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Novel System Architecture for Online Gait Analysis

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***Abstract*— Although wearable devices can be used to perform continuous gait analysis in daily life, existing platforms only support short-term analysis in quasi-controlled environments. This paper proposes a novel system architecture that is designed for long-term, online gait analysis in free-living environments. Various aspects related to the feasibility and scalability of the proposed system are presented.**

I. INTRODUCTION

Advancements in MEMS technology have led to miniature and inexpensive inertial sensors that can be easily embedded into wearable devices; thus making it possible to conduct online gait analysis in real-life settings. However, this remains a major challenge as current system architectures have mainly focused on short-term gait analysis in quasi-controlled environments [2, 3]. This paper proposes a novel cloud-based mobile system architecture that is intended for continuous, online gait analysis in free-living environments.

II. SYSTEM DESIGN

The proposed system consists of the following components as shown in Fig.1: (1) wearable device/s with embedded inertial sensors and capable of streaming data via Bluetooth, (2) a mobile application running on a smartphone that collects and synchronizes the streaming data from multiple devices and sends it to the cloud by setting a dedicated communication channel and session for each client; and (3) a cloud back-end that contains a publisher/subscriber system implemented as a Websocket Server in Node.js, a database, and any gait analysis algorithm/s. In this case, a gait event detection (GED) algorithm implemented in MATLAB was used [1]. Once the data stream is received from the mobile application, it is simultaneously propagated to the subscribers, stored in a database for offline analysis and buffered to meet the minimum input requirements of the GED algorithm, i.e. the minimum number of samples required by the algorithm to detect events from the input signal. When the buffer is reached, the GED algorithm is executed and the output (gait events) is stored and propagated to the subscribers.

III. PRELIMINARY RESULTS AND OUTCOMES

To evaluate the performance of the proposed system, two metrics were computed when accelerometer data from a wearable device was streamed to the cloud back-end by the mobile application (refer Fig. 1): (1) result projection average time or RPT, defined as $RPT = BT + AET$, where BT is the average buffering time and AET is the average GED algo execution time; and (2) scalability cost ratio (SCR) of adding a new client, i.e. $SCR = ((RPT_{cn}-RPT_{c1})*100)/RPT_{c1}$ where the subscript cn denotes the number of clients. The cloud back-end was deployed on a virtual server with 4 CPUs (2.3 GHz Intel Xeon) and 10 GB RAM. Table 1 shows the results of simulating the system with various streaming rates and adding extra clients to execute the GED algorithm from accelerometer data collected during walking. In order to show the feasibility and scalability of the proposed system for online gait analysis, the corresponding RPT and SCR values are reported when the number of sensors is increased from 2 to 4, for each SR.

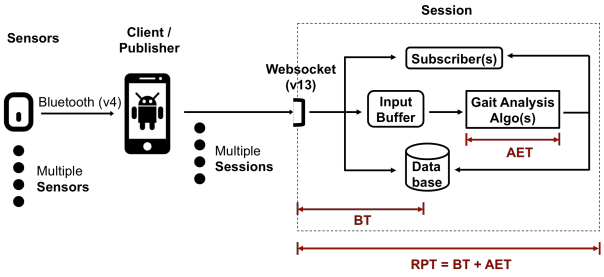

Figure 1: Description of the proposed system architecture.

The results reveal the trade-off between streaming rates and cost of adding extra clients. Table 1 shows that SCR increases exponentially with increasing SR as adding extra clients at higher streaming rates is highly demanding in terms of computational resources (CPU and RAM) required by the gait analysis algorithms and the Websocket Server. These preliminary outcomes indicate the feasibility of the system for online gait analysis and the next step is to scale and evaluate different components of the proposed system.

TABLE I. RESULTS OF THE SYSTEM SIMULATION, WHERE EACH CLIENT HAS TWO WERABLE SENSORS.

#Clients	SR(Hz)	BT(s)	AET(s)	RPT(s)	SCR(%)
1	20	67.08	2.65	69.73	**1.83**
2	20	67.43	3.58	71.01	
1	40	34.34	2.71	37.0	**3.72**
2	40	34.78	3.65	38.43	
1	62.5	22.65	2.94	25.59	**7.03**
2	62.5	23.03	4.36	27.39	
1	80	17.63	3.01	20.64	**19.47**
2	80	17.93	6.73	24.66	
1	128	12.26	3.08	15.34	**91.06**
2	128	12.14	17.17	29.31	

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