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Remote Multimodal Study - Case: OM Chant

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Abstract. This paper delves into the remote multimodal data collection from sensors attached to smart mobile devices (SMD). Mobilemicroservices Architecture (MMAs) facilitates this data collection through Mobilemicroservices (MM). This paper presents a practical framework for collecting data from SMD sensors in a time-series database. External sensors are often connected to SMDs using the Bluetooth Low Energy (BLE) protocol. This paper introduces a tool that supports the multimodal use of various SMDs' BLE sensors by translating the HEX data into JSON format with the variables' names and values. Movensense (ECG, IMU) and Shirary (EEG) BLE sensors were used to monitor breathing, HR, and EEG during the changing OM mantra. The mantra chanting is reported to lower blood pressure.

Keywords. Telemedicine, Wearable devices

1. Introduction

Many diseases and physical exercises uniquely affect human physiology [1]. To capture these effects comprehensively, we employ a set of sensors, a strategy known as multimodal data collection. This approach has shown promise in studying various diseases, including Parkinson's [2]. However, its application in everyday living environments is still relatively uncommon. Our research demonstrates how SMDs can be harnessed to collect data remotely from various sensors using Bluetooth Low Energy (BLE) protocol. The selection of sensors and data collection methods should be tailored to the specific physiological features affected by the phenomena under study [1].

OM chant breathing exercises' medical effects on nervous systems and blood pressure have been studied [3,4]. MMA supports multimodal data collection, enabling simultaneous data collection from multiple sensors using MMs [2]. A study explains how data security can be handled using Virtual Private Mobile Networks (VPMNs) with MMA [2]. Several studies have addressed the accuracy, security, and validity of the devices used in a chronic disease (see [2]).

2. Literature discussion on the case setup

Multimodal refers to integrating and utilizing multiple modes of communication or sensory channels simultaneously [1]. Combining numerous modalities in multimodal

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systems allows for more affluent and more versatile interaction, enabling machines to understand better and respond to human input. By leveraging multiple channels of communication and perception, these systems enhance the overall user experience and expand the possibilities of human-machine interaction.

Breathing exercises such as an OM chant are utilized in meditation, yoga, and mindfulness to induce relaxation, reduce stress, and promote overall well-being. Some potential features that could be measured and analyzed include:

1. Heart Rate Variability (HRV): HRV refers to the variation in the time interval between heartbeats. It is considered an indicator of the autonomic nervous system's activity and overall physiological resilience. Multimodal analysis can examine changes in HRV patterns during breathing exercises and relaxation, providing insights into the body's stress response and relaxation states. [5]
2. Brain Activity: Techniques such as EEG can examine changes in brainwave patterns during breathing exercises and relaxation. Multimodal EEG data analysis may reveal alterations in brain activity, such as increased alpha or theta waves, which are associated with relaxation and meditative states. [5]
3. Respiratory Parameters: Monitoring respiratory markers like respiratory rate, tidal volume, and breath pattern can provide information about the efficiency and depth of breathing during relaxation practices. Multimodal analysis can assess how these parameters change during different breathing techniques. [6]

By integrating these biological markers and analyzing them multimodally, researchers can understand the physiological effects of breathing exercises when practicing the OM mantra chanting. This analysis may provide insights into how these practices induce relaxation, stress reduction, and well-being, thus making this study medically relevant [4,5].

3. Technical case setup to collect multimodal data

Figure 1 describes the extended MMA stack with related example devices. A client can request data using the HTTP interface. Sensor data is stored in Mobilemicroservice (MM), an HTTP server, in an SMD. MM provides a unified interface to access SMD resources remotely, for example, through Telegraf [7]. It can store sensors' data in various time series databases, such as Influx [7]. SMDs' internal accelerator and gyroscope sensors provide the data in a readable format that can be accessed by a tool such as Telegraf. Grafana [7] is employed for online or offline visualization.

The data from external BLE-based external sensors are usually in HEX format and must be translated into a readable format. Each BLE device has its unique data format. We need to set up a system that easily describes the content of HEX data from various BLE sensors to support its use in various multimodal applications.

The solution consists of (1) a JSON file for each sensor's BLE HEX data format, (2) a Python subroutine for conversion of this HEX data to readable data, (4) a subroutine to convert readable data to an outcome JSON file, and (5) an overall program to that employs this outcome JSON file. (6) For example, this data can be stored with the help of the Python Influx library in the Influx time series database.

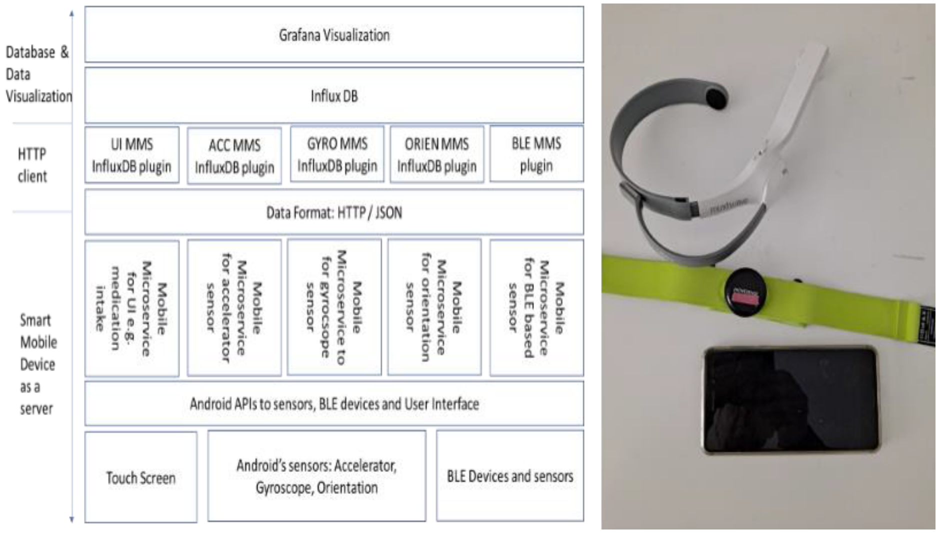

Figure 1. Extended MMA's stack with example devices

We collect BLE hex data from Movesense, including several sensors (ECG, HR/RR, IMU6, and IMU9) [2]. Data was also collected from Sichray EEG. Several external sensors can be connected to SMDs, and BLE provides the data in a HEX format. The example JSON format file (see Table 1) describes the Movesens sensor's BLE data format to report HR / RR. Sensor devices employ various HEX lengths, including byte, int16, int24, int32, singed int 32, and float32.

Table 1. JSON description for Movesense HR/RR sensor's BLE data

```
"HR":{
"out":["cmd","ref","hr","RR"],
"typ":["byte","byte","float32","int16"],
"version":"HexToNum001HRandRR"
}
```

4. Method

The multimodal data collection occurred with the Movesense sensor and Movesense HR belt (see Figure 1). One can collect data from 4 sensor sources, from which I employed two sensors: HR/RR and accelerator. The HR belt is flexible and extends and shrinks while inhaling and exhaling. Thus, we can measure the breath accelerator in three directions. A sampling rate of 52 Hz was used to follow the breathing. We also employ Sichiray's portable Mindway EEG (Neurosky) devices to measure various brain wave signals with 512 Hz (see Figure 1). This EEG device measures attention and meditation signals on top of the traditional brain waves. These BLE devices are on the right low corner of the stack (see Figure 1: BLE devices and sensors).

We employ an SMD with the related MMs concerning the Movesense and Sichiray devices. The data collection occurred with the help of a Python script that collects the data after two minutes from Movesense MM. The data was collected from Sichiray's MM after three minutes. Each recorded data was time-stamped by the MM using the same epoch "wall" clock or system clock expressed in milliseconds for each MM.

Employing the same wall clock significantly helps deal with the time synchronization of the various measurements. MMs run in Nokia 6 (see Figure 1). We use Network Time Protocol to keep devices in synchronization with "wall" clocks

From the research methodology's perspective, we apply a Constructive research approach to create a practical solution and scientific contribution (e.g., see [2]). In the constructive research approach, one can apply a single case study that follows a qualitative single case study strategy (e.g., see [2]). A single case study strategy can be used to test new concepts.

5. Results

Figure 2 describes breathing acceleration (m/s^2) in the z-direction (orthogonal to the chest) while practicing the OM mantra. RR in Figure 2 represents the heart rate variability in milliseconds (ms). Visually, it seems to follow the breathing cycle, as Brown et al. reported [8].

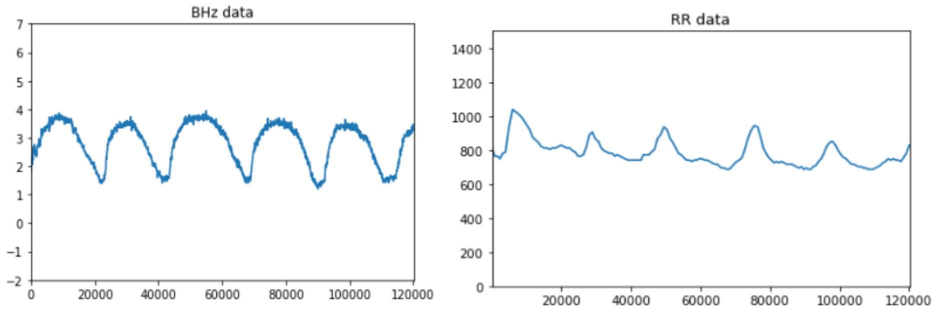

Figure 2: Breathing acceleration data (m/s^2) and RR data (ms)

Brain wave data, Theta (see Figure 3), is measured by EegPower (µV2). According to Klimesch [9], the Theta EegPower varies from 2.5 to 3.4 depending on the age of the children. According to Takahashi [10], Theta2's EegPower varies between 2.75 – 3.25 in a meditation practice for undergraduate adults. This article's measurements were done for a healthy elderly male adult with no medication. This person has a long history in Yoga, Tai Chi, and other martial arts. In this OM meditation, the Theta brainwave indicates much lower EegPower (see Figure 3).

In Klimesch's study for children [9], the Low-Alpha brainwave's EegPower varies from 2.3 to 2.8. Takahashi [10] states that the Alpha brain wave, EegPower, varies between 1.5 and 4. The low-alpha brainwave varies between 0 and 4 in this study's measurements (see Figure 3). Interestingly, the meditation signal varies between 0 and 200 or more. Sichiray EEG does not use EegPower to measure meditation. Instead, Sichiray indicates the level of meditation (see Figure 3). The attention signal seems very low (see Figure 9). Venkateam [11] states that the Neurosky EEG's meditation and attention signal averages between 48 and 53. The contrast to this study is clear. Thus, this result suggests a significant difference from previous studies.

The caption texts mention the y-axis scale of Figures 2 and 3. The X-axis scale is in milliseconds (ms) in these exact figures.

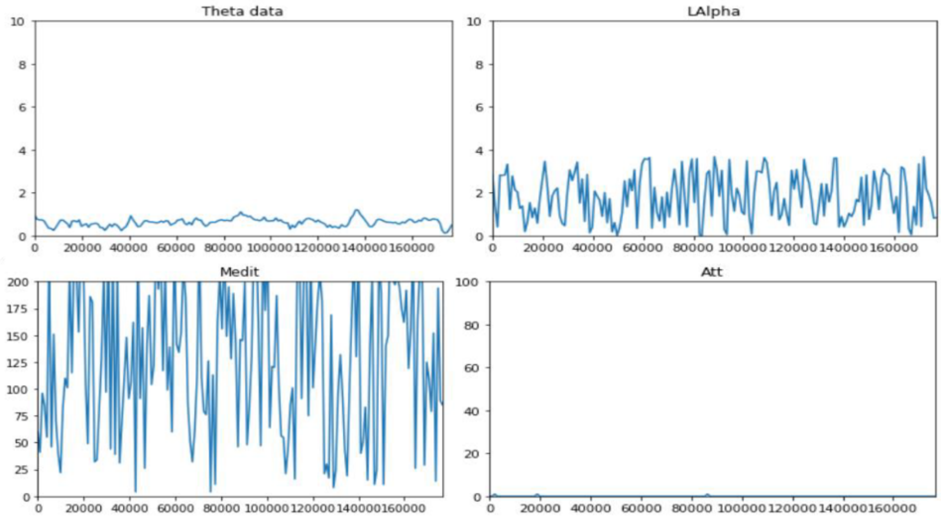

Figure 3: Theta (μV^2), Low Alpha (μV^2), Meditation level, Attention level

6. Discussion and conclusion

This case study proposes that OM chant meditation's multimodal data outputs depend on an individual's meditation skills, history, used practices, and practice environment. This type of multimodal remote data collection seems to be worth further studies.

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