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UbiEi-Edge: Human Big Data Decoding Using Deep Learning on Mobile Edge

Jiadao Zou, Qingxue Zhang, *IEEE Senior Member*

Purdue School of Engineering and Technology
Indiana University-Purdue University at Indianapolis

***Abstract*—Human big data decoding is of great potential to reveal the complex patterns of human dynamics like physiological and biomechanical signals. In this study, we take special interest in brain visual dynamics, e.g., eye movement signals, and investigate how to leverage eye signal decoding to provide a voice-free communication possibility for ALS patients who lose ability to control their muscles. Due to substantial complexity of visual dynamics, we propose a deep learning framework to decode the visual dynamics when the user performs eye-writing tasks. Further, to enable real-time inference of the eye signals, we design and develop a mobile edge computing platform, called UbiEi-Edge, which can wirelessly receive the eye signals via low-energy Bluetooth, execute the deep learning algorithm, and visualize decoding results. This real word implementation, developed on an Android Phone, aims to provide real-time data streaming and automatic, real-time decoding of brain visual dynamics, thereby enabling a new paradigm for ALS patients to communicate with the external world. Our experiment has demonstrated the feasibility and effectiveness of the proposed novel mobile edge computing prototype. The study, by innovatively bridging AI, edge computing, and mobile health, will greatly advance the brain dynamics decoding-empowered human-centered computing and smart health big data applications.**

***Index Terms*—Health Informatics, Edge Computing, Mobile Health, Electrooculography, Big Data.**

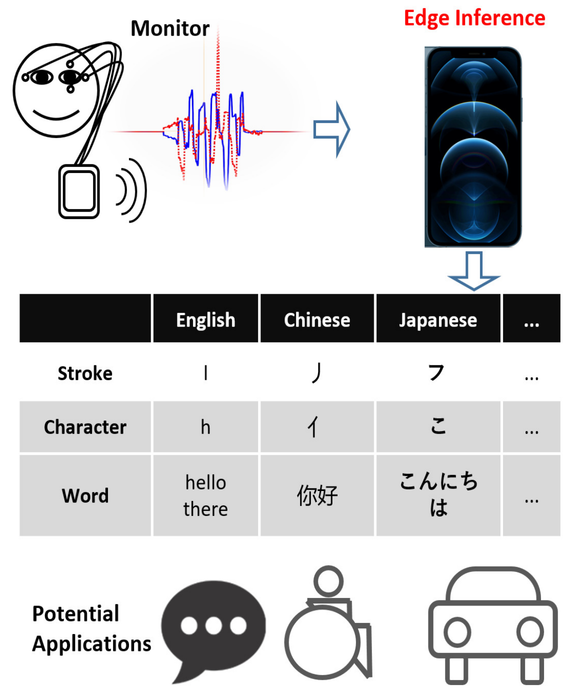

Fig. 1 A systematic concept of how human big data decoding on the edge can enable promising applications. Here we take special interested in decoding the brain visual dynamics, i.e., the Electrooculogram (EOG) signal, for the voice-free communication application for ALS patient.

I. Introduction

The complex patterns of human physiological and biomechanical systems, if decoded, are expected to advance many promising practices [1, 2]. Brain visual dynamics, directly reflected by eye movement dynamics, are encoding cognitive activities like thinking 'where', 'how' and 'what', as well as attention levels. Potential applications include voice-free communication, cognitive load monitoring, driver state monitoring, human-computer interaction, and many others. In this study, we take special interest in voice-free communication for Amyotrophic Lateral sclerosis (ALS) patients [3, 4]. ALS is a kind of neural degeneration disease and the patients gradually lose their control of muscles – even the breath muscles (so they usually need a breath supporter finally). Worldwide, about half a million people suffer from ALS diseases, and there is a new patient every 90 minutes [5]. The worst thing is that there is no cure for this disease. The patients are like 'locked-in'! But a good thing is that, the patients can usually still move their eyes, which provides the possibility to capture and decode eye movements, to allow them to communicate with the external world.

Empowered by technological advancements, mobile devices become lightweight, wireless, user-friendly and intelligent, thereby enabling many exciting smart health and human-centered computing applications. We propose to design and develop a smart computing platform that can run deep learning decoding algorithms, as well as visualize the brain dynamics/decoding results, called UbiEi-Edge (Ubiquitous Embedded Intelligence on the Edge). In this study, we design, develop, and validate UbiEi-Edge based on the voice-free communication application for ALS patients (Fig. 1). It can also be further generalized to other brain dynamics decoding practices.

Jiadao Zou (Ph.D. Student) and Qingxue Zhang (Assistant Professor, qxzhang@purdue.edu) are with Department of Electrical and Computer Engineering, Purdue School of Engineering and Technology, on the joint Campus of Purdue University and Indiana University, Indianapolis, Indiana, USA. This study is supported by USA National Science Foundation Career Award Grant.

We focus on decoding visual dynamics with the eye Electrooculogram (EOG) signal, which is measured as the bio-potential difference between cornea and ocular fundus, and can express complex patterns of brain and eyes. Compared with Electroencephalogram (EEG) [6, 7], EOG offers high-fidelity representation of visual dynamics. Compared with camera-based methods [8, 9], EOG-based methods also have several favorable properties: 1) insensitive to environmental light changes, 2) no privacy concerns, and 3) less need of computing resources. Our major contributions include:

a) Develop UbiEi-Edge, a generalizable wireless, mobile edge computing platform for real-time human big data dynamics decoding and visualization.

b) Implement a lightweight deep learning model on UbiEi-Edge for decoding the eye EOG signal in real-time, thereby avoiding large latency due to cloud server-based signal analysis.

c) Validate the whole system based on the voice-free communication application for ALS patients.

d) Minimize the risk of data disclosure and security/privacy concerns since there is no intensive data transmission to cloud.

II. Approaches

A. Architecture of UbiEi-Edge

The proposed UbiEi-Edge mobile platform, as shown in Fig. 2, includes: a Wireless Communication Module, a Deep Learning Module, a Visualization Module and a Data Storage Module. We will then detail how the new system is designed and implemented on the mobile edge.

B. Wireless Communication Module

To enable human big data streaming, we have developed the wireless communication module, based on the Bluetooth-Low-Energy (BLE) protocol on the Android smart phone. This protocol greatly saves the battery consumption through automatic power-saving communication mechanisms. This is essential for continuous data transmission of human big data. Further, to enable real-time data streaming, we have applied the data segmentation method to transfer small-size data packets. More specifically, to transmit an eye word, it is split into several pieces and the BLE transmits the word piece by piece.

C. Intelligent Inference Module

We have designed a deep convolutional network (CNN) framework for eye EOG signal decoding [10], and we further propose to implement it efficiently on the mobile platform for real-time inference. The CNN architecture is shown in Fig. 2, which includes a spatial feature extraction stage and a fully connected neural network stage. The former one has four convolutional layers (and also corresponding max pooling layers), to gradually abstract the patterns in the EOG signal. The latter one forms a conversion function to derive the eye-written word ID from the extracted features. EOG is a 2-D vector consisting of horizontal and vertical eye focusing information, where could be treated as many 2-D images along the time axis. CNN has proved its amazing capability in solving computer vision tasks. Therefore, we expect a good performance of CNN on EOG. The model is a 12-layer model initialized with Glorot uniform distribution using the Adam optimizer to learn in 0.0005 each step to minimize the categorical loss of each 60-sample batch till reaching 120 epochs.

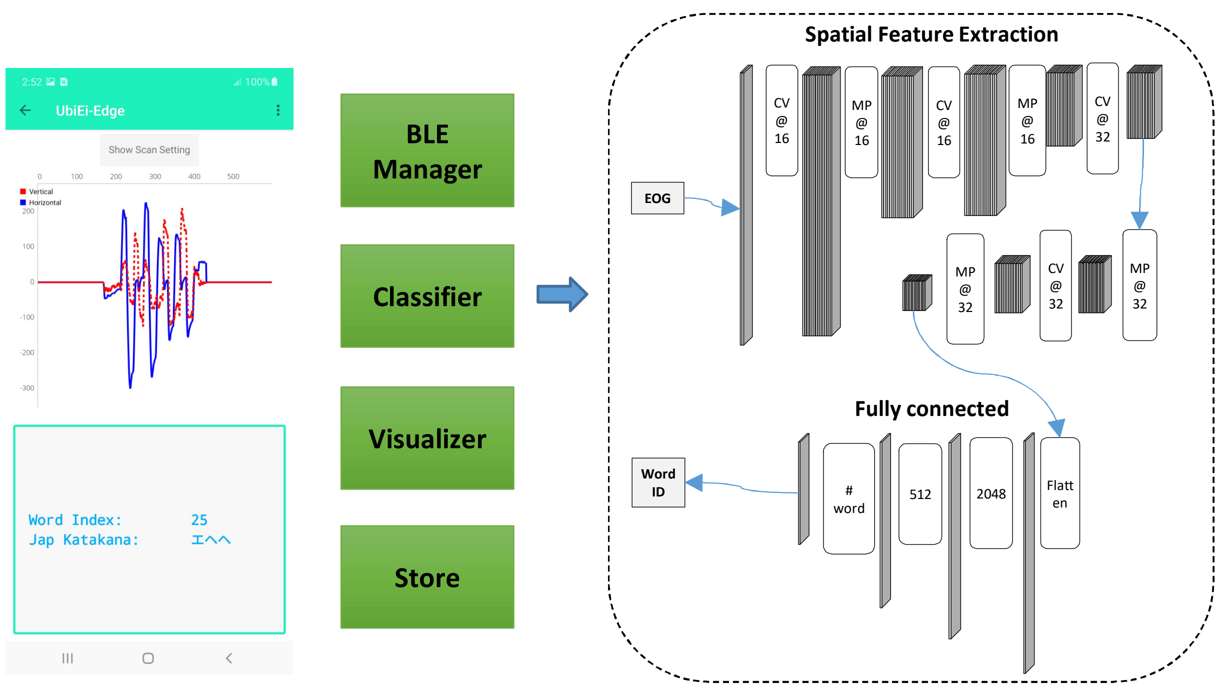

Fig. 2 A system diagram of the proposed UbiEi-Edge mobile platform, which receives the wireless signal via Bluetooth-Low-Energy (BLE), executes the deep learning model, visualizes both the signal and deep learning detection results, and stores the results on the phone. In this study, we will further demonstrate that UbiEi-Edge can enable voice-free communication for ALS patients by decoding eye-written words.

In the past, mobile phone hardware greatly limited the implementation of neural network models due to constraints of both computing and storage resources. Here we choose a powerful smart phone: Samsung Galaxy Note 10+, which has a 2.8 GHz application processor and 512 GB storage.

Once the wireless connection is established, the data transfer starts automatically. At the same time, the deep learning model takes in and analyzes the EOG signal. More specifically, the CNN model intelligently performs spatial motif learning and pattern abstraction. The fully connected network summarizes the extracted partial features and yields the final detection result. In short, the 2D-image (both horizontal and vertical EOG channels) is fed into the CNN model, which generates the probability map for the word dictionary and reports the word ID that is of the highest probability.

CNN is very efficient for edge implementation, because of its parameter sharing strategy used by the convolutional filters. This feature extraction strategy usually requires significantly less parameters than the traditional fully connected feature extractor. Besides, the max pooling operation further helps reduce the dimension for computation load minimization.

Furthermore, we have applied the Tensorflow-Lite tool [11], provided by Google LLC, to convert the on-PC deep learning model to mobile-specific lightweight deep learning model. The converted model is optimized for mobile phones and can perform data inference more efficiently. With all above consideration, design, and optimization, our deep learning module can provide real-time EOG decoding, showing the feasibility of real-world voice-free communication for ALS patient.

D. Visualization Module

The visualizer module has an animation function to smoothly contemporize the display chart. It also supports zooming, highlighting, touch screen guesting, animating and other visualization enhancement.

Meanwhile, the deep learning detection results are in real-time given on the screen, which, as shown in Fig. 2, givens the Word ID, and the Japanese Word (the Japanese dataset will be detailed in next section). In future, we will also add the speaker function to the APP to enhance the interaction capability.

III. Results

A. Experimental Setup

UbiEi-Edge is designed for Android systems now, but can be easily extended to iOS mobile systems. A GPU is not necessary because of the design considerations and optimizations introduced previously. We have validated UbiEi-Edge on two phones: Samsung Galaxy Note 10+ (SM-975U) and Samsung S8+ (SM-G955F). For now, we have used a public EOG dataset [12] to demonstrate the feasibility of UbiEi-Edge. The dataset has eye-written words collected from six subjects, and each subject eye-wrote 150 Japanese words for five trials. The leave-one-trial-out cross validation strategy is used to evaluate the performance. More specifically, one phone is mimicking the eye-worn monitor to send EOG signal to the UbiEi-Edge phone, which receives the signal, executes the deep learning model, and visualizes both the EOG signal and deep learning detection results. In future, we will further use our eye-worn monitor to evaluate UbiEi-Edge. But UbiEi-Edge has already successfully demonstrated the effectiveness of data streaming and inference functions.

B. Real-time Data Visualization

The visualizing chart contains time axis and magnitude axis and illustrate two-channel EOG data into different colored curves. With the new data keeps coming in, the data visualization block centers the latest data point and zooms the axis for better view (Fig. 3). The real-time visualization provides an informative way to reflect the eye-written words and underlying dynamics, which is not only important to indicate the intension and action of the user to the doctors and/or family, but also beneficial to give the feedback to the user on how the eye movements generate the interactive message. As shown in Fig. 3, different eye-written words have different dynamics and waveform morphologies, which will then be learned by the deep learning algorithm on the phone in real-time too.

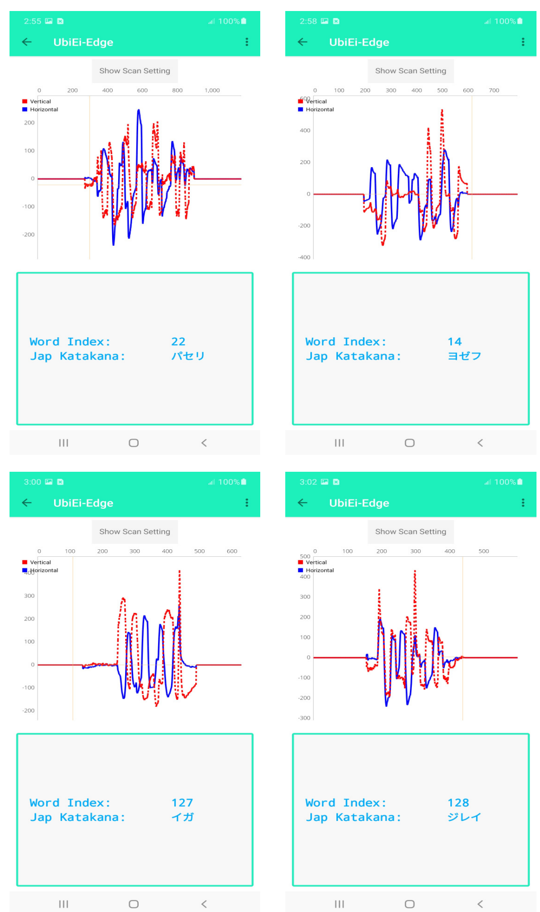

Fig. 3 The screenshots of UbiEi-Edge about visualization and decoding of the visual dynamics of different users, which demonstrates the effective illustration of the real-time visual dynamics and the deep learning-based inference results.

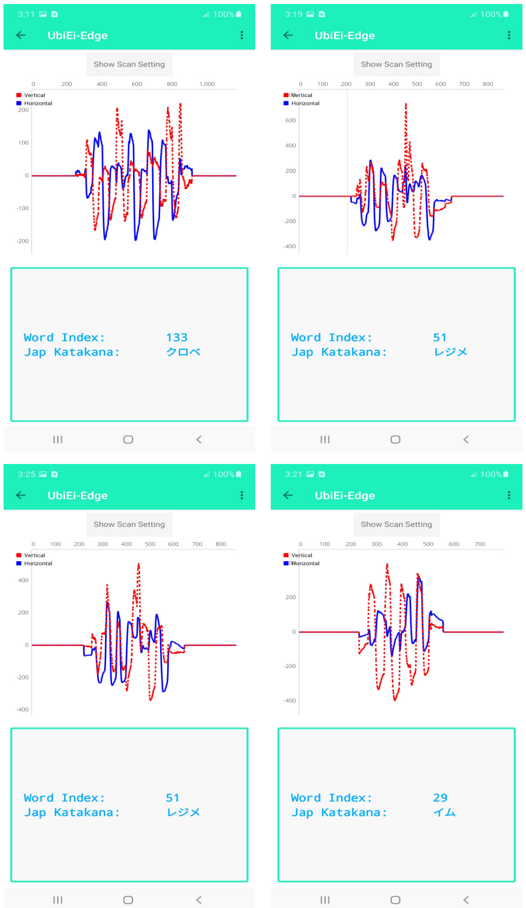

Fig. 4 Further screenshots of UbiEi-Edge about visualization and decoding of the visual dynamics, which demonstrates the effective illustration of the real-time visual dynamics and the deep learning-based inference results.

C. Real-time Visual Dynamics Inference

Targeting the diverse visual dynamics, we have implemented our deep learning model (Fig. 2) on the smart phone, as shown in Fig. 3 and 4. On the APP, the bottom part shows the real-time inference results. The deep learning classifier keeps updating the results based on the incoming eye-written signals. In the illustrated examples, we have shown that UbiEi-Edge can successfully decode the eye dynamics to Japanese words for different eye movements from different users. The accuracy is as high as 90.58%. Other language like English can be easily generated too based on a lookup table to match Japanese to English. Currently, we have evaluated the system on the eye-written Japanese words, but we are also interested in evaluating the system on other languages, thereby broadening the usage and benefit to potential users worldwide.

D. Future Work

We will further enhance our algorithms and the edge computing implementations to improve eye decoding accuracy and computing efficiency. Last but not least, user's experience is vital to us, so we would also have it tested on target users and keep enhancing the system according to the feedbacks.

IV. Conclusion

We have designed and developed a mobile and intelligent mobile edge system: UbiEi-Edge. We also further validated the platform on the voice-free communication application for ALS patients, for which, UbiEi-Edge automatically receives via Bluetooth, demonstrate the eye dynamics with real-time visualization, and decodes the streamed eye EOG dynamics leveraging our deep learning algorithm. Tensorflow-Lite has been applied to convert our deep learning model to a lightweight implementation for the smart phone. And our APP, with sophisticated design, manages the whole software flow to handle data parsing, data visualization, deep learning, and detection result visualization. In addition to help ALS patients, the validated system also has great potential for emerging applications like wheelchair control, cognitive-loading measurement, human-computer interaction, driver state monitoring, and others. The study, by innovatively bridging AI, edge computing, and mobile health, will greatly advance the brain dynamics decoding-empowered human-centered computing and smart health big data applications

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