An unobtrusive sensing solution for home-based post-stroke rehabilitation.

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This paper proposes the use of unobtrusive sensing solutions to facilitate post-stroke rehabilitation exercises in home-based settings. Radar and thermal sensors are used to collect real-time data from a human subject as they perform rehabilitation exercises. The data collected is then compared with a gold standard exercise, which has been clinically prescribed, to allow feedback to be provided on how the exercises have been completed. The first iteration of the technical platform is presented and plans for its further development are outlined.

Keywords—Post-stroke, Rehabilitation, Unobtrusive sensing

I. INTRODUCTION

The World Health Organisation (WHO) revealed that approximately 15 million people worldwide suffer from stroke each year. Furthermore, an increase of 3.4 million incidents is anticipated by 2030 [1]. These statistics evidence the significant burden being placed on post-stroke rehabilitation centers, facilities and devices, which are aimed at retraining the affected neuromuscular functions of post-stroke sufferers.

A. Post-Stroke Rehabilitation Techniques

A range of post-stroke rehabilitation techniques have been explored in the past three decades [2]. These have included neurofacilitatory therapies such as the Bobath concept; isolated approaches such as isokinetic muscle strengthening and stretching; motor skill learning like constraint-induced movement therapy (CIMT); mirror neuron and motor imagery intervention; adjuvant therapies and technology based rehabilitation (TBR) [3] [1].

A systematic review by Pollock *et al.* [4] acknowledged that some physical rehabilitation activities can help recovery of motor functions post stroke. Some of these activities include CIMT, stretching and forced-use. While wearable devices can help monitor these activities they do, however, suffer from a range of problems relating to battery life, wearability, and adoption. Furthermore, rehabilitation centers pose a range of logistical complexities such as transportation constraints [5]. These challenges, amongst others, make home based unobtrusive sensing solutions, which offer benefits such as convenience and a feeling of relaxation and self-empowerment attractive offerings [6].

Unobtrusive sensing also offers the advantage of non-disruptive monitoring without the user having to wear or charge a device which may sometimes slip-off, be forgotten or become uncomfortable [5] [7]. It enables the user to perform activities of daily living (ADLs) without cuffs, belts and adhesives as could be the case with wearables. This work presents a novel unobtrusive sensing solution based on a heterogeneous sensor fusion technique to monitor post-stroke rehabilitation exercises within a home-based environment.

II. UNOBTRUSIVE MONITORING: THERMAL AND RADAR

Unobtrusive monitoring can be defined as the use of sensors for data acquisition from a target without any physical connection between the sensor(s) and the target(s) itself [8]. Some examples of unobtrusive sensors include: video camera; thermal, radar, ultrasonic and depth sensors. Thermal and radar sensors are considered suitable for this study because of the added advantages they provide over the above-mentioned [9] [10]. While the video camera is illumination dependent and has privacy concerns [11], the ultrasonic sensor has low range and temperature dependability [10]. Furthermore, thermal sensing is capable of measuring the surface temperature of its target in all lighting conditions [7] and also protects the user's privacy. These capabilities have been demonstrated by recent research on home based ADLs and workplace sedentary behavior monitoring by Hevesi *et al.* [12] and Synnott *et al.* [7], respectively. Furthermore, radar sensor is preferred to depth sensor because the latter suffers from pattern interference and depth accuracy when the user distance increases above 2.5m from the sensor [13]. Other advantages of radar sensing solutions include the ability to generate velocity calculations, resistant to temperature, dust, humidity and non-interference with legacy systems and radio frequency [10].

III. THE PROPOSED APPROACH

The proposed approach considers the fusion of thermal and radar sensors due to the aforementioned advantages and complementary data gathering. This implies that raw measurement data from both sensors will be sent to a fusion centre for spatial and temporal alignment. This would be followed by gating and association algorithms before central track management, filtering and prediction [14]. This fusion architecture is known as the centralized fusion architecture (CFA). It will be explored due to its ability to optimise estimated positions, reduced weight, cost and power requirement [14]. Here, the thermal sensor images will be complemented by the radar sensor's velocity (rate of displacement) calculation based on Doppler effect. This effect is very useful in determining the rate of displacement of the upper limb on instances of extension and flexion using multi-scale image decomposition algorithms (which will continuously track, average and analyse waveforms of body segments of interest) [15]. These algorithms provide flexible control over data reporting, improved tracking and performance [16].

IV. MATERIALS AND METHODS

A Heimann HTPA 32x31 thermal sensor and HB100 radar were used for this experiment. The thermal sensor was connected to Sensor Central [17]. Frame images were stored after implementing adaptive background subtraction algorithms.

The sensor was positioned horizontally above the ground. Data were collected at the instances of adduction, abduction, extension and flexion (Fig. 1) of the forearm with a human subject standing 1.5m distance from the sensor.

The HB100 radar sensor was programmed to run on MATLAB R2018a. It was connected to a PC via Arduino Uno microcontroller. Two signal types were gleaned from the radar sensor. These were analog (blue) and digital (red) output (Fig. 2). The digital output operated between two voltage levels (0 – 5V); 0 represented 'no displacement' while 5V represented a 'high displacement'. The analog output ranges from 2.5V to 5V. Measured displacement rates were represented by different voltage levels (Fig. 2).

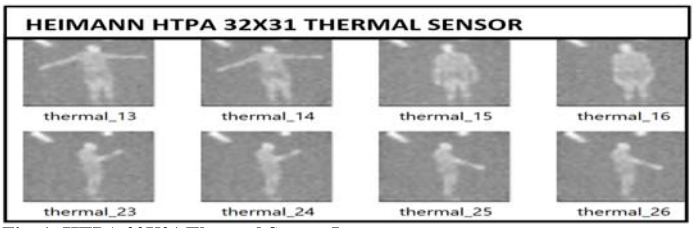

Fig. 1: HTPA 32X31 Thermal Sensor Images

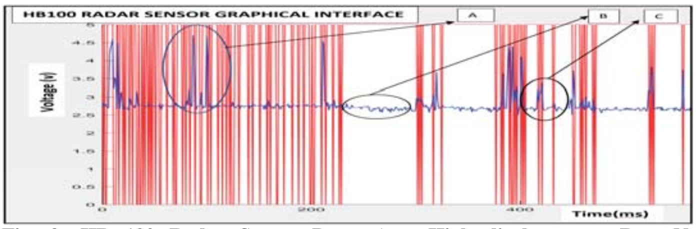

Fig. 2: HB 100 Radar Sensor Data. A = High displacement, B = No displacement and C = Low displacement.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The HTPA 32x31 sensor generated thermal (grey) images based on the temperature of the body. In Fig. 1, thermal_13-14 and 15-16 showed abduction and adduction, respectively while thermal_23-26 indicated flexion and extension. Nevertheless, the image quality depreciated when the human subject was more than 3m from the sensor.

Fig. 2 presents the HB 100 radar sensor data. It was observed that its analog output was able to distinguish between different displacement levels (an analogy of voltage levels) with time represented by A, B and C. This characteristic will help to determine the rate and velocity at which the upper extremity is stretched post stroke.

Further work will involve the CFA and development of an avatar user interface (Fig. 3) to provide feedback to users of how well their exercises are following what they have been prescribed.

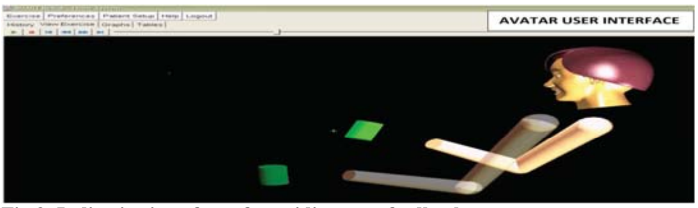

Fig.3: Indicative interface of providing user feedback.

VI. CONCLUSION AND FUTURE WORK

This paper presented a novel unobtrusive sensing solution aimed at assisting post-stroke sufferers in home-based settings. Experimental results presented thermal and radar sensor data of human subjects as they performed rehabilitation exercises. The next phase of this work will feature data fusion and avatar superimposition. Future work will attempt to monitor human subjects at any location within the line-of-sight of the sensors.

ACKNOWLEDGMENT

This project is supported by the European Union's INTERREG VA Programme, managed by the Special EU Programmes Body (SEUPB).

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