Gait Characterization via Pulse-Doppler Radar

Tarik Yardibi*, Paul Cuddihy*, Sahika Genc*, Corey Bufi*, Marjorie Skubic^, Marilyn Rantz+, Liang Liu^, Calvin Phillips II^

{yardibi, cuddihy, gencs, bufi}@ge.com, skubicm@missouri.edu, rantzm@health.missouri.edu, llpfd@mail.mizzou.edu, calvinepii@gmail.com

*Computing and Decision Sciences, GE Global Research, Niskayuna, NY

^University of Missouri, Electrical and Computer Engineering Dept., Columbia, MO

+University of Missouri, Sinclair School of Nursing, Columbia, MO

Abstract

Falls are a major cause of injury in the elderly with almost 1/3rd of people aged 65 and more falling each year [1]. This work aims to use gait measurements from everyday living environments to estimate risk of falling and enable improved interventions. For this purpose, we consider the use of low-cost pulse-Doppler range control radar. These radars can continuously acquire data during normal activity of a person in night and day conditions and even in the presence of obstructing furniture. A short-time Fourier transform of the radar data reveals unique Doppler signatures from the torso motion and the leg swings. Two algorithms that can extract these features from the radar spectrogram are proposed in this study for estimating gait velocity and stride durations. The performance of the proposed radar system is evaluated with experimental data, which consists of 9 different walk types and a total of 27 separate tests. A high accuracy motion-capture camera system has also been used to acquire data simultaneously with the radar and provides the ground truth reference. Results indicate that the proposed radar system is a viable candidate for gait characterization and can be used to accurately track mean gait velocity, mean stride duration and stride duration variability. The gait velocity variability can also be estimated but with relatively larger error levels.

1 Introduction

Falls are a major concern, and the most common cause of serious injuries and hospitalization in elderly people [2]. Therefore, it is essential to develop methodologies for reliably predicting falls before they actually happen. Changes in gait characteristics over time, such as in gait velocity and stride length, were shown to be highly correlated with increased fall risk [1]. In this study, we aim to use gait measurements from everyday living environments to estimate risk of falling and enable improved interventions.

Most commonly employed methods for gait characterization to date involve the use of high frame rate camera or motion-capture camera systems. These systems require the person under testing to wear special markers and are typically operated by trained professionals. Both the cost of the camera setup and the experiments are therefore high. As an alternative, we consider the use of a very low-cost range control radar system for estimating four major gait characteristics that were shown to be important indicators of fall risk in elderly people [1]: i) mean gait velocity, ii) gait velocity variability, iii) mean stride duration and iv) stride duration variability. Range control radars can be placed in the elder's home and acquire data during normal day-to-day activities of the person to provide continuous rather than periodic monitoring (which is the common practice today), thus significantly increasing the chances of promptly detecting any changes in gait characteristics. Radar is mostly immune to various lighting conditions and furniture obstruction (it does not require a clear line-of-sight view as in, for instance, a camera), making it very suitable for this application. In addition, radar does not require the person to wear any special markers, which is another desirable feature. The privacy of the user is not violated with the radar system as it only measures gait characteristics and no other additional information such as video or sound.

There are a number of existing studies in the literature that employ a radar system for gait characterization. [3] uses Ku-band radar and estimates the gait velocity from the frequencies with the highest reflection levels. The estimated gait velocities are then used to estimate the stride rate. [4] makes use of continuous wave radar for stride rate estimation. The stride rate is estimated by taking the Fourier transform at each Doppler frequency bin after computing the radar spectrogram. [5] shows that different human body parts generate different radar signatures. [6] shows that continuous wave radar can be used to distinguish between different persons or other moving objects. [7] uses an acoustic Doppler radar and a microphone to show that the footstep instants correlate with the secondary peaks in the radar spectrogram (see also [8]). [9] also uses an acoustic Doppler radar and develops a training based classification method for human gait characterization.

The radar employed in this study is an off-the-shelf pulse-Doppler range control radar (see, e.g., [10]), which has been modified so that the baseband analog measurements can be recorded, and it makes use of the Doppler principle to estimate the relative velocities (with

This project was supported by grant number R01HS018477 from the Agency for Healthcare Research and Quality. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality.

978-1-61284-937-9/11/$26.00 ©2011 IEEE

respect to the radar) of the targets within its range. To the best of our knowledge, this radar has not been used in an indoor application to determine gait characteristics before. The radar transmits an electromagnetic wave at a certain frequency and measures the frequency shifts in the reflected waves. These frequency shifts can then be used to obtain the velocities (in the radar's direction) of the person's body parts; different body parts create distinct Doppler signatures when a person moves. Since the torso has the largest surface area, the frequency shift with the highest reflected energy will yield the gait velocity. Legs generate a much higher frequency shift due to their motion being faster than that of the torso. However, the reflected energy from the legs is lower due to their smaller radar cross-section area. Nevertheless, the reflections from the legs are still visible in the radar spectrogram and this information can be used to extract stride duration information.

In order to evaluate radar performance, we have employed a high accuracy motion-capture camera system, named the Vicon system hereafter, which tracks the 3-D positions of multiple markers attached to a person in real-time (see, e.g., [11]). This system provides accurate location estimates over time and hence can be used to obtain the ground truth values of many parameters including but not limited to gait velocity, gait velocity variability and foot step instants. The Vicon system has found wide application in health care and human gait related studies (see, e.g., [12], [13]).

Utilizing the radar and Vicon system simultaneously, we have conducted experiments in order to evaluate the radar's gait characterization performance in detail. Various different types of walks at different paces were measured. There were also two regular cameras recording the experiments during data collection for further verification purposes. Our study is different from the aforementioned prior studies in several aspects: i) the type of radar used, ii) the availability of high-quality ground truth data, iii) the scale of the experiments conducted, and iv) the complexity of the radar signal processing algorithms developed.

The rest of this paper is organized as follows. In Section 2, the experimental setup is described and the initial data processing steps are presented in Section 3. Algorithms for estimating the gait velocity and stride durations from the radar measurements are introduced in Section 4. Section 5 presents experimental results after which the concluding remarks follow in Section 6.

2 Experimental setup

The radar used in this study is a pulse-Doppler range

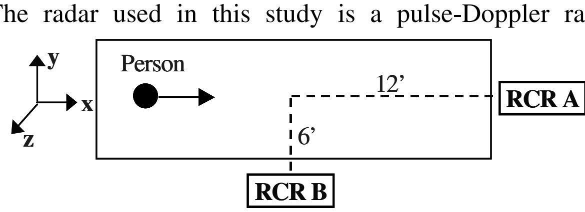

Figure 1 The experimental setup.

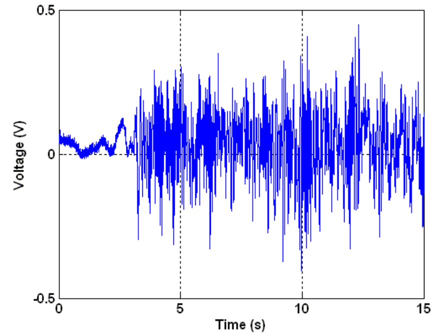

Figure 2 The raw analog signal from the radar.

control radar (RCR), which has a carrier frequency of 5.8 GHz, a pulse repetition frequency of 10 MHz and a duty cycle of 40% (see, e.g., [10]). The radar has variable range settings from 20 to 50 ft, where we have used the 20 ft setting in our recordings. We deployed two RCRs in our experiments: one right across the walking path of the person (RCR A) and one on the side (RCR B), as shown in Figure 1 (note that similar results are obtained when the person walks in the opposite direction). The emphasis is on RCR A in this paper. RCR B can only estimate the radial velocities but it can potentially be used for stride duration extraction in future studies. The coordinate system used throughout the paper is shown in Figure 1. The radars were placed 8 inches above the ground and 2x2 ft metal shielding was used behind each radar to reduce interference.

The RCR mixes the transmitted and reflected signals and then passes the resulting waveform through a low pass filter to capture the frequency shifts. The radar outputs this low pass filtered signal, which is then digitized, sampled at 1 kHz and stored. Figure 2 shows a sample radar output (after mean subtraction). The Vicon system employed in the measurements comprises of seven cameras, a controller hardware module and motion capture software installed in the host computer (see, e.g., [11]). During the data collection procedure, the cameras transmit infrared light signal and receive the reflection light signal from the retro-reflective markers of the wearable devices on the moving subject. The Vicon sampling frequency is 100 Hz. The spatial location for each marker is recorded in x, y, and z coordinates.

3 Preliminary data processing

The Doppler principle states that the radial velocity component, v in ft/s, of the target reflecting the radar wave is related to the measured frequency shift via

$$v = \frac{c \times \Delta f}{2 f_c}, \qquad (1)$$

where c is the velocity of light in ft/s, Δf is the frequency shift in Hz and f_c is the carrier frequency in Hz. Since velocity is a function of frequency, the analog signal is first

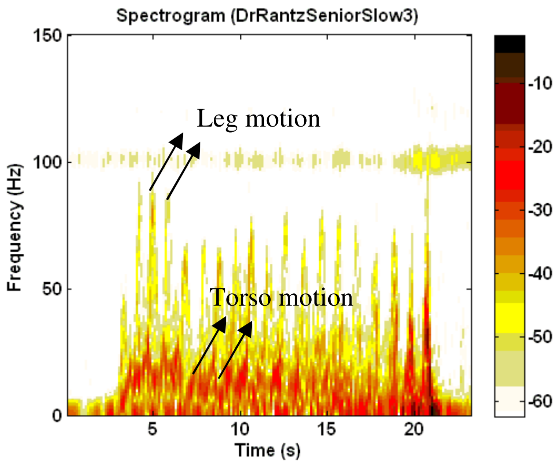

Figure 3 The spectrogram of the radar signal. The unique signatures of the torso and leg motion can be clearly observed. Levels are in dB.

converted into the frequency domain by using a short-time Fourier transform (STFT) defined as [14]

$$\mathrm{STFT}(t,f)=\int r(t+\tau)w(\tau)\exp(-j2\pi f\tau)d\tau, \quad (2)$$

where t and f denote time and frequency, respectively, $r(t)$ denotes the radar signal at time t and $w(t)$ is a sliding spectral window (e.g., the Hanning window). In other words, the recorded data series is divided into overlapping time segments and the fast-Fourier transform (FFT) of each segment is computed (note that appropriate zero-padding is applied). The reason for computing a time-varying frequency spectrum is to capture the dynamics of gait characteristics over short periods of time. This results in the so-called spectrogram, which shows the time varying frequency spectrum of the signal as observed in Figure 3 (the radar signatures due to the torso motion and leg motion are also noted in the figure).

4 Gait velocity and stride rate extraction

4.1 Vicon

The reflective markers used for the Vicon system were placed at the elbows, back, wrists, toes and knees. In this study, out of the 21 markers employed, we only utilize the ones that were placed on the lower backside, and the right and left toes. The gait velocity is estimated by using the lower back marker and simply by dividing the distance traveled in the x-axis (see Figure 1) by time (over 10 ms intervals). The stride durations, on the other hand, are estimated by measuring the instants at which the markers at the toes are closest to the ground (i.e., the z-axis measurements are minimized), which yields the footstep instants. The Vicon data can also be used to estimate the shoulder swings among many other gait parameters in possible future studies.

4.2 Radar

Two different algorithms are employed for gait velocity and stride rate extraction with the radar. For estimating gait velocities, the radar data is first passed through a band pass filter. Filtering out very low frequencies removes any remaining DC contamination after mean subtraction and since the gait velocity is not expected to be larger than certain levels (e.g., around 8.5 ft/s, or 100 Hz), high frequencies can also be filtered. Next, the spectrogram of the filtered signal is computed and at each time instant, the frequency with the peak energy level is used to estimate the gait velocity. In order to refine the results further, the band pass filter cut-off frequencies are adaptively adjusted by using the mean of the most recently estimated gait frequencies (or, equivalently, gait velocities). The band pass filter initially passes frequencies in the interval [5, 100] Hz. In the following iteration, the lower cut-off frequency is set to half the mean gait frequency estimated in the previous iteration or to 5 Hz, whichever is largest. The higher cut-off frequency is set to twice the mean gait frequency estimated in the previous iteration or to 50 Hz, whichever is largest. This procedure is repeated 5 times, after which the algorithm was observed to converge.

For stride rate estimation, the raw radar data is passed through a band pass filter, where the lower cut-off frequency is set to twice the gait frequency estimate at each time instant and upper cut-off frequency is set to 250 Hz, and the spectrogram is computed similar to before. Different from the gait velocity estimation algorithm, a median and an averaging filter are applied to the spectrogram at each time instant (along the frequency dimension) in order to reduce noise levels (the signal-to-noise ratio is lower in the case of leg swings due to the smaller reflections). After applying the de-noising filters, the algorithm employs a refined peak selection method both in frequency and in time to find the time instants corresponding to the leg swings.

4.3 Comparing the radar and Vicon results

The data from the radar and the Vicon system were time synchronized and therefore the gait velocity estimates from the two systems can be compared directly. For the stride durations, however, some adjustments are necessary since the Vicon is measuring the footstep instants (when the velocities of the feet near zero), whereas the radar is measuring the instants at which the feet velocities near their maximum during the leg swing. To account for this difference, a constant shift in time is applied to the Vicon data so that the first footstep instant is aligned with the nearest leg swing peak observed by the radar. Such an alignment, as shown in the results later on, works very well in most of the cases. However, when the motion is very irregular, better time alignment techniques might be required in future studies.

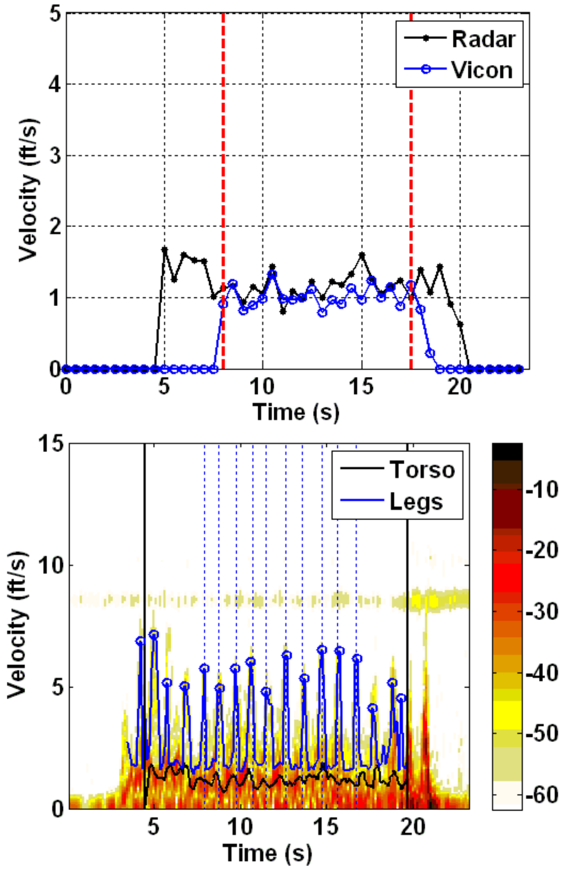

Figure 4 Senior slow walk gait velocity and stride duration plots. The vertical dashed lines in the bottom plot are the Vicon footstep instants shifted in time.

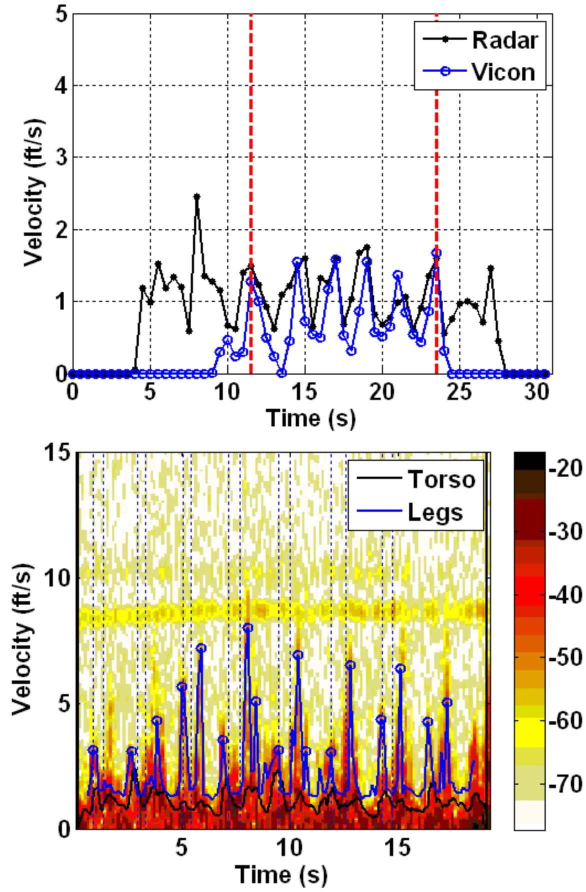

Figure 5 Stroke walk gait velocity and stride duration plots. The vertical dashed lines in the bottom plot are the Vicon footstep instants shifted in time.

5 Experimental Results

5.1 Walk types

There are a total of 9 different walk types considered in our experiments, which are categorized into 3 classes: i) regular, ii) senior and iii) irregular, as shown in Table 1. Three paces: i) slow, ii) normal and iii) fast, have been considered in the first two classes (regular and senior walks). All of these walks have been simulated by a single person. In addition, stroke, dizzy and Parkinson's type of walks have been considered in the last class (irregular walks). For each case, 3 separate tests have been conducted adding up to a total of 27 test cases.

1. Regular	**2. Senior**	**3. Irregular**
Slow	Slow	Stroke
Normal	Normal	Dizzy
Fast	Fast	Parkinsons

Table 1 Walk types considered

5.2 Example cases

In this section, we consider three individual test cases in detail and compare the radar and Vicon estimated gait velocities and stride durations over time. Note that the velocities are averaged over a 0.5 sec. sliding window in the results shown.

First, consider the senior slow walk test #2. The velocity estimates obtained by the radar and Vicon are shown in the top plot in Figure 4. It is observed that the radar can track the velocity very accurately over the entire walking period. In the bottom plot of Figure 4, we compare the stride duration estimates of the radar and Vicon. This plot shows the radar spectrogram together with the velocity estimates (the black curve) and the stride duration estimates (the blue circles indicating the peaks due to the leg swing) obtained by using the algorithms described previously. The dashed vertical lines are the footstep instants estimated by the Vicon system (after applying the aforementioned constant time shift). It is observed that the stride instants from the two systems match very well.

Secondly, we consider a more irregular type of walk, specifically, the stroke walk test #2 in Figure 5. It is observed that the stride instants do not align as well in this

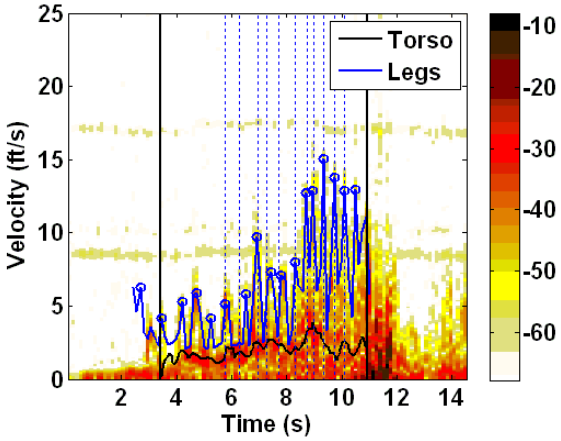

Figure 6 Parkinson's walk stride duration plot. The vertical dashed lines are the Vicon footstep instants shifted in time.

case. The reason is that in this particular walk, the footsteps are not immediately followed by the leg swings, as is the case in a regular walk, but instead the feet are shuffled. There are also other irregularities: for instance, after several normal steps, the person stands on one foot for some time before stepping ahead. Therefore, a constant shift in time does not satisfactorily align each footstep from the Vicon with each leg swing instant from the radar. Moreover, the shuffling of the feet causes the radar spectrogram to be noisier which in turn decreases algorithm performance. It is interesting to note that, in almost all other tests (other than the stroke walks), the constant time shift was sufficient to obtain an accurate alignment from the Vicon and radar (as seen in Figure 9 and Figure 10, which will be explained in the following section).

Finally, we consider the Parkinson's walk test #2. In this walk, the person first walks slowly and then suddenly accelerates. This behavior is readily observed from the radar spectrogram as shown in Figure 6, where the Vicon and radar stride durations again match well.

5.3 Overall results

In this section, we compare the following estimates from the radar and Vicon systems: i) mean velocity, ii) velocity variability (sample standard deviation), iii) mean stride duration, and iv) stride duration variability (sample standard deviation) for all of the 27 test cases. The results are shown in Figure 7, Figure 8, Figure 9 and Figure 10, respectively. In these figures, for each test case, an empty circle denotes the Vicon estimate, whereas a filled circle denotes the radar estimate. The three tests for each walk type are color-coded (black for test #1, blue for test #2, red for test #3). It is observed that the mean velocity, mean stride length and stride duration variability estimates obtained by the radar are very close to the Vicon estimates. An exception is the stroke walk due to reasons mentioned in the previous section. In the case of velocity variability, the differences between the Vicon and radar are rather large. One reason for this phenomenon is that the velocity

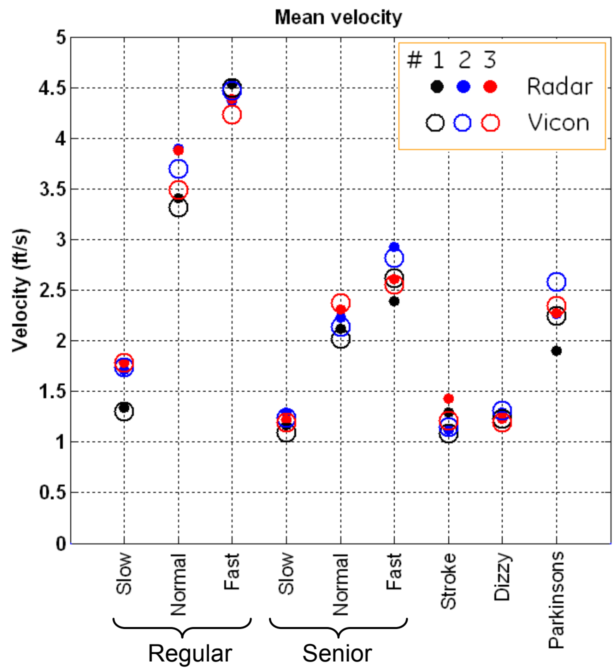

Figure 7 Mean gait velocity estimates obtained from the radar and Vicon.

variability values are relatively small and therefore error levels naturally become higher. However, the trends observed from the radar are still consistent with those observed from the Vicon system.

6 Conclusions

The use of low-cost pulse-Doppler radar for gait characterization, specifically, for estimating mean gait velocity, gait velocity variability, mean stride duration and

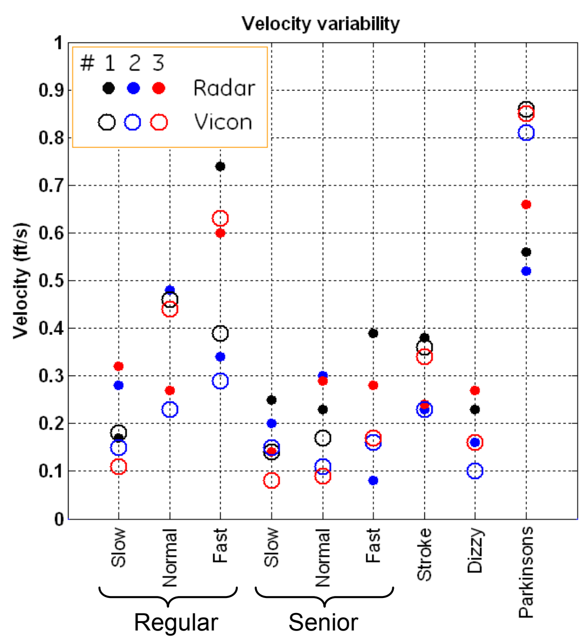

Figure 8 Gait velocity variability estimates obtained from the radar and Vicon.

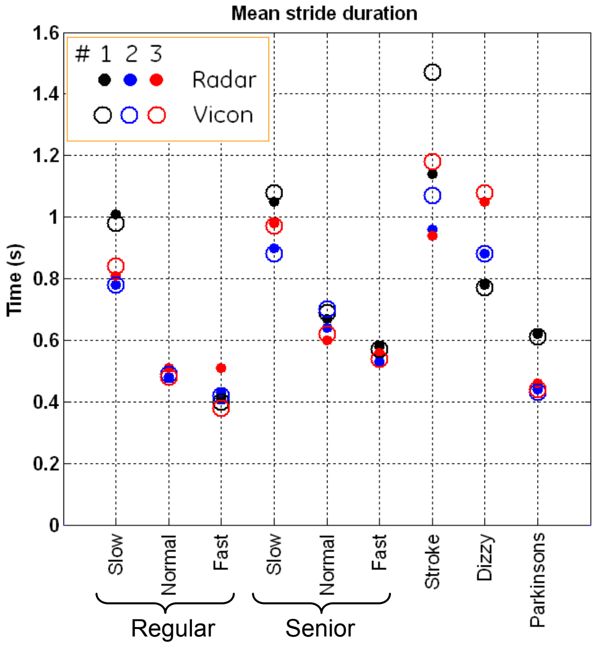

Figure 9 Mean stride duration estimates obtained from the radar and Vicon.

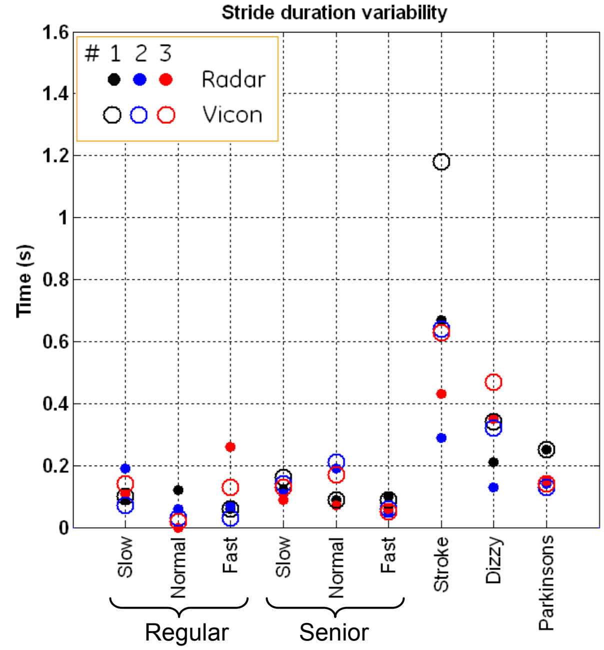

Figure 10 Stride duration variability estimates obtained from the radar and Vicon.

stride duration variability, has been considered in this study. A radar system is especially appropriate for fall risk monitoring in elder-residing homes due to its non-intrusive and versatile nature. In addition, the radar is immune to furniture obstruction and can work in day and night conditions. Two separate algorithms for estimating the gait velocity and stride duration have been proposed. The radar performance has been evaluated by using the ground truth data obtained from a motion-capture camera system. The results indicate that the proposed radar system is a viable candidate for gait characterization. The radar can track the mean velocity, mean stride duration and stride duration variability very accurately. (Note that cadence can also be estimated naturally from the mean stride durations.) It can also estimate the trends in the gait velocity variability although the errors are relatively high when compared to the ground truth.

References

[1] J. Verghese, R. Holtzer, R. B. Lipton, C. Wang, "Quantitative gait markers and incident fall risk in older adults," J Gerontol A Biol Sci Med Sci., vol. 64, no. 8, pp. 896-901, 2009.

[2] Centers for Disease Control and Prevention, National Center for Injury Prevention and Control, 2005, available at: http://www.cdc.gov/ injury/wisqars/index.html

[3] D. Tahmoush, J. Silvious, "Radar stride rate extraction,"
13th International Machine Vision and Image Processing Conference, pp. 128-133, 2009.

[4] M. Otero, "Application of a continous wave radar for human gait recognition," The MITRE Corporation, 2005.

[5] J. L. Geisheimer, W. S. Marshall, E. Greneker, "A continuous-wave (CW) radar for gait analysis," Signals, Systems and Computers, vol. 1, pp. 834-838, 2001.

[6] C. Hornsteiner, J. Detlefsen, "Characterisation of human gait using a continuous-wave radar at 25 GHz," Adv. Radio Sci., vol. 6, pp. 67-70, 2008.

[7] A. Ekimov, J. M. Sabatier, "Human motion analyses using footstep ultrasound and Doppler ultrasound," J Acoust Soc Am., vol. 123, no. 6, pp. 149-54, 2008.

[8] Z. Zhang, P. O. Pouliquen, A. Waxman, A. G. Andreou, "Acoustic micro-Doppler radar for human gait imaging," J Acoust Soc Am., vol. 121, no. 3, pp. 110-113, 2007.

[9] K. Kalgaonkar, R. Bhiksha, "Acoustic Doppler Sonar for gait recognition," Mitsubishi Electric Research Laboratories, Inc., 2007.

[10] Information available at:
http://www.gesecurity.com/portal/GESDownload?ID=773&DID=773&documenttype=Data%20Sheet

[11] Information available at:
http://www.vicon.com/products/viconmx.html

[12] R. Trevino, M. Frye, C. Qian, "Development of a full body balance model using an artificial neural network approach," IEEE Int Conf on Systems, Man and Cybernetics, pp. 4238-4242, 2009.

[13] R. A. Bachschmidt, G. F. Harris, G. G. Simoneau "Walker-assisted gait in rehabilitation: a study of biomechanics and instrumentation," IEEE Tr on Neural Systems and Rehab Eng, vol. 9, no. 1, pp. 96-105, 2001.

[14] A. V. Oppenheim, R. W. Schafer, "Discrete-Time signal processing," Prentice-Hall, Englewood Cliffs, NJ, pp.713-718, 1989.