14.5 (2012): 21-22.
[10] Ruff, Kelley McCabe, and Elizabeth R. Mackenzie. "The role of mindfulness in healthcare reform: a policy paper." Explore: The Journal of Science and Healing 5.6 (2009): 313-323.
[11] MFKF, Michel Bedard Dwight Mazmanian, Carrie Gibbons Gary Mack, and Rupert Klein. "A Mindfulness-Based Intervention to Improve Quality of Life Among Individuals Who Sustained Traumatic Brain Injuries: One-Year Follow-Up." The Journal of Cognitive Rehabilitation (2005).
[12] Kabat-Zinn, Jon, and Thich Nhat Hanh. Full catastrophe living: Using the wisdom of your body and mind to face stress, pain, and illness. Delta, 2009.
[13] Smalley, Susan L., and Diana Winston. Fully present: The science, art, and practice of mindfulness. Da Capo Press, 2010.
[14] Elliott, Nina. "Exploring mindfulness meditation in occupational therapy: An introduction to basic practice." Occupational Therapy Now 17.1 (2015): 6-8.
[15] Mahesh Yogi, Maharishi. Maharishi Mahesh Yogi on the Bhagavad-Gita: A new translation and commentary with Sanskrit text, Chapters 1 to 6. Harmondsworth: Penguin Books, 1969.
[16] Yogi, Mahesh. "The science of being and art of living." (1963).
[17] Pavlov, S. V., et al. "Effects of long-term meditation practice on attentional biases towards emotional faces: An eye-tracking study." Cognition and Emotion 29.5 (2015): 807-815.
[18] Jian-Zhou, Zhang, Li Jing-Zhen, and He Qing-Nian. "Statistical brain topographic mapping analysis for EEGs recorded during Qi Gong state." International Journal of Neuroscience 38.3-4 (1988): 415-425.
[19] Fernando Lopes da Silva. “EEG: Origin and Measurement. ” URL= http://webcache.googleusercontent.com/search?q=cache:Cx4xXMFDePsJ:www.springer.com/cda/content/document/cda_downloaddocument/9783540879183-c1.pdf%3FSGWID%3D0-0-45-883705-p173899505+&cd=3&hl=en&ct=clnk&gl=us
[20] Berger, Hans. "Über das elektrenkephalogramm des menschen." European Archives of Psychiatry and Clinical Neuroscience 87.1 (1929): 527-570.
[21] Aftanas, L. I., and S. A. Golocheikine. "Human anterior and frontal midline theta and lower alpha reflect emotionally positive state and internalized attention: high-resolution EEG investigation of meditation." Neuroscience letters 310.1 (2001): 57-60.
[22] Echenhofer, F. G., M. M. Coombs, and L. Samten. "EEG and P300 differences during meditation and rest in advanced Tibetan Buddhist and beginning meditators." meeting of the Society for Psychophysical Research, San Diego, CA. 1992.
[23] Wallace, Robert Keith. "Physiological effects of transcendental meditation." Science 167.3926 (1970): 1751-1754.
[24] Fenwick, P. B. C., et al. "Metabolic and EEG changes during transcendental meditation: an explanation." Biological Psychology 5.2 (1977): 101-118.
[25] Travis, Fred, et al. "Patterns of EEG coherence, power, and contingent negative variation characterize the integration of transcendental and waking states." Biological psychology 61.3 (2002): 293-319.

[26] Ming-Feng Chen, Hsi-Ming Yu, Shu-Fang Li and Ta-Jung You, “A Complementary Method for Detecting Qi Vacuity”, *BMC complementary and alternative medicine*, Vol. 9, No. 12, 2009.

[27] Ke-Feng Huang, *Effects of Energy Absorption on Meridian System* (能量攝取對經絡系統影響之效應), Doctoral Dissertation (in Chinese), Institute of Biomedical Engineering, National Yang-Ming University, Taiwan, June 2011.