# NEW ANALYSIS OF RADAR MICRO-DOPPLER GAIT SIGNATURES FOR REHABILITATION AND ASSISTED LIVING

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## ABSTRACT

Radar for indoor monitoring has recently attracted much attention that is driven by its safety, privacy-preserving, and non-wearable sensing mode. Micro-Doppler signatures offered by radars operating in the K-band can disclose intricate details and characteristics of human gait. This paper reveals key Doppler features associated with human legs in gait motions which have been overlooked or ignored by existing work in this area, including biomechanics simulators and electromagnetic modeling. These features are used to detect gait abnormalities and distinguish gait from other translational motions which exhibit similar signatures in the time-frequency domain, such as assistive walking devices.

***Index Terms—*** human gait, micro-Doppler signature, time-frequency analysis, assisted living

## 1. INTRODUCTION

Worldwide, the elderly population aged over 65 years is growing [1]. In particular, its ratio to the age population over 20 is predicted to be 50% by 2050 [2]. Older adults desire to stay at their own homes as long as possible. However, a major challenge hindering seniors to live independently at their own home is the risk of falling. According to the World Health Organization (WHO) falls are the second leading cause of death in the elderly population aged over 65 [1]. Changes in gait characteristics have been shown to be associated with the risk of falling [3]. Therefore, it is important to detect gait abnormalities and monitor alterations in walking patterns over time.

Radar-based indoor monitoring of humans has become of increased interest in recent years and is promising to become a leading technology in assisted living in the near future [4, 5]. Radar is able to reflect nuances in target motions and it is well suited to detect falls and screen changes in gait characteristics while enabling the elderly to live independently at home.

Human motion activities may be recognized using radar by exploiting features caused by the micro-Doppler (mD) effect, so-called micro-Doppler signatures [6]. They are represented in a joint time-frequency (TF) domain that provides an additional time dimension to exploit the time-varying nature of human locomotion. The mD signatures reflect human kinematics by capturing velocity, acceleration, and rotation of individual body parts and are the basis of discriminating movements. The advantage of mD signatures is that they are not sensitive to range, lighting conditions, and background complexity that usually affect visual images.

Existing work in the field of radar-based gait analysis focuses on extracting the stride rate information and walking velocity to assess human walking patterns. Using a continuous wave radar, Otero [7] extracts both these features from the cadence-velocity diagram to detect and classify humans. Orović *et al.* [8] propose a human gait classification method that relies on the motion signature from arm and leg movements. Only few works consider human movements with the radar having a back-view, see e.g. [9, 10]. However, none of them elaborates on the differences in mD gait signatures when receding from or approaching to the radar system.

Besides empirical studies of human gait, various walking models have been developed to study mD signatures of human gait in more detail. A widely used empirical model is the Boulic-Thalmann model [11]. It describes a global human walk model derived from a large number of biomechanical experimental data based on averaging parameters. Irrespective of the model used, the conversion of the time-varying trajectories of the different body parts to radar scattered electromagnetic (EM) data, that can be used to generate mD signatures, may be achieved using simple modeling or complex full wave EM prediction techniques [12, 13]. Also, radar Doppler signatures of humans are simulated utilizing data obtained from motion capturing systems [14] or using computer animation data [15].

In this paper, we provide a novel analysis and interpretations of the mD signature of human gait. Based on extensive experiments conducted at the Radar Imaging Lab, Villanova University, we point to impulsive-type and sinusoidal TF features associated with leg motion when the radar is placed in a

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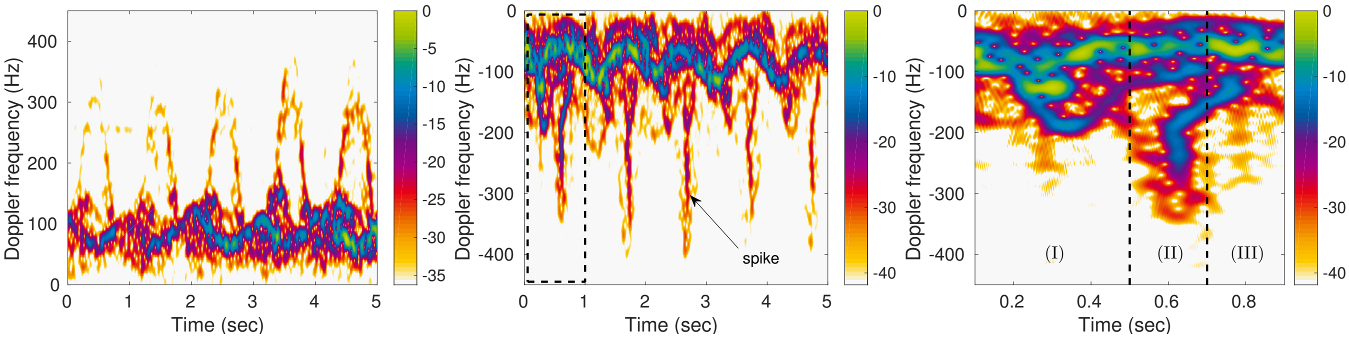


(a) (b) (c)

**Fig. 1**: Spectrograms of the same person walking slowly (a) towards and (b) away from the radar. (c) Extracted mD stride signature from the spectrogram in (b) that corresponds to a swing phase of one leg and shows a spike.

non-oblique back-angle view. We show that these features are substantially different from those corresponding to the case where the radar is placed in front of the human and that they are absent in existing human mD signature simulators utilizing e.g. kinematic models such as the Boulic-Thalmann human walking model. In fact, there has not been any work in the literature distinguishing gait characteristics in towards- or away-from-radar motions. The salient features are the key to understanding the fundamental composition of mD gait signatures and, as such, assessing abnormalities in physical and cognitive conditions of the elderly.

## 2. RADAR MICRO-DOPPLER GAIT SINGNATURES

### 2.1. Time-Frequency Representation

Due to its highly non-stationary and multi-component nature the radar return signal of a walking person is best analyzed in the TF domain [6]. The most common choice of time-frequency representation (TFR) is the spectrogram, which reveals characteristic mD signatures of target motions. The spectrogram is given by the squared magnitude of the short-time Fourier transform of the back-scattered radar signal. In the following, we will use the spectrogram to interpret human mD gait signatures.

### 2.2. Experimental Setup

The measurements presented in this work were obtained using a UWB radar [16]. The radar was set to FMCW mode with linear frequency modulation sweeps and a carrier frequency of 25 GHz. Doppler filtering was applied to obtain the velocity information of the target by utilizing the phase shift between different sweeps. All measurements were conducted in a semi-controlled lab environment at the Radar Imaging Lab at Villanova University, PA, USA. In total seven subjects were asked to walk slowly back and forth between two points in front of the radar, approximately 4.5 m and 1 m from the antenna feed point. The feed point of the antenna was positioned 1.15 m above the floor. Data were collected with a non-oblique view to the targets and at a $0°$ angle relative to the radar line-of-sight. All subjects were asked not to swing their arms. A list of the performed walks is given in Table 1. In total, a set of 42 measurements are considered.

**Table 1**: Walking styles being analyzed.

| Walking style | Description of the walk | # of Exp. |
|---|---|---|
| Normal | slowly without arm swinging | 7 |
| Assisted | slowly with 1 cane | 18 |
| | slowly with 2 canes | 9 |
| Abnormal | without bending knees | 2 |
| | bending only one knee | 6 |

### 2.3. Biomechanical Interpretation

Figure 1(a) shows a typical spectrogram of a human walking towards the radar system. The mD signatures of the feet show a clear sinusoidal shape, representing five steps here. Note that the walk is rather slow, mimicking an elderly person, and there is no arm swinging involved. In all figures, the color indicates the received power in dB, which is proportional to the cross-section area of the target. In contrast, a typical signature of a person walking away from the radar is shown in Figure 1(b). Clearly, the mD signatures of the strides are different compared to the towards-radar measurement. By carefully examining numerous human gait signatures from experimental radar data, we next give a biomechanical interpretation of the observed away-from-radar mD stride signatures.

To gain insights on the above differences, Figure 1(c) shows an excerpt of the spectrogram in Figure 1(b) corresponding to the swing phase of one leg during the human walking cycle. The swing phase consists of an acceleration, mid-swing and deceleration phase [6]. In the acceleration phase, marked with (I) in Figure 1(c), the heel comes off the ground and the thigh swings forward. As the latter is considered a pendulum-like motion, it reveals a sinusoidal-shaped mD signature in the spectrogram, which can be seen between 0.2 and 0.5 s with a maximum Doppler frequency of 200 Hz. In the mid-swing phase, (II), the swinging of the foot causes the highest Doppler frequency, i.e., it has the highest velocity, here up to 350 Hz between 0.5 and 0.7 s. Again, due to its pendulum-like motion the mD signature has a sinusoidal shape. Embraced in the foot signature, the lower leg signature becomes visible in the form of a spike, i.e., an impulse-like behavior in the TF domain at 0.6 s. Accordingly, there are two dominant signatures that constitute the lower leg's mD signature when the radar is facing the back of the human. However, due to the larger cross-section area in comparison to the foot, the calf reveals a higher energy in the TFR and is eclipsing the foot signature. Hence, the foot signature may not be noticeable by standard feature extraction techniques. The spike appears during the mid-swing phase when the swinging foot causes the highest Doppler shift corresponding to its highest velocity. Progressing in time, see 0.6-0.8 s, the spike passes into a half sinusoidal-shaped mD signature. This phase represents the straight leg swinging to the front of the body during the deceleration phase, (III). This part of the signature is attributed to the reflections from the upper calf. It experiences the same deceleration as the foot, for which reason the signature is in parallel with the foot's signature. However, the calf's motion leads to a smaller Doppler frequency as the swinging angle with respect to the knee joint is smaller compared to that of the foot.

In order to support the previous observations we conducted an experiment where a person was walking away from the radar, while the lower legs up to the knee area were covered by absorbers that were moved along on the floor. The resulting mD signature is shown in Figure 2(a). Obviously, the characteristic spike signatures are absent, underscoring the fact that they are due to EM wave reflections from the lower legs. The spectrogram reveals the torso's motion, which can be identified by the maximum power, as well as the mD signature of the upper legs. The latter appears shortly after the maximum torso Doppler frequency and is typically of sinusoidal shape due to its pendulum-like motion.

## 3. DETECTION OF GAIT ABNORMALITIES

In order to study the contribution of individual body parts to the overall mD gait signature, it is inevitable to resort to simulations based on mathematical or empirical models. A widely used empirically developed model to generate mD signatures of walking humans is the Boulic-Thalmann model [11]. The signatures are generated by utilizing a global human walk model describing the position and orientation of 12 human body parts. A simulated mD signature of a human walking away from radar is given in Figure 2(b) using the implementation given in [6]. We observe that it is fundamentally different from that of real measurements, particularly because it does not show the impulsive-like signature of the lower leg.

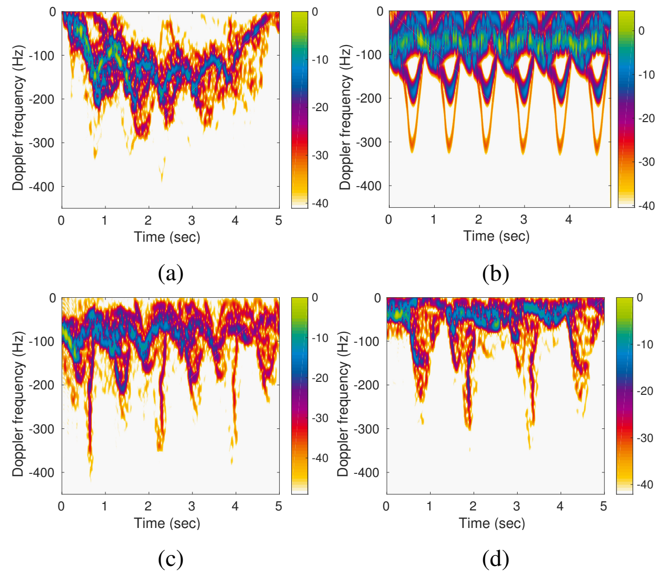


**Fig. 2**: (a) Spectrogram of a person walking away from radar while an absorber covers the lower legs by being moving along on the floor. (b) Simulated mD signature of human walking away from radar using the global walking model proposed in [11]. (c) Spectrogram of a person walking abnormally away from the radar, i.e., the knee is not bent in the second, forth and sixth stride signature. (d) Spectrogram of a person walking slowly with a cane away from radar. The cane motion is out of sync with the legs' motion, i.e., distinct cane and leg signatures are revealed (cane - leg - leg- cane).

Using the previous analysis, we aim to detect abnormalities in human gait. A walk is considered abnormal if the person is e.g. limping which is characterized by unbent or slightly bent knees compared to a normal walk. A spectrogram of a person walking with only one knee bending is shown in Figure 2(c). The mD signatures of the legs clearly differ: the bending of the knee while taking a step leads to the characteristic spike signature, as previously discussed, whereas an unbent knee reveals two overlaying sinusoidal signatures caused by swinging the straight leg forwards.

Here, we also consider a walk using assistive walking devices, such as a cane, as abnormal, indicating a level of physical or cognitive impairment. Figure 2(d) shows the spectrogram of a person walking with a cane, where the cane is moved independently from the legs. Clearly, the cane has a different signature compared to a leg.

Utilizing wavelet transform we aim to capture these salient mD features in away-from-radar measurements from the back-scattered radar signal for discriminating normal from abnormal mD stride signatures.

### 3.1. Wavelet Transform

The leg's movement reveals high-frequency components of short bursts. The Fourier transform is unsuitable for analyzing signals of this kind because it has the limitation of constant time and frequency resolutions for both low and high frequencies. Using the wavelet transform (WT), the resolution is varied with scale (proportional to frequency), meaning that a higher time resolution can be achieved for high frequency components, which is particularly relevant for our application. The continuous wavelet transform is defined as [17]

$$\mathrm{WT}(t, a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(\tau) h^* \left( \frac{\tau - t}{a} \right) \mathrm{d}\tau, \tag{1}$$

where $h(\cdot)$ is the wavelet function, and $a$ is the scale.

### 3.2. Feature Extraction

A major challenge in human gait classification is the choice of features to discriminate different walking styles. Many works have presented extraction methods for human motion classification and recognition [9, 18, 19]. Here, we use time-scale features from the WT of the back-scattered radar signal to classify motion abnormalities in mD stride signatures.

#### 3.2.1. *Prescreening*

In order to find the time location of an mD stride signature, we use the wavelet coefficients at scale four, where the used wavelet function is the reverse biorthogonal 3.3 (rbio3.3) as in [20]. Here, scale four corresponds to a Doppler frequency range of 320 to 640 Hz and was found to best reveal the impulsive-like behavior of the spike in the frequency domain. The stride signature location in time is determined by detecting maxima in the short-time energy of the corresponding wavelet coefficients $\mathrm{WT}(t, 4)$ obtained using (1) as

$$D(k) = \sum_{t=1}^{N} \{w(t)\, \mathrm{WT}(t + k \cdot N/5, 4)\}^2, \tag{2}$$

where $w(\cdot)$ is a Hamming window of length 0.5 s, $N$ is the window length in samples, and $k$ denotes the frame index. The windows overlap by 80%, i.e., the resolution in time for detecting a stride signature is 0.1 s.

#### 3.2.2. *Time-scale Features*

We extract features from the time-scale domain by forming a feature vector for each detected frame during prescreening as follows. Let $E(t, a)$ be the relative energy of a wavelet coefficient at scale $a$ and time lag $t$, we calculate an energy profile as

$$F(t) = \sum_{a=1}^{M} E(t, a), \tag{3}$$

where $M = 8$ is the number of scales used. Next, we determine the time-span occupied by the signature by thresholding the energy profile $F(t)$ at $20\%$ of its maximum. The rationale behind it is that due to its impulsive-like behavior the normal stride signature spans a much shorter interval than abnormal ones. Thus, the first feature is defined as the time duration $t_{\text{span}}$ that contains the wavelet coefficients with the highest energy over all scales. Further, we observe that the spike manifests itself in higher frequency bands or scales. Hence, we define the sum of the relative energy of the wavelet coefficients at scale $a$ as

$$G(a) = \sum_{t=1}^{N} E(t, a), \tag{4}$$

where $N$ is the number of times samples in the detected frame. The final feature vector for a detected mD stride signature is then given by

$$\mathbf{v} = [t_{\text{span}}\; G(1)\; G(2) \ldots G(M)]^T \,. \tag{5}$$

### 3.3. Micro-Doppler Signature Classification

From the experiments listed in Table 1, 216 mD stride signatures were detected by the prescreener with a false alarm rate of 6% and a missed detection rate of 5%. There are 104 normal gait signatures and 89 abnormal signatures available. Using the feature vector defined in (5), we train a linear support vector machine [21, 22] using 70% of the detected frames, whereas the remainder is used for testing. Classification results are shown in Table 2. All rates are obtained by averaging 100 classification results, where training and test samples were randomly chosen. The overall detection rate is $76\%$. Note that we only evaluated measurements of 5 s duration with 3-7 stride signatures present. In practice, the observation time could be much longer and, additionally, the classifier could be trained to be person specific, which would likely improve the classification performance.

**Table 2**: Correct classification rates for mD stride signatures.

| | | *predicted* | |
|---|---|---|---|
| | | normal | abnormal |
| *true* | normal | 80% | 20% |
| | abnormal | 29% | 71% |

## 4. CONCLUSION

This paper contributes to the growing subject of assisted living and focuses on the radar technology for indoor monitoring of human motions. Experimental results of the gait, when interrogated by a K-band radar, depicted a new and persistent feature of the leg kinematics. An impulse-like behavior in the spectrograms was revealed when the radar is placed facing the human back. Forming characteristic mD signatures, they lend themselves to distinction of normal walk from abnormal walking patterns or the use of an assistive walking device. This will enable monitoring of progression in recovery from physical and possibly cognitive impairments.

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