Augmented Brain Computer Interaction based on Fog Computing and Linked Data

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***Abstract* — An augmented brain computer interface that can detect users' brain states in real-life situations has been developed using wireless EEG headsets, smart phones and ubiquitous computing services. This kind of wearable natural user interfaces will have a wide-range of potential applications in future smart environments. This paper describes its ubiquitous system architecture and introduces its enabling technologies, which include machine-to-machine publish/subscribe protocols, multi-tier fog/cloud computing infrastructure and a linked data web. Its real-time responsiveness and easiness-of-use will be demonstrated by playing a multi-player on-line BCI game *EEG Tractor Beam* at the Intelligent Environment Conference.**

***Keywords* –Brain Computer Interface; Fog Computing; Linked Data; Machine-to-Machine Communication**

I. INTRODUCTION

AUGMENTED brain-computer interfaces (A-BCI) are electroencephalogram (EEG) monitoring systems that can be used in the real world to determine users' brain states in real time. These wearable systems provide a direct communication path between human brains and electronic devices and show a wide-range of promising applications. However, two basic questions remain to be answered before A-BCI can be accepted as a reliable appliance:

1. Can A-BCI identify EEG correlations among similar mental tasks and classify their patterns by analyzing vast amount of data gathered from large user population? If so, how can we implement this big data approach?
2. Can A-BCI ensure its robustness and accuracy by adapting its classification models to the ever-changing brain states of its users through continuous analysis of their EEG data? If so, how can we implement this adaptive system approach?

To tackle these questions, we developed a ubiquitous brain state monitoring and data sharing system using wireless EEG headsets, smart phones and ubiquitous lightweight servers. With the aid of MQTT publish/subscribe protocol [1] and fog computing paradigm [2], we succeeded to conduct real-time synchronous data streaming and launch a multi-player on-line BCI game *EEG Tractor Beam* among multiple sites in the United States and Taiwan. With the aid of Linked Data Web [3], we enabled users to search for on-line data streams and their archives using semantic queries. Brain state classification is among the most computationally intensive signal processing tasks. The cooperation between fog and cloud servers enables the system to perform continuous real-time brain state classification at the fog servers while calibrating the classification models regularly in the cloud servers based on the EEG data and features extracted by the fog servers.

We are not the only team trying to apply cloud computing in physiological signal processing and data management; several on-line data repository including BrainMap, PhysioNet and HeadIT have been established over the years. Among them, PhysioNet received the highest acclaim by offering a wide-range of data banking and analysis services. However, none of these on-line services can accept streaming data or interact in real time with their client applications.

The rest of this paper is divided into four sections. An overview of our system is given in Section II. It is followed by a highlight of the key technologies in Section III. The live demonstration is briefly described in Section IV and the plan for on-going and future work is mentioned in the conclusion.

II. SYSTEM

Figure 1 illustrates the architecture of our pervasive A-BCI system. The central piece is an on-line data broker/server known as the *fog server*. This ubiquitous computing node can be installed on users' personal computers, television set-top boxes or gaming consoles. Each fog server works as both a data hub and a signal processor. It collects the multi-modal multi-channel data streams captured by the EEG sensors and publishes them on the Linked Data Web. Authorized user can receive live data streams and process them on their own machines. In addition, the fog server also performs signal pre-processing, source identification and autoregressive model fitting [4]. Hence, it can extract time-frequency characteristics and correlations from the signals and send them to the brain state classifiers. It can also upload these features to the cloud servers for further processing and archiving.

The presence of a fog server in the vicinity of the wireless sensors and the user's personal device, such as a smart phone, creates a *triangular interconnection* among these nodes. This three-way interconnection can be exploited to enhance the performance and flexibility of our system. More than often, the wireless sensors will connect directly to the fog server, which likely has more computing power and communication bandwidth than the mobile phone. In this case, the mobile phone will serve merely as a graphic interface to the user. This mode of operation will offer both a boost in system performance and a save in the smart phone's battery power. In the unlikely case that the user and the sensors wonder beyond the network coverage of the fog server, the mobile phone will then serve as the

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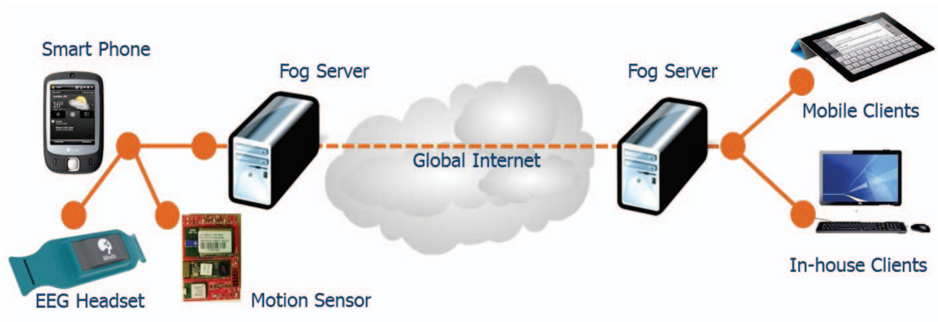

Figure 1: Architecture and functional components of Pervasive Neuroimaging System

ad-hoc bridge to the fog server. The data transfer speed and the system performance will be slightly hampered in that situation.

Security is a paramount concern of this pervasive system. Hence, secure communication, multi-domain user authentication and authorization have been put in place since the initial design of the system. Transport layer security (TLS) protocol is always used to protect both the machine-to-machine publish/subscribe exchanges and the server-to-server HTTP transactions. In our pilot system, users were authenticated by logging into their Facebook® accounts.

III. Technology

The ubiquitous A-BCI system is powered by state-of-art distributed computing and internetworking technologies. This section describes only our use of these technologies. Readers are referred to on-line resources for further information.

A. *Fog Computing*

Fog computing [2] was coined by Flavio Bonomi of Cisco to refer to an emerging ad-hoc distributed computing paradigm that employs computers near the end nodes to off-load their computing burden and speed up their responses [Figure 2]. In our system, we install fog servers close to the sensors and the mobile phones also to share their workload. However, the fog servers are designated for specific data aggregation and processing tasks so that the performance gains are more predictable.

B. *Machine-to-Machine Publish/Subscribe Protocols*

In order to support real-time interactions between the wireless EEG headsets and the ubiquitous fog servers, the system must provide reliable event-based communication. Publish/subscribe protocols have become the favorite data transport mechanism for machine-to-machine (M2M) communication and the Internet of Things (IoT). Data publishers and subscribers use meta-data strings, known as *topics*, to identify the exchanged data. A broker or rendezvous point is employed to mediate these exchanges. We used the de-facto standard protocol MQTT [1] to carry data streams between fog and cloud servers, and its lightweight version MQTT-S [5] to transport data from the wireless EEG headsets to the fog server. The fog servers always function as both a MQTT broker and a MQTT-S message translator for data exchange between the headsets and the mobile phones.

C. *Interoperable Data Formats*

How to manage data in different formats produced by various EEG headsets is another major issue. We proposed a two-level *data representation* and *encoding scheme* to provide interoperability among heterogeneous data formats used by various vendors. At the upper data representation level, we employed *Piqi*, a unified specification language, to incorporate data/meta-data fields of popular data formats in a generic data schema. At the lower data serialization level, we adopted Google *protocol buffers* as the compact binary data encoding for both streaming and archiving data. Figure 3 shows an example of the Protobuf data format and the Piqi data conversion tools.

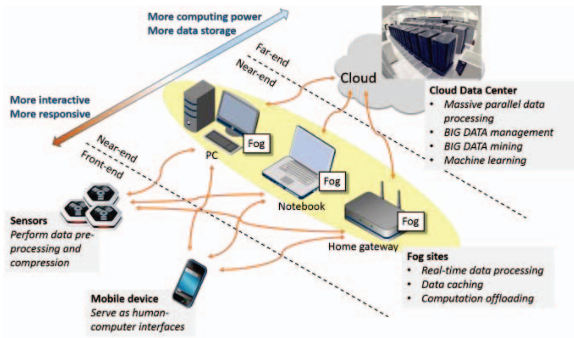

Figure 2: Concept of multi-tier fog/cloud computing

```
message EEG {
  required sfixed32 id = 1;
  required uint64 timestamp = 2;
  required double channel_1 = 3;
  required double channel_2 = 4;
  required double channel_3 = 5;
  required double channel_4 = 6;
}
```

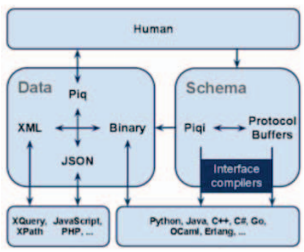

Figure 3: (a) Protobuf data format and (b) Piqi data conversion

D. Semantic Linked Data Structure

An important feature of this A-BCI system is its ability to manage a distributed on-line repository of raw EEG data and extracted features and to search for these data and feature sets using semantic queries. We used Linked Data [6] and Semantic Web [7] technologies to annotate, publish and interconnect these data with semantic meta-data.

The semantic data structure of this repository is specified by a BCI Ontology we are developing relentlessly as an extension of the Semantic Sensor Network (SSN) Ontology [8] proposed by the World Wide Web Consortium (W3C) Semantic Sensor Network Incubator Group. The basic concepts and attributes of the BCI data were imported from the vocabulary containing in the Extensible Data Format (XDF) [9], the EEG Study Schema (ESS) and the Hierarchical Event Descriptor (HED) tags all developed by our collaborators at the Swartz Center for Computational Neuroscience (SCCN) in the University of California, San Diego (UCSD). The semantic data model we developed aligned closely with the Stimulus-Sensor-Observation ontology design patterns underlying the SSN Ontology [10]. As an example, Figure 4 depicts the semantic data model of a BCI Device. The model is represented as a graph connecting *concepts* (in rounded rectangles) such as Sensor, Record, AccessMethod with *properties* (in sharp rectangles) such as hasDeviceType and hasOrganizationName of a Device through *relations* (edges), each of which is specified as a RDF predicate [11]. A semantic data model can include concepts from different *domains* or *namespaces* abbreviated as *prefixes*. The specification of the ontology was expressed in the Web Ontology Language (OWL) [12].

We use Protégé v.3.4.8 [13] modeling tool to design the BCI Ontology and use OpenLink Virtuoso Universal Server v.6.01 (VUS) [14] to host the RDF repository. The semantics searches are conducted using the W3C SPARQL Protocol and the RDF Query Language (SPARQL) [15], which can retrieve and manipulate data stored in heterogeneous RDF repositories. Each Virtuoso Server implements a SPARQL endpoint. It can connect with any SPARQL endpoint on the Web it is authorized to access.

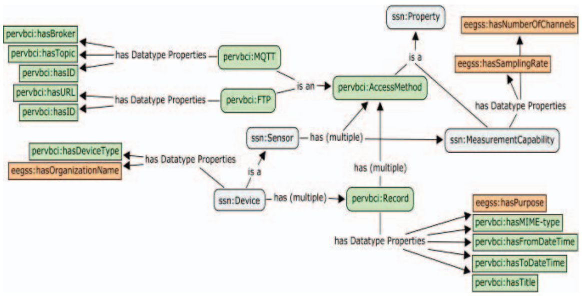

Figure 4: Proposed Semantic Sensor Model

IV. Demonstration

The engineering teams has successfully performed real-time synchronous EEG and motion data streaming between NCTU and UCSD in March, 2013 and then running a multi-player on-line BCI game *EEG Tractor Beam* among NCTU, and NCHC (Taiwan) and SCCN (USA) in September, 2013. Since then, the game has been played in several public occasions with players joining from both US and Taiwan.

In order to play the *EEG Tractor Beam* game, each player needs to wear a MINDO®-4S wireless EEG headset and has her smartphone connected to a local fog server. The fog servers associated with different users may exchange information with one another. The game was running as a mobile app on each user's smartphone serving. Raw EEG data streams were sent to the fog server through the smartphones. Real-time signal processing and prediction were performed on the fog servers. The brain states of individual users were published by the fog servers via MQTT and sent to the mobile apps. On the display, the multiplayer game shows all the players on a ring surrounding a target object. Each player can exert an attractive force onto the target in proportion to her level of concentration (estimated using a ratio of the *average power spectral density* in the *EEG* α, β and θ bands of the player). In order to win the game, a player should try to pull the target toward her by exercising concentration while depriving other players of their chances to grab the target. The game implements a "winner-take-all" strategy: a player is awarded points at a rate proportional to the percentage of total attractive force she exerts on the target, which is calculated by dividing that player's concentration level by the sum of the levels among all the players. However, a player can only start to accumulate points if she contributes at least her fair share to the total sum. A *tractor beam* will appear between that player and the target when her concentration level surpasses that threshold. That was when she starts to cumulate her points. Figure 5 shows a picture of four players engaging in the game across the Pacific Ocean.

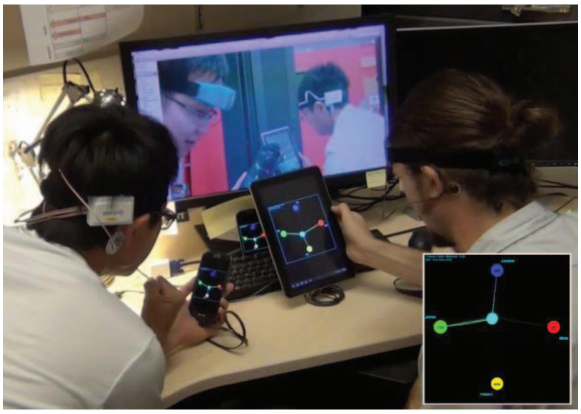

Figure 5: An EEG Tractor Beam session with four people playing over the Internet: two players in San Diego (USA) were shown in the foreground while two players in Hsinchu (Taiwan) appeared in the monitor. The inset at the lower right corner shows a captured view of the game display.

In all the gaming sessions, the data rates and transport latencies over the Internet have been low since the fog servers published short messages merely containing players' identifiers and concentration levels. While *EEG Tractor Beam* is a somewhat frivolous demonstration of the capability of the A-BCI system, it does demonstrate some powerful concepts that may have applications far beyond on-line gaming. Foremost, the system has the ability to acquire and process EEG data in real time from large number of users all over the world and feed their brain states back to these individuals as well as any professionals authorized to monitor their cognitive conditions. With a distributed infrastructure made up of fog and cloud servers, our on-line BCI infrastructure can be scaled indefinitely without adding unsustainable traffic load onto the Internet. As such, it presents a viable way to realize *interactive* BCI. Furthermore, the system has the ability to process, annotate and archive vast amount of real-world BCI data collected during the BCI sessions. Unlike the existing EEG databases, which depend on researchers to donate their data sets, this pervasive BCI infrastructure collects data sets—with users' approval—as an essential part of its normal operation. This intrinsic data collection provides a natural way to implement the *big data BCI* as well as *adaptive BCI* in the near future.

V. CONCLUSION

The pervasive neuroimaging system presented in this paper is merely a pilot prototype. We will enhance and expand it into a production system in the coming year. Specifically, we will further develop its semantic data model and offer various means to access both the real-time data streams and the archived data. We are also working with two clinical teams to conduct validation experiments on our system: (1) Dr. Irene Litvan's team at the UCSD Department of Neurosciences to monitor EEG, ECG and gait patterns of Parkinson patient, and (2) Dr. Shuu-Jiun Wang's team at the Taipei Veteran General Hospital to monitor migraineurs' brain states.

The *EEG Tractor Beam* game will be demonstrated on site during the Intelligent Environment Conference in Shanghai, July 2–4 2014.

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