Radar Micro-Doppler for Long Range Front-View Gait Recognition

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Abstract—We seek to understand the extraction of radar micro-Doppler signals generated by human motions at long range and with a front-view to use them as a biometric. We describe micro-Doppler algorithms used for the detection and tracking, and detail the gait features that can be extracted. We have measurements of multiple human subjects in outdoor but low-clutter backgrounds for identification and find that at long range and front-view, the probability of correct classification can be over 80%. However, the micro-Doppler signals are dependent on the direction of motion, and we discuss methods to reduce the effect of the direction of motion. These radar biometric features can serve as identifying features in a scene with multiple subjects. Ground truth using video and GPS is used to validate the radar data.

I. INTRODUCTION

For observing humans, radar has some advantages over other sensors. The transmitted radar signal is insensitive to day and night, while smoke, dust, and fog only slightly reduce the signal. This is why radar can be used in situations where other sensors give low performance or cannot be used at all. Radar signals also penetrate most clothing, preventing disguise from being effective. Using radar in conjunction with other biometric identification systems can help to reduce the susceptibility of the combined system to poor visibility conditions and intentional deception.

Detailed radar processing can reveal many characteristics of human motions and of the human body, including gait characteristics. Micro-Doppler signals refer to Doppler scattering returns produced by the motions of the target other than gross translation. Parts of the human body do not move with constant radial velocity; some of the small micro-Doppler signatures are periodic and therefore analysis techniques can be used to obtain more characteristics [1, 2]. Micro-Doppler gives rise to many detailed radar image features in addition to those associated with the bulk target motions. Modulations of the radar return from arms, legs, and even body sway are being investigated by researchers [3, 4, 5]. There are also some tutorials on micro-Doppler phenomena [2, 6, 7].

Several micro-Doppler models have been developed which analyze and attempt to predict the human micro-Doppler response [8, 9, 10]. Extraction of micro-Doppler features is typically performed in the joint time-frequency domain. Chirplet techniques can be used to perform feature extraction [5, 11] as well as linear FM basis decomposition [12]. Independent component analysis (ICA) can be used to extract independent basis functions from the spectrogram to be used as features in a classifier [13]. Micro-Doppler signatures have been suggested as a biometric [14], and micro-Doppler features have been used in classification algorithms in [14, 15, 16, 17]. Micro-Doppler signatures and direction-of-arrival (DOA) estimates have been extracted at over nine meters range through a brick wall [18]. Fully polarimetric human radar signatures at different approach angles with respect to the radar have been collected [19]. Automatic target classification has also been done on data including multiple humans, wheeled vehicles, clutter, and animal classes [20]. This paper attempts to extract pure gait characteristics from the radar data and analyze the gait characteristics as a biometric.

There are several silhouette-based video approaches for 2D gait recognition [21, 22, 23], but only few are tested on front-view images [24, 25, 26]. They present interesting results on a limited number of subjects or low recognition rates on a larger dataset. Video techniques are also often tested at a distance of less than 100 meters or by synthesizing the sagittal view of the human body from other arbitrary views [27, 28, 29]. However, it has to be noted that the fusion of radar and video techniques would provide a true 3D motion at long ranges.

Section II of this paper discusses the micro-Doppler phenomena that is being used to determine human motion from radar signals. Section III discusses the feature extraction. The usefulness of the features in classification is discussed in Section IV, while section V discussed reducing the angular dependence of radar micro-Doppler on the classification. Section VI discusses the potential of sensor fusion of radar and video techniques, while section VII discusses model-based approaches. The conclusion and future work is in Section VIII.

II. RADAR MICRO-DOPPLER PHENOMENOLOGY

The equation for computing the non-relativistic Doppler frequency shift, \( F_d \), of a simple point scatterer moving with speed \( \nu \) with respect to a stationary transmitter is

\[
F_d = \frac{\gamma \nu \cos \theta \cos \phi}{c}
\]

where \( \gamma \) is the frequency of the transmitted signal, \( \theta \) is the angle between the subject motion and the beam of the radar in the ground plane, \( \phi \) is the elevation angle between the subject and the radar beam, and \( c \) is the speed of light. For complex objects, such as walking humans, the velocity of each body part varies over time. Additionally, the radar cross-section of various body parts is a function of aspect angle and
frequency. Ka-band frequencies have the potential to measure very fine details of the micro-Doppler spectrum [5].

The breakdown of the micro-Doppler signals from different body parts of a person walking is shown in Figure 1. The spectrogram, which is the short time Fourier transform of the radar data, is shown in Figure 2 and this represents the summation of the signals from all of the separate body parts shown in Figure 1. We are going to extract the signal presented by the torso (stomach) and try to determine the period of its motion, which is associated with the stride rate of the person’s gait. Alternatively the stride rate can be determined from the leg swing. We will also be looking at the correlation of the spectrograms of different subjects to each other to determine whether robust classification using radar micro-Doppler will be possible.

![Fig. 1. Simulated Doppler motions for a man walking, with the signatures of each part of the man displayed. This simulation is noiseless. Note that body-part interactions are eliminated from this plot, and this simulated motion that is in the radial direction to the radar.](image1)

III. FEATURE EXTRACTION

Gait features can be extracted from the spectrogram and then used to perform a classification. An example of a spectrogram of two walking humans is shown in Figure 3. This is a simplified case of how a radar can be used as a biometric to identify people in a scene. The first gait feature we extract from the spectrogram is the stride rate. There are five parts to the approach to extract the stride rate from the radar data: person detection and range gating, Doppler filtering to eliminate clutter, torso extraction from the spectrogram, torso filtering to reduce noise, and peak period extraction using a Fourier transform.

![Fig. 3. Spectrogram of two humans walking in different directions. Note that here the leg swing is not that easily discernable, but the torso line is still strong. Comparing this data to the cleaner data in Figure 2 shows the variability in data quality that must be addressed by algorithms that utilize radar data.](image2)

Once features like stride rate are extracted, they can be used as a biometric and their features can be compared to other dismounts whose tracks have been lost to determine whether the dismount has reappeared or whether the detection is a new dismount. Future work will be done to compare classifiers, though it has been noted that the choice of classifier is not as important as the choice of feature when classifying micro-Doppler measurements [30]. In addition to gait features, the radar cross section (RCS) features from the radar can also be used to develop a biometric radar signature.

![Fig. 4. Standard deviation detection of Ku-band RCS of two dismounts walking past each other that is used for detection. Note that the position can easily be isolated to within a meter in range. This data corresponds to the spectrograms from Figure 3. The two subjects cross, and the tracking approach can no longer tell which person is which. Here is where utilizing the micro-Doppler gait signature can improve tracking. This data is at short range.](image3)

A. Detection, Tracking, and Range Gating

Detecting subjects in radar data has been extensively researched, and a complete discussion is outside of the scope of this paper. Some of the detections used in this paper were
found by taking the standard deviation of the range-gated signal as is shown in Figure 4. This method performed well enough for this application by providing a rough distance to the walking subjects. Once the transmitter and receiver are synchronized, the integrated high-speed electronics digitizes the data and the range gating can be performed in software [31]. Gating technology lets operators select a specific slice of space, so they view just the target area. Through range gating, the radar obtains smoother, more accurate images with less noise. The range gating also helps to isolate an individual signature, though there can still be confusion when subjects are in the same range gate. When subjects are in the same range gate, their individual signatures will combine together unless there is suitable angular resolution to the radar system.

An algorithm was developed to track subjects and extract the micro-Doppler motions centered on them as they moved in time. The technique is specific to searching for single moving subjects in the beam of the radar. As range cells are scanned, the mean of the negative frequency Doppler cells is compared with the mean of the positive frequency Doppler cells. An exclusion zone around the clutter Doppler cells is created to prevent fluctuations in clutter from causing extraneous background signals. The standard deviation of the imbalances over all ranges is used to set a threshold. Range cells exceeding this threshold are flagged as having a possible target. If the imbalance is negative, negative Doppler frequencies dominate and an outbound target is indicated. A positive imbalance results when positive Doppler frequencies dominate, indicating an inbound target. A sub-image is extracted around flagged range gates. The sub-images are then sequenced in time. This provides a continuous video-like motion capture centered on the subject.

Once the range gates with the subject are isolated and stitched together in time, the spectrogram is created and then filtering can be done in Doppler, or in velocity, to remove the zero-velocity clutter line. This is done to remove the potentially noisy area of the spectrogram and isolate the signals of the moving subject from the slowly moving background clutter. This is the thick line around zero velocity in Figure 3. Clutter subtraction is also a large area of research in radar analysis [32], but in this case the simple digital filtering in velocity can be used because the signal velocity is significantly away from the clutter line and this is a low-clutter environment. This approach is also computationally efficient. In other cases where the target motion is slow or the clutter line is stronger, more complicated approaches to clutter line suppression are necessary.

### B. Torso Extraction, Filtering, and Peak Detection

The torso line is isolated from the spectrogram by isolating the maximum signal for each time from the spectrogram. This approach assumes that the signal-to-noise ratio of the radar is quite good. Otherwise this type of extraction can be extremely noisy. The extraction using this technique on human targets is still extremely noisy, as can be seen in Figure 5. This is because the radar return is often not isolated to the torso line, but knee and arm motions can also be picked up as the strongest signal depending on the angles and RCS of each body part. The result of the torso extraction is converting a noisy 2-D image into a noisy 1-D function that is focused on the torso signature.

![Figure 5. Torso line extracted from the spectrogram in Figure 3 of a man walking. Note the noisiness around time with no motion at 20 seconds.](image)

Torso filtering can compensate for the noisy torso extraction. Using median filtering can create an average torso line that is not distorted by outliers. The filtered torso line is shown in Figure 6. Median filtering involves selecting a window size in time and performing a median operation over the data. The median is much less sensitive to outliers than an average and the median is described as the number separating the higher half of a sample from the lower half. The median is a special case of a low-pass filter which is less sensitive to outliers but which acts like a standard low-pass filter when the window is large enough.

![Figure 6. Filtered torso line extracted from the spectrogram of a man walking.](image)

Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise [33]. Median filtering is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges.
We perform median filtering of the torso line in one dimension.

Now that the data has been converted to a 1-D function and filtered to reduce the noise, the peak period and thus the stride rate can be extracted. The stride rate is determined by first removing the average of the torso line to remove the zero hertz line, then taking the Fourier transform and measuring the peak frequency [34], which is the stride rate in Hertz. The Fourier transform of Figure 6 is shown in Figure 7. The extraction of the peak from data with so little noise can be done by simply taking the maximum of the power spectrum. The low-frequency noise has been suppressed by removing the mean of the data to be transformed, and the data was taken from times when the subject was in motion.

![Figure 7](image)

**Figure 7.** Stride rate extracted from the filtered torso line. The shape in frequency space was more accurate in classification than the stride rate. This matches the less accurate video measurement of the stride rate.

IV. CLASSIFICATION

Now that the stride rate could be reliably extracted, we wanted to determine how effective stride rate could be as a feature for classification. We had experiments with multiple people moving together, mixing, and then separating again. Classic radar approaches could detect the people, but once they had mixed into the same range gate they would become indistinguishable. We ran an experiment to determine whether radar could enable the identification of people in a small group. Experiments involving two human subjects were performed to determine whether algorithms could be devised that discriminate and maintain track of two interacting individuals. In the experiment, subjects stood 25 meters apart and walked toward and past each other, providing front and back views, respectively. They then turned and retraced their path. Range profiles were generated and the standard deviation of the radar cross section (RCS) of each range bin was computed over 0.1 seconds. This motion is shown in Figure 4.

The spectrograms were computed and the stride rates were extracted. The inter-person stride rates did vary, but the intra-person stride rates varied more over the duration of the experiments. The gait feature of stride rate did not lead to effective classification by itself, but the incorporation of less variable gait features should improve the classification technique.

Before extracting more gait features, we evaluated the potential effectiveness of radar micro-Doppler by using the correlation of the spectrograms from previous time periods to determine identification. We have a radar experiment on eight subjects walking the same path in the same outdoor terrain. We broke their motion up into two-second intervals and created test sets and a signature database. We then calculated the three-dimensional correlation (range, Doppler, and time) of the test cases with the signature database. We used the maximum correlation as a distance function and used a nearest neighbor classification approach to achieve an accuracy of over 80% on front-view, long range subject recognition. However, as the angle $\theta$ varied, the classifications degraded significantly to below 40% at the worst angle. This is because the size of the Doppler is dependent on the angles of motion, as is shown in Equation 1. The micro-Doppler is therefore compressed, and less distinguishable. We also noticed a stronger tendency to misclassify subjects who just began walking as their gait had not entirely settled.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>COMPARISON OF TECHNIQUES</th>
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<tr>
<td>Chen 2007 [24]</td>
<td>65%</td>
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V. REDUCING THE ANGULAR DEPENDENCE

The angular dependence of micro-Doppler classification was investigated in order to try to mitigate the effect on classification algorithms. Measurements were done across a range of azimuth and elevation angles in order to characterize the micro-Doppler signature response of humans with respect to angle. The result of these experiments in azimuth is shown in Figures 8 and 9. The measurement of the micro-Doppler is significantly more difficult as the motion approaches an angle $\theta$ of ninety degrees (perpendicular to the path of the radar illumination).

![Figure 8](image)

**Figure 8.** Measured spectrogram of a man walking at an angle of $(\theta, \phi)$ of $(0, 15)$ which is close to front-view.

The degradation of the micro-Doppler signature with elevation is not as severe. This is due to the coordinated rise
and fall of the body with a walking motion. These results imply that measurements with reduced but still viable signal levels can be made with a system that is at a higher elevation. Measurements at sixty degrees of elevation show measurable Doppler even at $\theta$ of ninety degrees, as shown in Figure 10. However, as the elevation increases, the offset from the zero velocity clutter line is diminished, making detection more challenging. This is especially true for measurements at ninety degrees of azimuth since the motion is centered at the clutter line.

VI. SENSOR FUSION

The approach of using radar micro-Doppler to measure gait can be effective at front-view and at long range, but has difficulty with the sagittal view. Conversely, video capture of gait has more difficulty at front-view gait recognition, with some notable exceptions [35]. This implies that the incorporation of both techniques would provide an improved overall system with a simple fusion at the classification level. A more detailed sensor fusion could extract actual 3D motion at long range from subjects moving in any direction. The accurate distance information measured by the radar system can even be used to calibrate the motions measured in the video. Additionally, the radar can provide triggering information for the video. This type of fusion at the data level is more complicated but holds the promise of being able to perform identification at long range and with a single camera/radar system as well as current 3D gait recognition systems with multiple set cameras at very short range.

VII. MODEL-BASED MICRO-DOPPLER GAIT DETECTION

The approach that has been used so far for classification did not take advantage of our detailed knowledge of the motions of the human body. However, the modeled spectrograms that we can create are approaching the point where model-based methods can be applicable, as is shown in Figure 11. Many of the parts of the motion have been simulated and decomposed, including foot and torso motion. However, this methodology is not yet robust enough in the analysis of micro-Doppler for identification.

VIII. CONCLUSION

The extraction of gait features from radar data has been shown to be feasible, and a straight-forward approach to determining the stride rate has been demonstrated, as well as the extraction of the torso line. The use of stride rate alone did not provide effective classification on its own, but could be part of a larger feature set for classification. We found that the radar micro-Doppler data did provide a significant amount of information through calculations of the 3D correlation of motions with captured signatures, enabling a classification accuracy of better than 80% of front-view long-range gait recognition. This demonstrates that there is enough information in radar data for gait recognition. We also outlined an approach for long-range 3D motion capture and gait detection.

REFERENCES


Fig. 11. Measured spectrogram of a man walking compared to a simulated model. Much of the structure is apparent, but the model should be improved before attempting model-based gait recognition.