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Unobtrusive, Continuous LIDAR-Based Measurement of Gait Characteristics at Home

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Abstract— **This paper describes a novel approach to the unobtrusive assessment of a subset of gait characteristics using a light detection and ranging (LIDAR) device. The developed device is poised to enable unobtrusive, nearly continuous monitoring and inference of patients' gait characteristics to assess physical and cognitive states. The device provides a rapidly sampled signal representing the distance of a participant's body from the LIDAR device. The densely sampled distance estimation is processed by custom algorithms that can potentially be used to estimate various gait characteristics such as step size, cadence, double support, and even step-size symmetry.**

Clinical Relevance— **Since gait is a complex behavior that requires seamless cooperation of multiple systems, including sensation, perception, muscular synergies, and even cognition. Subtle changes in gait may, therefore, indicate issues with physical and mental functionality. In addition to the walking speed, the gait monitoring results can provide inferences about the physical and cognitive states of the unobtrusively monitored individuals using their own data as a baseline.**

I. Introduction

The ability to walk is a fundamental skill determining the quality of life, yet it is often taken for granted. Gait requires finely-tuned cooperation of many low and high-level neuropsychological processes. Assessment of gait characteristics is, therefore, an essential component of personalized, proactive care. The rapidly increasing proportion of older adults is emerging as a significant challenge to both United States and global healthcare. In addition, a variety of deficits associated with aging, including traumatic brain injury (TBI), stroke, brain tumors, and neurodegenerative diseases, pose additional challenges to healthcare systems throughout the world. For example, the U.S. Centers for Disease Control and Prevention estimates that over 1.7 million Americans sustain a TBI each year, 275,000 of whom are hospitalized for over two days. While early detection and rehabilitation are often possible, their effectiveness is frequently thwarted by the sporadic nature of in-clinic neurological assessments.

Unfortunately, the reliability of current sparse assessments is limited by (a) the variability resulting from the time-varying and context-dependent health states of participants (e.g., having a "good" or a "bad" day) and (b) limited specificity of the tests. In particular, the typical approach to assessing gait is the timed-get-up-and-go (TUG) test that only measures the total duration of a fixed length walk. There is a need to enable unobtrusive, frequent or continuous measurements of gait in natural settings outside the clinic. Moreover, several characteristics – in addition to the speed of gait – are important indicators of an individual's well-being, including physical and cognitive states. Therefore, developing economically feasible technology that would allow such objective measurements to be embedded in the individuals' homes would positively transform our ability to provide optimal care.

In this paper, we describe an approach to unobtrusive measurement of gait characteristics using emerging technology based on an inexpensive Light Detection and Ranging (LIDAR) device. We describe our current implementation of the device and demonstrate its ability to estimate walking speed and other gait characteristics with algorithms for transforming the raw distance observations to inferences of gait characteristics. To develop the theoretical underpinnings of the analytic strategy, we used laboratory measurements where the gait characteristics were obtained using video-based motion capture system. Subsequently, we compared the LIDAR results to inertial monitoring devices attached to the legs and center of the torso. Because of the inability to run in-lab experiments due to the pandemic, we only describe a demonstration rather than validation of the approach from previously collected data.

II. Background

A. Gait Characteristics as Health Metrics

Gait is a critical determinant of quality of life and is often used to assess individuals' physical and neuropsychological health-related characteristics. Gait assessment is particularly useful for older adults and those with a variety of neurological conditions, including multiple sclerosis, Parkinson's and Alzheimer's diseases, ALS, etc. There is evidence that aspects of gait interact with various cognitive functions [1-3]. In fact, speed of walking is predictive of cognitive decline in older adults [4, 5]. This decrement in gait speed while performing a cognitive task is taken as a measure of the interference between cognitive and walking tasks and may well reflect the cognitive reserve [6, 7]. In addition, assessment of symmetry [8] can be useful in optimizing rehabilitation [9]. Kinematic characteristics of gait, such as cadence, which are unobtainable with a TUG test, are typically measured in a clinic or

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laboratory using expensive devices based on video monitoring. Besides the high cost, these systems usually require placing fiducial markers on the participants and sophisticated data analysis. Alternate approaches based on Inertial Measuring Units (IMUs) allow measurements in natural environments but need the participant to wear sensors attached to their limbs and possibly other parts of their body. Moreover, these devices require frequent charging and downloading of the data. Although these devices have been successfully used for research [10], their requirements represent barriers to using such devices for continuous monitoring and assessment.

To overcome existing shortcomings, we investigated an alternate solution that would enable unobtrusive monitoring of additional gait characteristics. This was in part stimulated by our understanding of the biomechanics of walking and further supported by recent research relating center of mass (CoM) movements to limb movements [11]. Our goal was to demonstrate the feasibility of this general approach when applied to unobtrusive monitoring.

B. LIDAR-Based Approach

The novel approach presented in this paper is to use a LIDAR-based distance measurement device to infer individuals' gait characteristics. This paper focuses on extending the use of the LIDAR-based device initially developed to measure gait speed in a clinic more precisely and objectively [12].

III. METHODS

This section describes the prototype of the device, the LIDAR data, and a theoretical underpinning together with initial laboratory results with a video-based system for movement capture. Finally, we describe the current version of our algorithms.

A. GAITBOX - Engineering Design of the LIDAR device

The device, called GAITBOX (GB), shown in Fig. 1, is a low-cost and accurate alternative to clinical gait speed measurements with stopwatches [12]. In the GB, the distance measurements are realized using a Light Detection and Ranging (LIDAR) device and microcontroller that calculates and displays estimates of walking speed. LIDAR makes these distance measurements by measuring the time of flight from the device to and from the object. Since light travels 15 cm in a nanosecond, the device requires very high temporal resolution, which only became available very recently with the advent of affordable LIDAR systems. The particular LIDAR sensor used in the GB is Lidar Lite V3 made by Garmin. It generates approximately 1.3W of peak power at 905 nm. Since the pulse width is only 0.5 sec, the total energy impinging on a walker is on the order of 10^{-6} J, well within the safety limits (1 mW). The divergence of the beam ("field of view") is approximately 0.46 degrees, which means that at the distance of 10 meters, the beam diameter is approximately 8-10 cm. These characteristics provide a LIDAR cross-section in the infrared range that is adequate for detecting a human walking within the LIDAR beam.

To achieve our goal of assessing parameters such as symmetry of an individual's gait, our team had to increase the sampling rate to sample every 10 msec. At this sampling rate of 100 Hz, the sensed data would be sampled with a sufficient density to assure recoverable distance signal with a sufficiently high signal-to-noise ratio. Although the sensor does not incorporate an antialiasing filter, the integration time constant of the sensor corresponding to 10 msec sampling rate effectively provided sufficient suppression of higher frequency noise.

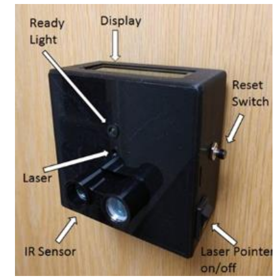

Figure 1. An image of the GB prototype.

The GB employs an Arduino Uno microcontroller interfaced to a Garmin LIDAR-Lite V3 Laser Ranging Module. The original version of the device, designed to facilitate the NIH Toolbox Walk Test (NIH-WT), recorded the "start" distance and the "end" distance of each walk to estimate the average speed of walking covering a distance up to 40 meters. To measure walking speed using the GB, the device is positioned approximately 1.2 m off the ground and pointed down the center of the walking path at the subject's torso. The device is powered either by wall power or a battery pack.

For this effort, we significantly modified the original device and added the ability to measure and record distance every 10 msec continuously while a subject is in the walking path. This modification required switching to a more powerful microcontroller with more internal memory and the addition of a shield to leverage a removable S.D. memory card. The ultimate design will include a wireless connection.

B. Foundations and Laboratory Study

The goal of this project was to estimate aspects of gait from the measurements of a torso movement as sensed by the GB. The first step then required us to determine the ability to infer leg movement from the torso center, which is well approximated by monitoring the anterior-posterior movements of the sacrum. One participant walked on a treadmill at a constant speed of 1.0 mph, while the kinematics of the sacrum, pelvis and both legs were collected using a 12-camera passive reflective marker motion tracking system sampling at 120 Hz (OptiTrack Flex 13; NaturalPoint, Corvallis, OR). Since the treadmill moved at a constant velocity v_0 along the x - axis (0.45m/sec), the instantaneous velocity $v(t)$ of a participant's center of mass (COM),

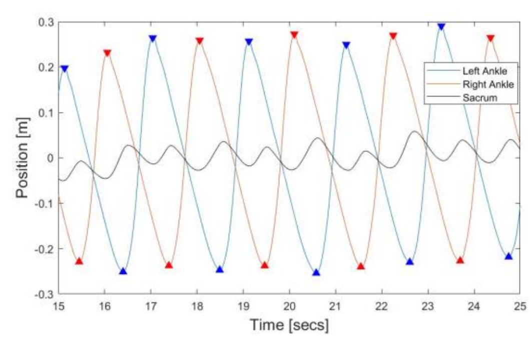

Figure 2. Raw data from the motion tracking system from a participant walking uniformly on a treadmill.

measured as $v_m(t)$ is given by $v_m(t) = v(t) - v_0$ and the observed instantaneous position is given by

$$x_m(t) = \int_{\tau=0}^{\tau=t} v(\tau)\, d\tau - v_0 t, \qquad (1)$$

where $t = 0$ is the starting time. An example of a segment of the resulting raw data is shown in Fig. 2. The position of each marker is referenced to the ground of the treadmill center. The blue and red lines represent the kinematics of the left and right ankle positions. Although the participant is walking forward, when their foot is planted on the treadmill, it moves in a negative direction $-v_0$ with the treadmill. The corresponding analytic estimates of toe lift-off and heal-strikes locations and times are shown by the up and down-facing triangles with corresponding colors. The black curve in this graph representing the sacrum kinematics suggests that aspects of gait phases are reflected in the sacrum position, albeit with a smaller amplitude. An illustration of the relationship between the different gait phases and the sacrum

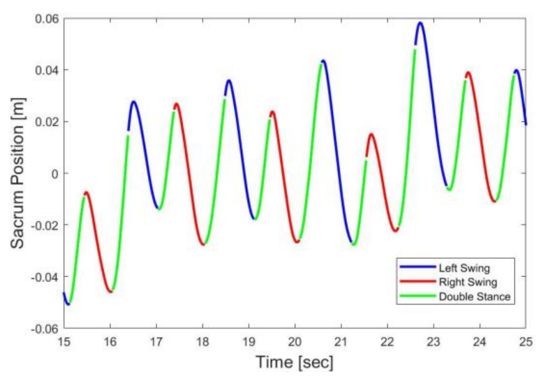

Figure 3. Movement of the sacrum with gait phases identified by different colors (see legend).

movements is shown in Fig 3. With left swing corresponding to the blue segments, right swing to red segments, and double stance to the green segment. This graph suggests that the sacrum extrema may be a reasonable approximation to the gait segment transitions times with positive parts of the sacrum movement corresponding to double stance. The negative slopes of the sacrum movements can be used as reasonable estimates of the duration and the size of the individual steps. Using these results, we can estimate a variety of gait parameters from the fine distance measurements of the torso from a fixed point.

IV. LIDAR Data Analysis

The GB raw data are essentially sequences of distance measured in meters sampled every 10 msec. These data are similar to the laboratory data described in the previous section except for the motion and constraints imposed by the treadmill motion.

A. Preliminary Experimental Assessment

The goal of our preliminary evaluation of the performance was to use the GB to monitor several participants (authors) with known issues affecting their gait. The general approach involves monitoring of walking individuals using the GB simultaneously with three commercial IMUs (Shimmer) attached to the torso and shins near the left and right ankles. For this demonstration, we collected GB data for simulated walks in a home environment, including natural, fast, slow, and asymmetric step-sizes The device was set up to synchronize with the IMUs by stepping on a floor switch. Subjects walked away from the GB with the first step on the footswitch. The GB started measuring distances every 10 ms when the switch was activated and stopped recording once he reached a distance of 5.5 meters. The data were analyzed offline using the Matlab programming environment.

The goal of the analytic effort was to assess the feasibility of extracting metrics relating to individual steps using methods similar to those applied to the laboratory video data in the previous section. For the initial proof-of-concept, we chose to identify the timing and size of steps using the GB. To this end, the raw GB data were used to estimate the average gait speed, analog to v_0 in (1) by computing a linear regression as shown by the straight line in the top of Fig. 4. The slope of the linear regression is an RMS estimate of the average speed v_0. The red trend line estimates slow variations in speed in the middle

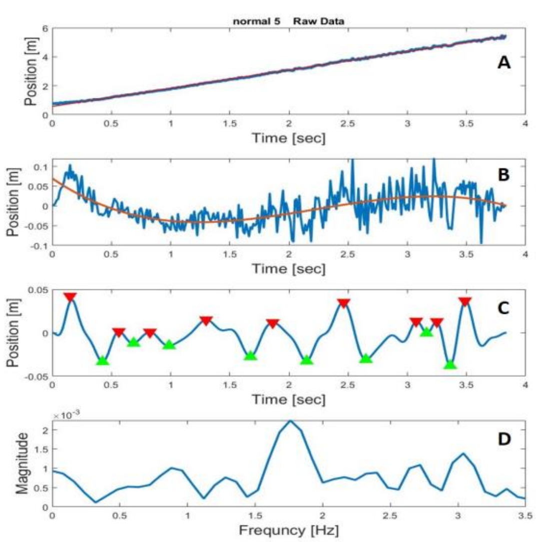

Figure 4. GB Data: A- raw data (blue), regression (red), B - residuals and slow trend, C-Band-Pass of the residuals, D-FFT of the residuals.

graph. To minimize noise enhancement due to differentiation, we use the residuals that represent the deviations from a uniform velocity in a similar manner as we observed the movement of the sacrum on the treadmill. To the extent that the gait is periodic, a standard fast Fourier transform (FFT) can be used to determine the cadence, and in combination with the speed estimate, the step size (bottom of Fig 4). The largest peak of the FFT represents a combination of the individual steps, and the subharmonics at ½ of the peak frequency represent the right and left steps. The FFT-based analysis, however, is most useful if the quasi-periodic gait pattern is nearly periodic and ergodic.

Since these assumptions are likely to be violated, especially by individuals with various dysfunctions such as

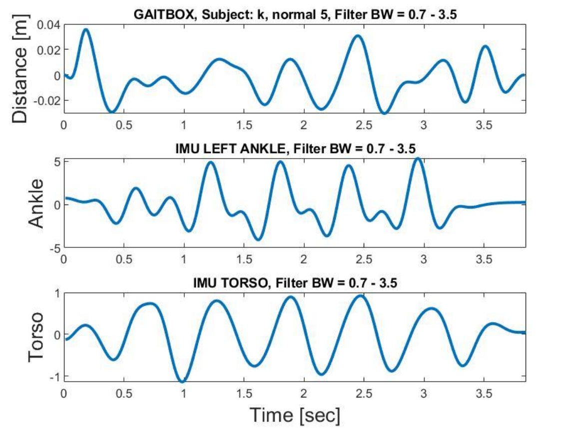

Figure 5. Comparison of GB results (top) with IMU measurements attached at the left ankle (middle) and at the center of mass, torso of the walker (bottom).

those with traumatic brain injury or stroke survivors, we chose to use an analysis based on continuous wavelet transform (CWT) [13]. Using CWT provides the advantage of analysis at multiple time scales, and therefore, it is useful for signals that are not ergodic and strictly periodic. The results of the CWT analysis with Morlet wavelet and band-pass filtering of the GB signal is shown in Fig. 5.

This CWT-based approach allowed us to compare the results of the GB measurements with those using a commercial inertial measurement system (Shimmer). The results of a healthy individual walking at an average speed are shown in Fig. 5. The smoothing (band-pass filtering) of the raw residuals enabled us to estimate the peak and valleys that signify changes in gait phases. The number of peaks in the GB signal corresponds to the number of steps. In addition, like in the laboratory experiments, the GB data suggest that the segments with a positive increase in the residual values correspond to the double support phases of the gait. To illustrate the ability to detect gait anomalies, the participants simulated asymmetric gait by taking longer steps with one leg than the other. A typical example of the results of this type of gait is shown in Fig. 6. There is a clear difference between the

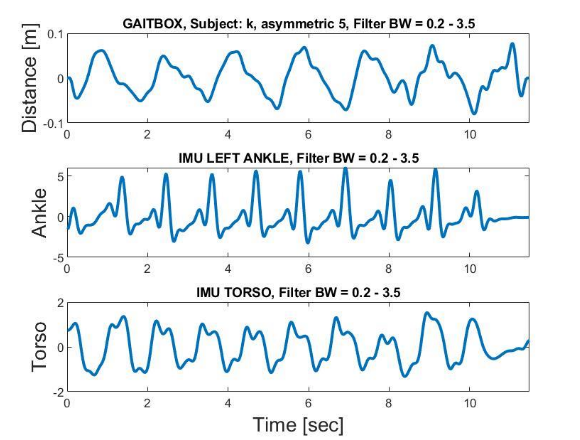

Figure 6. Same as Fig 5. but for an asymmetric gait simulated by healthy participants.

healthy gait patterns and those with asymmetric step size – the leg with the longer step size dominates the torso's movement.

Conclusion

This paper presents preliminary results of our investigation of a novel approach to the unobtrusive assessment of a subset of gait parameters. The reported results demonstrate a promising potential of the LIDAR-based approach for gait analysis. In our future work we plan to perform an empirical study and use machine learning to estimate gait characteristics extending previous work [13] inferring symmetry, timing and other gait characteristics.

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