Error Correction of Wearable Sensors using Sliding Window in Optical Camera Communication

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***Abstract*— In this article, we have implemented an optical camera communication-based system to collect data from the human body using a pulse oximeter sensor. The system is mainly designed for convenient operation, long-term use, warning status, etc. So, the data collection and process in the output can show some unusual data in the receiver, this unusual data is eliminated by using a sliding window technique. After the inclusion of the sliding window, we can eliminate the noisy data as a result the BER will improve as well. We have also shown the improvement of performance by using a sliding window at the receiver in Python 3.7.**

Keywords—optical camera communication, pulse oximeter sensor, sliding window

I. INTRODUCTION

Optical camera communication (OCC) is an interesting topic in the field of healthcare application because of its radiofrequency free properties. The healthcare data are collected using a wearable sensor connected to a communication device to provide healthcare services across the users. The transmission of health information can be done wired and wireless. Wired-connected sensors are odd, costly, and consume high power [1]. On the other hand, currently, radio-frequency (RF)-based devices, such as Bluetooth, ZigBee, and 6LowPAN are mostly used for wireless communication objectives [2-5]. However, it can cause serious damage to human health and negative biological effects in the human body when long-term involvement with electromagnetic radiation (EMR) originating for RF. Some literature has given the overall implementation of the OCC system for eHealth application, but the error rate is quite high. By motivating this we have designed a sliding window algorithm at the receiver to remove the unwanted signal for lower bit-error-rate. We have also designed a system that collects data of heart rate (HR) and blood oxygen saturation (SpO_2) from a pulse oximeter sensor and send the data using LED array as transmitter [6], [7]. The camera is used as a receiver and processed in python environment with neural network for LED detection and data collection. After collecting the data at the receiver, the sliding window technique is used to reduce the unwanted noise at the receiver. In that case, we can improve the error performance at the receiver. Actually the error is happened due to the motion interference of the input sensor or due to the channel noise at the receiver [8].

II. SYSTEM OVERVIEW

The system is designed considering indoor scenario, that monitored the patient's health simultaneously. The sensor is attached with a finger of a patient and collected the HR and SpO_2 data. The sensor is connected with a patch circuit attached as an arm in the patient's body. The patch is composed of an LED array and microcontroller, here LED array is used as a source of optical signal and the microcontroller as a processor for that optical signal. The signal is modulated with the data using color intensity modulation using the microcontroller unit. Based on the symbol characteristics the color of the RGB LED is changed inside the LED array. A camera is used for surveillance and receiving data from the LED array using OCC simultaneously. Neural networks are developed to detect and recognize each LED and its color in the LED array using the camera, which is also used for the surveillance objective, simultaneously. However, for detecting the individual LED of a 4×4 LED array we use Darkflow in python environment with Open CV for training huge amount of image datasets. The weight of the trained image is used to test and label of each LED. In that case each LED shows the variation of color in different intensity grayscale level of R, G, and B code. After, recognizing the proper signal based on that three code the program extracts the signal and store it for correction purpose. So before processing data and recognizing color the binary scale, grayscale in different threshold is performed. Afterward, deletion and erosion is performed based on the image stripe. So after reorganization the data is demodulated based on the color intensity in different level of gray scale. Afterward, the data are processed using sliding window technique in different window size. We take the average of every window sets. If the set of window containing any error, then the average value and threshold value shows large margin of variation. After assuming the error value of a window we can eliminate the value and store a clean data sets in separate file. Finally, the data are transmitted to a cloud server, which can be further accessed by any authorized person using a private user ID and password. Before sending to the cloud server the data is processed using sliding window to improve the performance. The entire system overview is shown in Figure 1, including the sliding window technique.

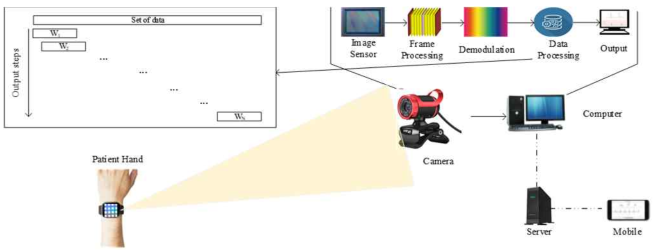

Figure 1: The overall OCC system architecture with sliding window algorithm in data processing at the receiver.

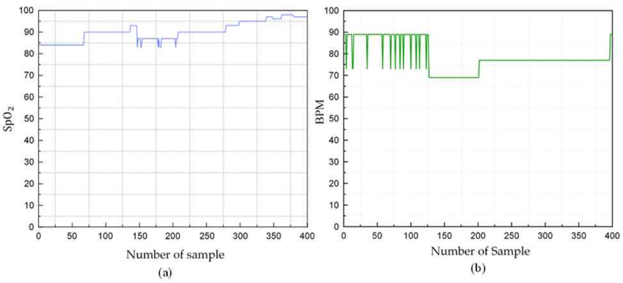

Figure 2: (a) Blood oxygen saturation and (b) heart rate, data collection after employing sliding window algorithm at the receiver.

III. Performance analysis

In the receiver, the SpO_2 and BPM data is collected using camera. Afterward, the data is processed using sliding window algorithm with different window size. The window size mainly depend on the number of sample in an interval data is collected. After applying sliding window scheme the SpO_2 and HR data is shown in Figure 2 (a) and (b) with respect to the number of sample. In the receiver, we took 400 samples of data in one interval for employing sliding window scheme to generate the graphs. As shown in Figure 2, several unstable spikes are generated within the initial samples. The reason is the initial stirs of the patch while attaching the sensor. The exact BPM and SpO2 values can be observed after 125 samples and 200 samples, respectively. The experiments were performed on a male volunteer whose basic information are: 62 kg weight, 167 cm height, and 26 years old. We also calculate the mean absolute error (MAE) of the data of the volunteer in different lighting conditions and considering four different indoor conditions. Firstly, in nighttime, the data is taken using multiple room light sources and a single light source with low intensity, separately. The same procedure is applied in daytime using slight sunlight entering the room. It can be seen that the MAE increases when the interferences are high. Finally, the data are sent to an IoT cloud server where an authorized person can access the data using a login ID and password.

IV. Data decoding

The retrieval of the received signal significantly depends on the orientation of the transmitter. It will not be sophisticated to maintain a fixed position of the patch as the placement of the hand may be altered based on the patients' requirement. However, different orientation of the LED array will generate substantial errors in the data. Thankfully, we have avoided the challenge by measuring the amount of inflection of the LED array. As mentioned in transmitter section, three LEDs are reserved in OFF position to indicate the starting and ending points of each IR, BPM, and SpO2 data. The three positions will be unchanged in the LED matrix disregarding any inflection. Thus, in the original LED matrix, the amount of orientation is calculated locating the positions of the OFF LEDs. The data may vary significantly, therefore, it is possible for any of the other LEDs to progress in the OFF state if the data is too small. However, as we defined the OFF LEDs at the end of each dataset, the newly OFF LEDs will appear sequentially just before the specific OFF LED, therefore, the positions of the OFF LEDs will be determined easily. After measuring the inflection angle, the starting point of the dataset is defined. Then, the symbols are decoded using the color code sequence in the LED matrix. Finally, the data for IR, BPM, and SpO2 are stored into three separate CSV files.

V. Conclusion

A real-time health monitoring system based on OCC with the improvement of system error performance is proposed in this paper. A MAX30102 sensor is used to collect the IR, SpO2, and BPM data, and connected to a patch mounted on the patient's hand. The patch is composed of an LED array that is used to transmit the data to a webcam. As the OCC system is itself a higher security system so we don't need any additional security protocol to improve the performance of the system. In the receiver, each LED in the array is detected using a NN. Also, another feature-extraction-based NN is used to recognize the colors precisely. In addition, a mechanism based on sliding window technique is developed to assuage the challenge error free data collection at the receiver. The whole data decoding and ECG signal generation procedures are performed in Python 3.7. Finally, the data is processed and accessed by a remote monitor and stored in a cloud server.

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