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Developing and exploring a methodology for multi-modal indoor and outdoor gait assessment

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Abstract— **Gait assessment is emerging as a prominent way to understand impaired mobility and underlying neurological deficits. Various technologies have been used to assess gait inside and outside of laboratory settings, but wearables are the preferred option due to their cost-effective and practical use in both. There are robust conceptual gait models developed to ease the interpretation of gait parameters during indoor and outdoor environments. However, these models examine uni-modal gait characteristics (e.g., spatio-temporal parameters) only. Previous studies reported that understanding the underlying reason for impaired gait requires multi-modal gait assessment. Therefore, this study aims to develop a multi-modal approach using a synchronized inertial and electromyography (EMG) signals. Firstly, initial contact (IC), final contact (FC) moments and corresponding time stamps were identified from inertial data, producing temporal outcomes e.g., step time. Secondly, IC/FC time stamps were used to segment EMG data and define onset and offset times of muscle activities within the gait cycle and its subphases. For investigation purposes, we observed notable differences in temporal characteristics as well as muscle onset/offset timings and amplitudes between indoor and outdoor walking of three stroke survivors. Our preliminary analysis suggests a multi-modal approach may be important to augment and improve current inertial conceptual gait models by providing additional quantitative EMG data.**

I. Introduction

Alterations in gait characteristics such as reduced step velocity, increased asymmetry in temporal parameters are common post-stroke, negatively impacting mobility and cause falls [1]. Following a stroke, 37% are able to walk independently, 12% can walk with assistance while 50% of patients have severe mobility impairment [2], such as asymmetrical gait. Therefore, regaining community-based ambulation has been identified as a major rehabilitation goal in clinics and rehabilitation centres. And gait assessment is commonly used to support rehabilitation programs by providing insight into postural stability, balance, and different aspects of impaired gait (e.g., muscle characteristics) [3].

Various technologies such as motion capture systems, instrumented treadmills, walkways, force platforms, EMG have been used as a gold/reference system to monitor different aspects of human movement in clinics. However, the use of more than one reference/gold standard gait system brings complexities (e.g., synchronization) when needing to collect diverse but complementary outcomes[4]. Thus, the number of studies investigating more than one physiological outcome remains limited. Consequently, failing to use multiple sensing modalities in gait studies is a limitation in the field, though studies have found clinically useful characteristics in EMG gait patterns for specific populations [5].

Contemporary wearables overcome the limitations of reference/gold standard systems by enabling multiple sensing modalities. Wearables also provide a cost-effective assessment of multiple gait characteristics for use during controlled environments (e.g., clinic/lab) and uncontrolled outdoor environments (e.g., home, garden). Previous studies developed free-living (outdoor) conceptual gait models using wearables to better understand the complexities in neurological gait and underlying mechanisms [6, 7]. Those models detail gait domains (e.g. pace) with subcategories of spatial and temporal characteristics (e.g., step velocity/time) [8]. Wearables offering numerous sensing modalities within a single wearable enables new opportunities to be taken, augmenting existing spatial and temporal gait models with additional data for more informed gait assessment.

Within this developmental pilot study, we propose a methodology using IMU and EMG data within a single wearable. Here, we (i) develop the methodology in a small group of older stroke survivors and (ii) broadly examine use of the methodology to provide additional insight for indoor (laboratory) and outdoor (free-living) gait. Specifically, the harmonised approach can identify initial and final contacts (ICs/FCs), and subsequently, the onset/offset times and amplitudes of the muscle activities within the gait cycle sub-phases. The main aim of this study is to provide a multi-modal outdoor gait assessment tool using the latest technology which overcome unimodal approaches of previous studies. Additionally, this pilot study contributes to preliminary investigation of muscle activity in the lower limb of those with stroke, by evaluating the relationship between temporal characteristics (e.g., swing times) and muscle characteristics (e.g., on/off set timing, amplitude) in indoor and outdoor environments.

II. Methods and Measurements

A. Subjects and Design

This pilot study recruited three male stroke survivors (72.3 ± 3.1yrs, 78.5 ± 12.1kg, 176 ± 8.2cm). Assessment and

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instrumentation were carried out by a physiotherapist and researcher, respectively. Ethical consent was granted by the Northumbria University Research Ethics Committee (REF: 21603). All participants gave informed written consent before participating in this study.

B. Data collection and physical task procedures

Each participant wore a single Shimmer3 EMG wearable (24.276 cm^3, 23.6g) with a strap on the shank level of the less affected side (left for all). Skin preparation was performed with alcohol swabs to achieve better skin-electrode contact. Disposable surface electrodes (circular - Ag/AgCI, silver/silver chloride) were placed bilaterally (inter-electrode spacing ≈ 30mm) on clean skin according to SENIAM recommendations and locations: tibialis anterior (TA) and gastrocnemius (GS), with a reference electrode around the ankle (fibula) [9].

The Shimmer3 wearable allows multi-modal capture of IMU and EMG data simultaneously. Signals were recorded at a sampling frequency of 512Hz, and the IMU was configured (16-bit resolution, ±8g, ±500°/s) prior to data collection. Here, participants were asked to perform (i) 2-minutes walking around a 20m circuit at their preferred self-selected speed inside the laboratory (ii) 20-minute scripted outdoor walking (free-living) with the same wearables. The free-living route consisted of a pre-defined route indoor and outdoor route, walking on different surfaces (e.g., laminate, asphalt). Data recorded during indoor and outdoor walking were analysed.

III. Data Processing and Analysis

IMU and EMG data were transferred to a workstation (Windows 10) from the Shimmer3 via proprietary software (Consensys). Custom programs (MATLAB®, R2018b; Mathworks, Natick, USA) analysed raw (sample level) IMU and EMG data.

A. IC and FC detection: Temporal gait

A previously validated method [10] was used, whereby shank sagittal plane angular velocity was used to identify IC (i.e. heel strike) and FC (i.e. toe-off) and corresponding time stamps. In brief, wavelet decomposition (5th order *coiflet* with ten scales) was used to split the signal into low (approximation) and high frequency (details) components.

Subsequently, drift and high-frequency movement artefacts were removed with an initial approximation. Then, two new approximations were obtained to enhance IC and FC events. For each approximation, the time corresponding to the global maximum (t_{ms}, mid-swing) of the signals were detected. Finally, IC/FC events were searched (local minima) in predetermined intervals [IC (t_{ms}+0.25s, t_{ms}+2s), FC (t_{ms}-2s, t_{ms}-0.05s)]. Temporal gait parameters were estimated according to identified IC/FC events in the following equations where i is the number of the gait cycle (or stride).

$$\text{Stride time} = IC(i+1) - IC(i) \quad (1)$$

$$\text{Stance time} = FC(i) - IC(i) \quad (2)$$

$$\text{Swing time} = IC(i+1) - FC(i) \quad (3)$$

B. Electromyography processing: Segmentation

Extracted IC and FC time stamps information were used to identify the sub-phases of the gait cycle (stance and swing phases). As Shimmer3 EMG provides synchronised IMU and EMG data, muscle activation characteristics were segmented for stance and swing phases using timestamp information. Once EMG data is segmented, appropriate filtering must be performed to ensure signals are physiological related and not corrupted by noise. Thus, all EMG data were bandpass filtered (zero-lag 4th-order Butterworth filter) with cut off frequencies of 20 Hz and 250 Hz, followed by full-wave rectification, and low-pass filtering (10 Hz, zero-lag 4th-order Butterworth) to achieve a smoother signal to identify muscle onset/offset. All EMG values for each subject underwent time normalisation (gait cycle %) and amplitude normalisation to the highest EMG value (Root Mean Square, RMS).

C. EMG time domain features

(i). Muscle activity/inactivity timing

Detection of muscle onset/offset and overall level of activity in a muscle at any time is relatively identifiable from the linear envelope of raw EMG signals. There are various methods to extract the linear envelope of EMG signal such RMS, mean of moving window, and use of a set of filters along with rectification [4]. Once the linear envelope is extracted, muscle onset/offset can be detected via a predetermined threshold, manual observation, or clustering algorithms [11]. The latter finds resemblances between data points and groups these according to their similarities.

Here, the filters introduced in Section III.B and full-wave rectification were used to extract the linear envelope of the EMG signal, while k-means clustering was used to search muscle bursts (onset). The reason for using k-means is that it does not require *a priori* setting of thresholds and has shown the ability to differentiate bursts (onset), even when bursts are short or have spike-like characters [12]. Similar to [13], each data point in the EMG linear envelopes are clustered into subsets of data using k-means. Then, EMG signals are dichotomized into periods of onset/offset according to the amplitude of each data point. Here, the numbers of centroids (clusters), which influence sensitivity was set to five after visual inspection for all EMG signals analysed [14]. Muscle offset is identified for the lowest two clusters whereas the remaining three clusters are accepted as muscle onset.

(ii). Muscle activity amplitude analysis

Root mean square (RMS) of an EMG signal represents the average power of muscle activation for a given period. RMS is used to extract the linear envelope and analyse variations in the amount of information between the abduction and adduction movements [15]. A linear relationship between the contraction force and the RMS value of the EMG signal was reported in previous studies [16]. Thus, normalized RMS values can be a useful parameter in terms of understanding physiological activity during contraction of lower limb muscles in gait assessment.

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x_k^2} \quad (4)$$

where N is the number of samples and x_k is the k-sample.

IV. Results

A. Temporal characteristics

Temporal characteristics extracted in the laboratory and scripted outdoor are presented in Table 1. Participant 1 and 3 experienced a decrease in temporal parameters (stride, stance, and swing time) during scripted outdoor compared to laboratory. Contrarily, Participant 2 experienced increased temporal parameters in outdoor compared to laboratory. Also, overall standard deviation in temporal parameters found higher during indoor walking compared to outdoor walking.

TABLE 1. INDOOR AND OUTDOOR TEMPORAL CHARACTERISTICS

	Subjects	Total Strides	Stride T. Mean (SD)	Stance T. Mean (SD)	Swing T. Mean (SD)
Indoor	1	60	1.33 (0.22)	0.84 (0.22)	0.49 (0.06)
	2	76	1.25 (0.09)	0.82 (0.1)	0.42 (0.08)
	3	110	1.09 (0.04)	0.63 (0.04)	0.45 (0.05)
Outdoor	1	245	1.11 (0.05)	0.67 (0.07)	0.43 (0.04)
	2	246	1.34 (0.06)	0.87 (0.07)	0.46 (0.06)
	3	247	1.03 (0.04)	0.60 (0.05)	0.43 (0.05)

T.= Time (seconds)

B. *EMG on/off set timing*

From IC/FC events, corresponding muscle activities of TA and GS are extracted during gait cycle sub-phases. Muscle onset is shaded using raw EMG signals in Fig. 1(a). Onset and offset detection are performed by using k-means clustering algorithm after the linear envelope is extracted, Fig. 1(b).

Muscle activity timing is extracted as percentage (%) of gait cycle (stride), stance and swing timings. Average of extracted time parameters are illustrated in Fig. 2 (a). Average muscle on time durations is longer during lab for all subjects and both muscle groups compared to outdoor. TA muscle on-time duration was found higher than GS across gait cycles for all stroke survivors. GS muscle was found more active during the stance phase, whereas TA muscle was more active during the swing phase. Also, the difference between the indoor and outdoor overall on-time duration of TA is minor, whereas the differences are noticeable for GS muscle.

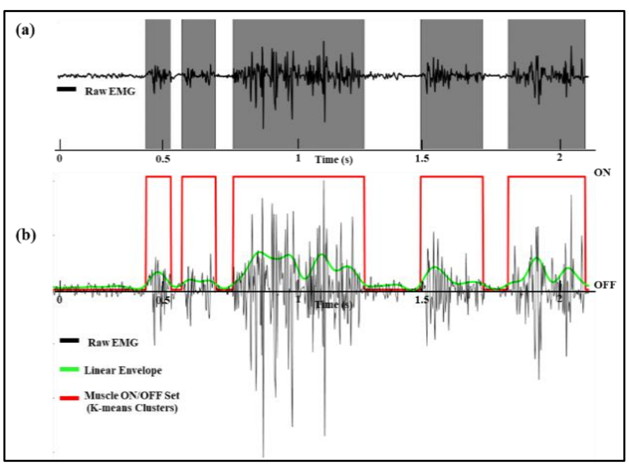

Fig 1. (a) On periods of raw EMG signal (shaded), (b) Detection of the on/off periods of muscle activity

C. *EMG-RMS parameters*

Intensity of muscle activities are normalized to peak RMS value in corresponding gait cycle and average RMS values are presented in Figure 2 (b). Amplitude (RMS) of GS is higher than TA in stance phase in both indoor and outdoor as expected [17]. All participant experienced increased RMS values in outdoor compared to lab assessment. Also, the RMS values of TA were found higher in swing phase compared to the stance phase.

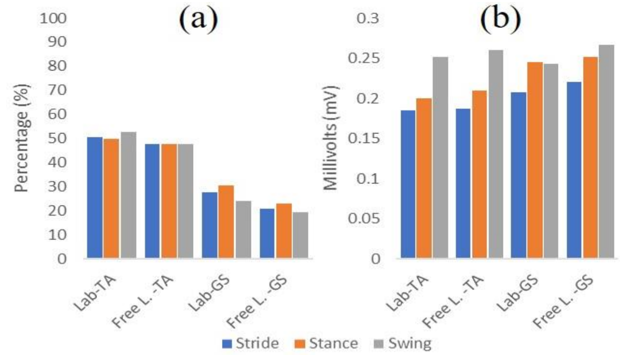

Fig 2. (a) Average-Stride-Stance-Swing (%) of muscle activity timing for TA and GS. (b) Average-Stride-Stance-Swing (mV) of peak muscle activity amplitude (RMS) for TA and GS

V. DISCUSSION

A multi-modal methodology is presented (Fig. 3) where raw IMU data helps identify the gait cycle and its sub phases by means of detecting IC/FC events which further segments synchronised EMG data. Our preliminary investigation (pilot study) shows that there are variances in the stride, stance, and swing times along with muscle characteristics in terms of temporal organisation of muscle onset/offset between indoor and outdoor. These differences may account for specific impairments and compensations in the lower limbs that contribute to poor gait quality [5].

Underlying reasons for differences in temporal parameters include, environmental factors (e.g., walking terrain) on the generated IMU signals [18] and instability of the developed algorithm are possible dominant factors [19]. This could also be due to the fact that stroke survivors may change the way they walk (e.g., increased speed) while under observation in controlled lab environment [20].

Muscle onset timings found shorter but more powerful for both muscle groups in all participants during outdoor compared to indoor. Changes in the temporal parameters, walking velocity and age may be associated with the variations in muscle activities during indoor walking [21]. However, the number of studies that investigate muscle activation level during outdoor is very limited [4] and so more research is needed to provide further insights.

The developed methodology can contribute to the field by investigating how muscle characteristics change during outdoor walking. Investigation of muscle characteristics in gait sub-phases may help clinicians to better understand an individual's muscle characteristics such as muscle onset-offset timing and RMS during outdoor walking. Conceptual gait models have been developed for ease of interpretation of gait assessment due to the redundancy of parameters and covariance amongst characteristics. The proposed models are developed based on spatiotemporal outcomes and do not include kinematic, kinetic or muscle activation characteristics, which could prove beneficial[4]. Previous limitations are complexity of design/instrumentation that is used to collect synchronized multiple gait characteristics in the indoor and outdoor. Therefore, the proposed multimodal approach here may contribute to the advancement of existing gait models by the integration of muscle characteristics.

This study has certain limitations, primarily the population size. However, this study is designed as a pilot aiming not only to provide a less complex design with a single wearable compared to previous studies but also to provide highly useful

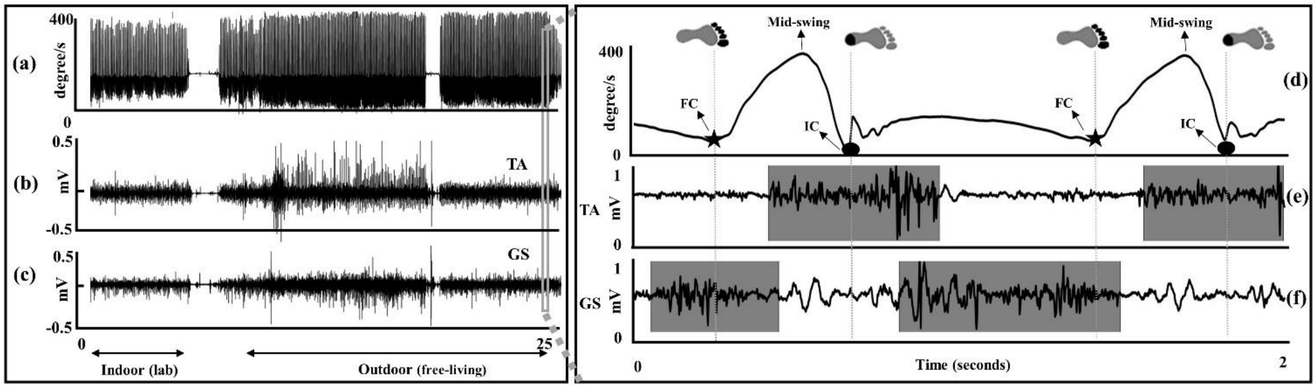

Fig. 3. Developed methodology; (a) IMU data (angular velocity), (b) Calibrated raw TA-EMG signals, (c) Calibrated raw GS-EMG signals, (d) angular velocity signal with identified initial contact (dot) and final contact (star) in the zoomed time interval, (e, f) Segmented EMG signals and onset/offset of TA and GS in the zoomed time interval, respectively

quantitative multiple gait characteristics in indoor and outdoor environments. Future studies will aim to increase the population size and implement the methodology on various cohorts (e.g., Parkinson's Disease).

VI. Conclusion

The methodology had promising potential for practical utility in multi-modal indoor and outdoor gait assessment. Integration of muscle characteristics into existing gait models can be more comprehensive and informative as muscle activity of the lower extremities during gait need to be well-coordinated to provide dynamic balance, propulsion, and foot clearance. Investigation of the validity on various cohorts with larger population size can contribute to field.

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