Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Stride Rate in Radar Micro-Doppler Images

Dave Tahmoush and Jerry Silvious
US Army Research Laboratory
Adelphi, MD, 20783

***Abstract*— We extract gait information from the radar micro-Doppler signals generated by human motion. We demonstrate the extraction of information associated with gait, especially the stride rate, from simulated and measured radar data. We describe micro-Doppler algorithms used for the extraction of stride rate, the radar sensors used for the measurements, and detail the gait features that can be extracted. We make measurements of human subjects in realistic outdoor clutter backgrounds. These features help identify subjects in a scene. We gather ground truth using video to validate the radar data. We conclude that although we can extract gait features like stride rate from radar data, more features need to be extracted before reliable identification or classification can be determined.**

***Keywords*—Radar, micro-Doppler, stride rate, gait**

I. INTRODUCTION

For observations of 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, tracked vehicles, clutter, and animal classes [20]. Micro-Doppler system performance variation with angle has been analyzed [21]. Micro-Doppler phenomena have been investigated in frequencies as low as UHF [22]. This paper attempts to extract pure gait characteristics from the radar data and analyze the radar characteristics for potential use as a biometric.

Section II of this paper discusses the micro-Doppler phenomena that are being used to develop radar biometrics. Section III discusses the sensor system, while Section IV demonstrates the data analysis and feature extraction. The usefulness of the features in classification is discussed in Section V, while the conclusion and future work is in Section VI.

II. PHENOMENOLOGY

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

$$F_d = F_t \frac{2v}{c} \cos\theta \cos\phi$$

where F_t is the frequency of the transmitted signal, θ is the angle between the subject motion and the beam of the radar in the ground plane, ϕ 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, of the simulated data is shown

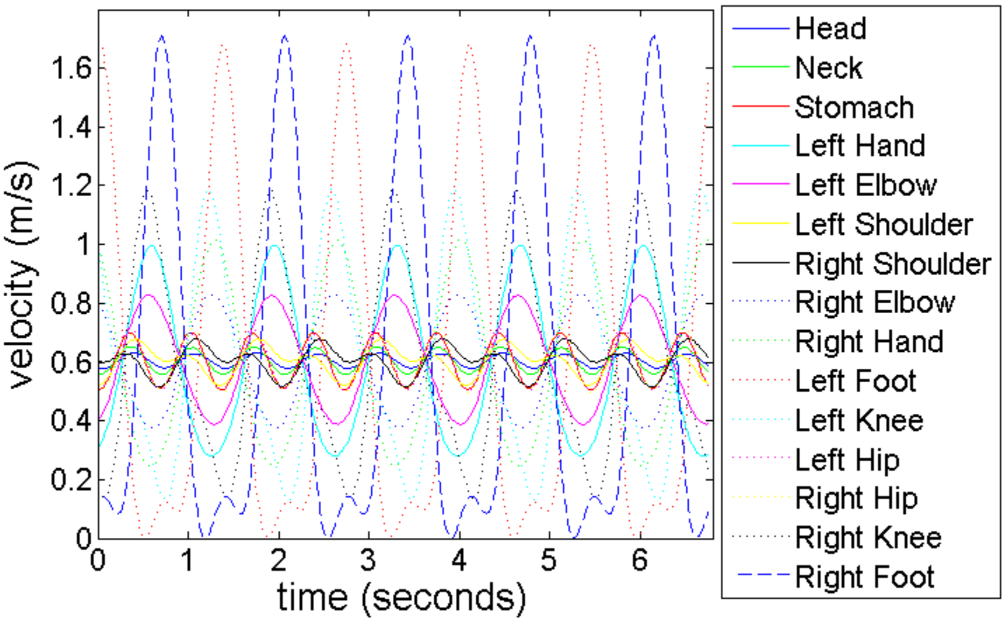


Figure 1. Simulated Doppler motions for a man walking, with the signatures of each part of the man displayed. This simulation is noiseless. Note that body-part interactions are eliminated from this plot, and this simulated motion that is in the radial direction to the radar.

in Figure 2 and this represents the summation of the signals from all of the separate body parts shown in Figure 1. This can be compared to a measured spectrogram of a person walking in Figure 3. 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.

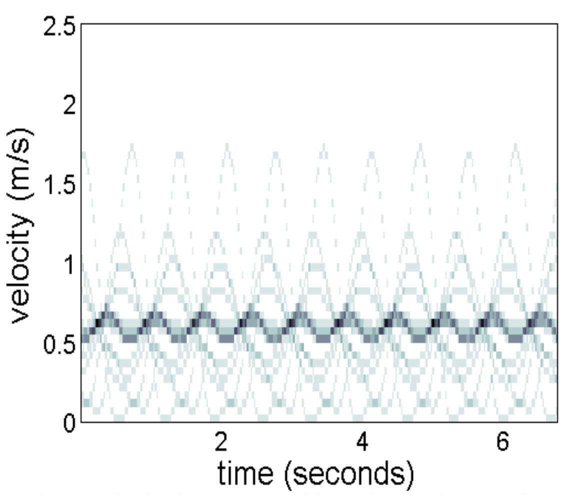


Figure 2. Simulated spectrogram of the motions in Figure 1. The motions of the separate parts of the body overlap and blur together, making extraction more difficult.

III. Data and Instrumentation

A human subject use protocol was developed to satisfy safety and privacy requirements for collecting RF measurements of humans. To provide corroborating data for understanding the signatures observed in the radar data, biometric measurements were collected. Respiration was monitored using a head-mounted microphone. The RMS voltage from the microphone measured occurrences of inhalation and exhalation. Speech was evident as a higher voltage output from the microphone. Accelerations of the body were monitored using a 3-axis accelerometer. The accelerometer provided measurements of motion in the forward, backward, side-to-side, and vertical directions. Video frames of the measurement were collected at 30 Hz using a high-definition video camera.

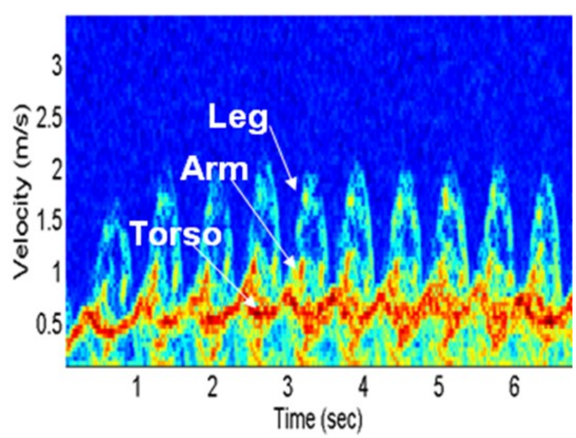


Figure 3. Measured spectrogram of walking person.

Example data of a simulated spectrogram is shown in Figure 2, and real data of a single human walking is shown in Figure 3. The simulated data was used to verify that the gait parameters were extracted accurately because it was

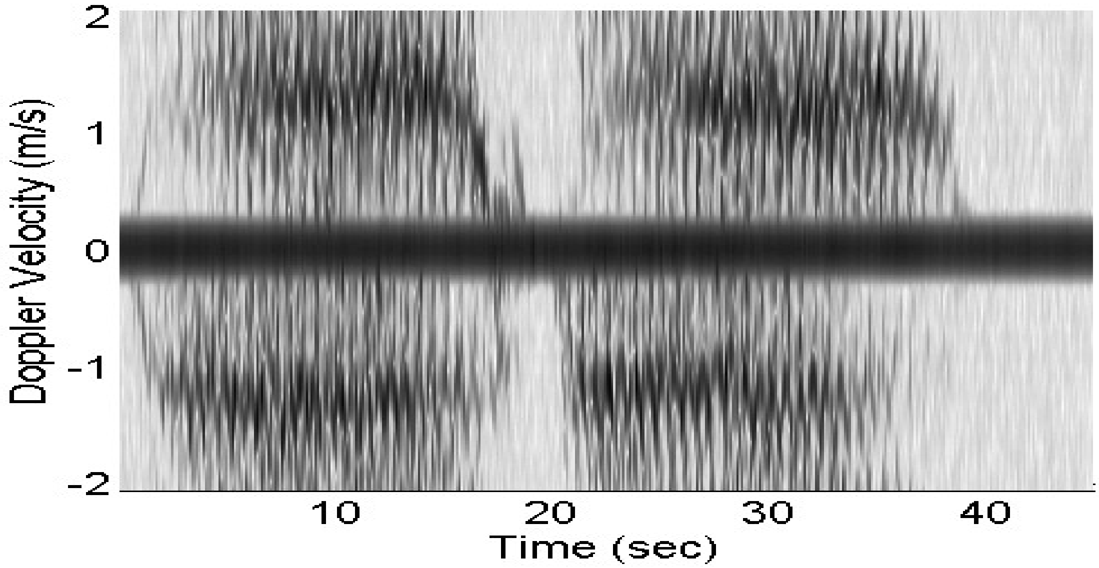


Figure 4. Spectrogram of two humans walking in different directions. Note that here the leg swing is not that easily discernable, but the torso line is still strong. Comparing this data to the cleaner data in Figure 3 shows the variability in data quality that must be addressed by algorithms that utilize radar data.

difficult to reliably and accurately collect the ground truth gait data from the human subject.

Ku-band and Ka-band radars were used in an outdoor environment with low clutter. The Ku-band radar transmitted a waveform consisting of 16 frequencies operating at 17 GHz. The Ka-band radar transmitted a waveform consisting of 16 frequencies operating at 34 GHz. A pulse rate frequency (PRF) of 464 Hz was the lowest useable PRF that prevented ambiguities in Doppler frequencies from foot motion.

IV. Feature Extraction

Features are extracted from the spectrogram and then used to perform a classification. An example of a spectrogram of two walking humans is shown in Figure 4. 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.

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 [21]. In addition to gait features, the radar cross section (RCS) features from the radar can also be used to develop a biometric radar signature.

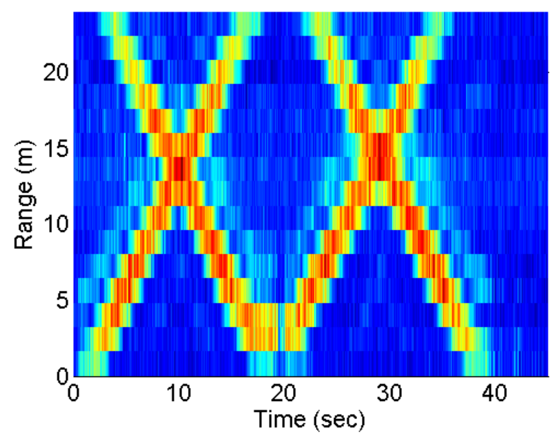


Figure 5. Standard Deviation of Ku-band RCS of two dismounts walking past each other that is used for detection. Note that the position can easily be isolated to within a two meters in range.

A. Detection, Range Gating and Target Isolation

Detecting targets in radar data has been extensively researched, and a complete discussion is outside of the scope of this paper. However, the detections used in this paper were found by taking the standard deviation of the range-gated signal as is shown in Figure 5. This method performed well enough for this application by providing a rough distance to the walking people. Once the transmitter and receiver are synchronized, the integrated high-speed electronics digitizes the data and the range gating can be performed in software. Once the detection has been made, the appropriate path length delay can be incorporated into the processing to filter out the radar returns from objects in front of and behind the object of interest [22]. The radar detections for the spectrogram in Figure 4 are shown in Figure 5.

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. Range gating is a standard radar technique and is effectively a filter in the radial distance from the radar.

B. Doppler Filtering as Clutter Suppression

Once the range gate with the target is isolated, 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 target 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 [23], 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 because this approach is 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.

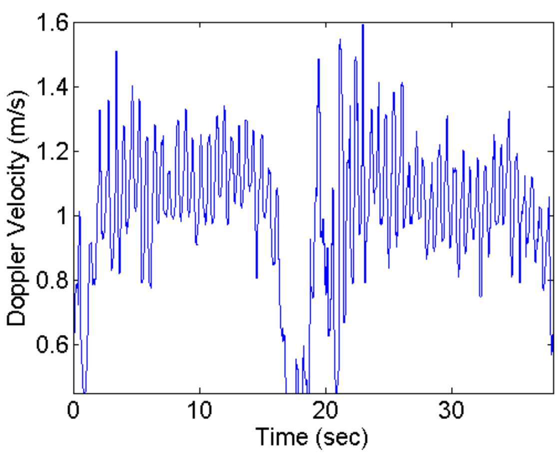


Figure 7. Filtered torso line extracted from the spectrogram of a man walking extracted from Figure 4.

C. Torso Extraction Through 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. 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.

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 7. 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.

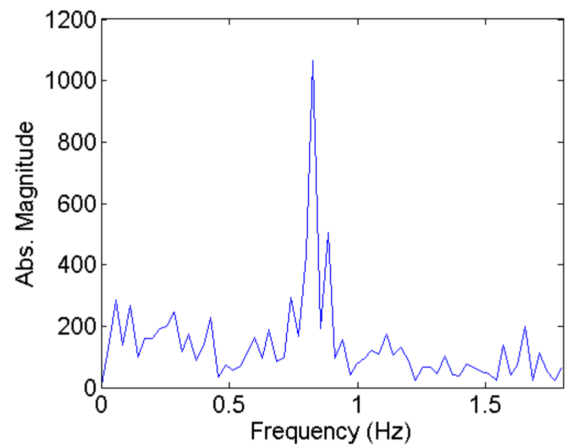


Figure 8. Stride rate extracted from the torso line. The shape in frequency space was more accurate in classification than the stride rate. This matches the less accurate video measurement of the stride rate.

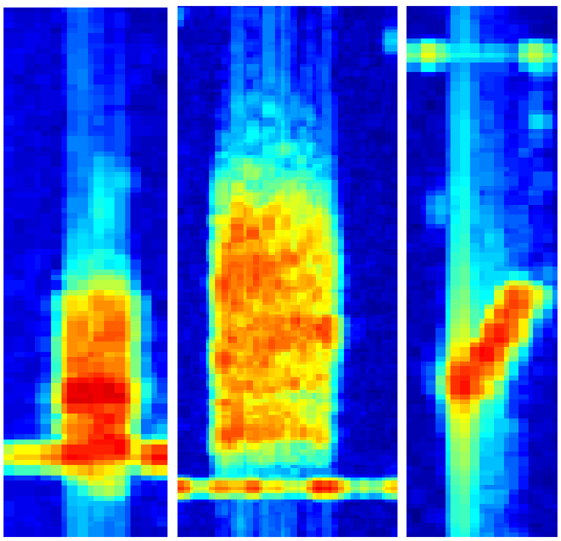
Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise [24]. Median filtering is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. We perform median filtering of the torso line in one dimension.

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 [25], which is the stride rate in Hertz. The Fourier transform of Figure 7 is shown in Figure 8. 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. The extracted stride rate does match the less accurate video measurement of the stride rate.

Once the stride rate has been extracted, other gait features which are more subtle could be extracted and the motion of the arms and legs could be extracted as well. There is significant information in the radar signature which has yet to be extracted, as can be seen in Figure 3.

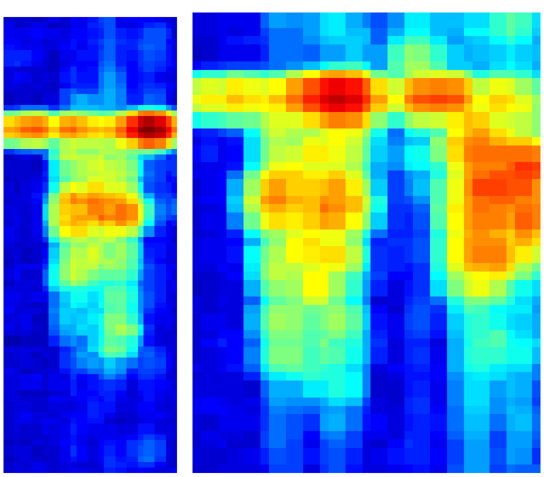
V. CLASSIFICATION

Now that the stride rate could be reliably extracted, we wanted to determine how effective stride rate could be as a feature for classification. 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.



A) B) C)

Figure 9. The time-integrated range-Doppler map of a man walking is in A). A man sprinting is in B), and a vehicle slowing down is in C). The classification of human activities such as running versus walking can be determined visually, as is the difference between vehicle and human motion. The lack of a stride rate in vehicles and the increased stride rate (when it can be observed) can provide information for classification.



A) B) C)

Figure 10. Time-integrated range-Doppler map of a man walking is in A), B), and C). The classification of individual humans through their activities such as walking is significantly more challenging. The interaction with the environment is also shown by comparing B) and C) where there is a multipath effect diminishing the signal.

Time-integrated range-Doppler maps of a man waking, a man running, and a vehicle are shown in Figure 9, showing that there are significant micro-Doppler characteristics to classify different activities. A time-integrated range-Doppler map is a compilation of range-Doppler maps over time that results in a spectrogram-like characterization of Doppler while maintaining the range information as well. These are compiled from the range-Doppler maps by taking the maximum value for each pixel over a time range. The time resolution is replaced by the range resolution, which is in effect a rotation of the traditional spectrogram which compresses range. This type of radar imaging allows multiple subjects to be viewed simultaneously, as can be seen Figure 10B and 10C, which are different walkers within the same image.

Time-integrated range-Doppler maps of three different subjects are shown in Figure 10. There is significant information contained within this radar data that has yet to be extracted. 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. However, the Fourier signature of the torso line did correlate consistently with the correct subjects. Though the stride rate did change, the shape of the Fourier signature did not. This implies that the Fourier signature could be an effective radar biometric signature.

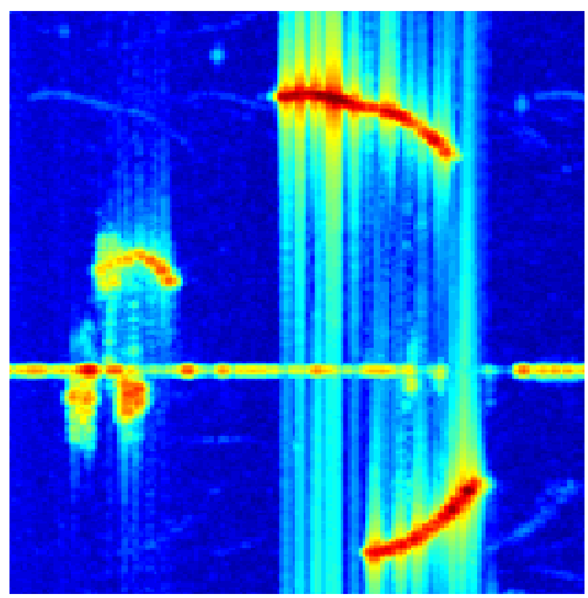


Figure 11. Time-integrated range-Doppler map of two men walking, a cyclist, and two cars. The RCS and micro-Doppler characteristics can all be used to visually classify. Using the velocity alone has the potential to confuse slow-moving vehicles with fast cyclists and runners.

Multiple movers and different types of movers can be seen in time-integrated range-Doppler maps, as can be seen in Figure 11, and the length of their tracks correlates well with their radial velocity. Time-integrated range-Doppler maps do have a difficulty with overlap, as can be seen in Figure 12. The two men walking near each other smear their signatures together if the integrated time it too long. However, the time-integrated range-Doppler maps can be an effective method for visualizing the time dimension as well as holding the information necessary for visual classification.

VI. 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. 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 as well as the development of a Fourier signature.

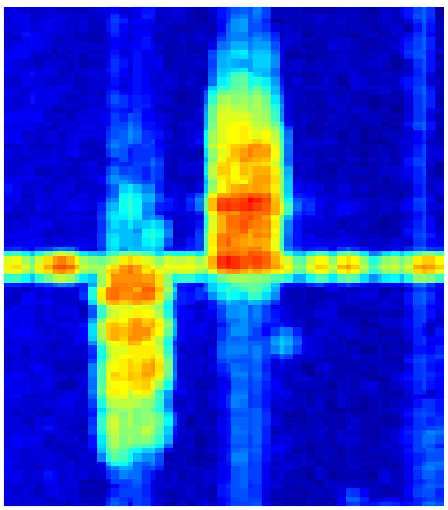


Figure 12. Time-integrated range-Doppler map of two men walking together and one walking alone. This demonstrates the problem with time-integrated range-Doppler maps since movers can overlap the tracks of too much time is used.

References

[1] L. Cohen, Time-Frequency Analysis. Englewood Cliffs, NJ: Prentice-Hall, 1995.

[2] V.C. Chen and H. Ling, Time-frequency transforms for radar imaging and signal analysis, Artech House, Norwood, MA, 2002.

[3] S.Z. Gürbüz, W.L. Melvin, and D.B. Williams, "Detection and Identification of Human Targets in Radar Data," Proc. SPIE Vol. 6567, 2007.

[4] Gene Greneker, "Very Low Cost Stand-Off Suicide Bomber Detection System Using Human Gait Analysis To Screen Potential Bomb Carrying Individuals," Proc. SPIE Vol 5788, 2005.

[5] J.L. Geisheimer, W.S. Marshall, and E. Greneker, "A Continuous-Wave (CW) Radar for Gait Analysis," Conference Record of the Thirty-Fifth Asilomar Conference on Signals, Systems and Computers, 2001, Vol 1, pp. 834-838, Nov 2001.

[6] V.C. Chen and R. Lipps, "Time frequency signatures of micro-Doppler phenomenon for feature extraction," Proceedings of SPIE, vol. 4056, Wavelet Applications VII, pp. 220-226, April 2000.

[7] V.C. Chen, F. Li, S.-S. Ho, and H. Wechsler, "Micro-Doppler effect in radar: phenomenon, model, and simulation study," IEEE Trans. on Aerospace and Electronic Systems, vol. 42, pp. 2-21, January 2006.

[8] J.L. Geisheimer, W.S. Marshall, and E.F. Greneker, "A high-resolution Doppler model of human gait," Proceedings of SPIE, vol. 4744 Radar Sensor Technology and Data Visualization, pp. 8-18, April 2002.

[9] P. van. Dorp and F.C.A. Groen, "Human walking estimation with radar," IEE Proc. on Radar, Sonar, and Navigation, vol. 150, pp. 356-365, October 2003.

[10] D.A. Tahmoush and J. Silvious, "Radar MicroDoppler for Security Applications: Modeling Men versus Women," Proceedings of the 2009 IEEE International Symposium on Antennas and Propagation, Charleston, SC, 1-5 June, 2009.

[11] J. Li and H. Ling, "Application of adaptive chirplet representation for ISAR feature extraction from targets with rotating parts," IEEE Proc. on Radar, Sonar, and Navigation, vol. 150, pp. 284-291, August 2003.

[12] P. Setlur, M. Amin, and F. Ahmad, "Analysis of micro-Doppler signals using linear FM basis decomposition," Proceedings of SPIE, vol. 6210, Radar Sensor Technology X, May 2006.

[13] V.C. Chen, "Spatial and temporal independent component analysis of micro-Doppler features," IEEE Radar Conference, pp. 348-353, May 2005.

[14] J.L. Geisheimer, E.F. Greneker, W.S. Marshall,, "High-resolution Doppler model of the human gait," Proc. SPIE 4744, 8, 2002.

[15] Y. Yang, J. Lei, W. Zhang, and C. Lu, "Target classification and pattern recognition using micro-Doppler radar signatures," Seventh ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parrallel/Distributed Computing, 2006, pp. 213-217, June 2006.

[16] P. Kealey and M. Jahangir, "Advances in Doppler recognition for ground moving target indication," Proceedings of SPIE, vol. 6234, Automatic Target Recognition XVI, May 2006.

[17] M. Otero, "Application of a continuous wave radar for human gait recognition," Proceedings of SPIE, vol. 5809, Signal Processing, Sensor Fusion, and Target Recognition XIV, pp. 538-548, May 2005.

[18] A. Lin and H. Ling, "Through-wall measurements of a Doppler and direction-of-arrival (DDOA) radar for tracking indoor movers," IEEE Antennas Propagat. Soc. Int. Symp. Digest, vol. 3B, pp. 322-325, July 2005.

[19] R. Tan and R. Bender, "Analysis of Doppler Measurements of People," Targets and Backgrounds XII: Characterization and Representation, edited by Wendell R. Watkins, Dieter Clement, Proceedings of SPIE Vol. 6239, 623908-1, 2006.

[20] I. Bilik, J. Tabrikian, and A. Cohen, "GMM-based target classification for ground surveillance Doppler radar," IEEE Transactions on Aerospace and Electronic Systems, vol. 42, No. 1, pp. 267-278, January 2006.

[21] D.A. Tahmoush and J. Silvious, "Angle, Elevation, PRF, and Illumination in Radar MicroDoppler for Security Applications," Proceedings of the 2009 IEEE International Symposium on Antennas and Propagation, Charleston, SC, 1-5 June, 2009.

[22] J. Silvious, J. Clark, T. Pizzillo, D. Tahmoush, "Micro-Doppler phenomenology of humans at UHF and Ku-band for biometric characterization," Proceedings SPIE Volume 7308, 2009.

[23] M. Anderson, "Design of Multiple Frequency Continuous Wave Radar Hardware and Micro-Doppler Based Detection and Classification Algorithms," PhD thesis University of Texas at Austin, May 2008.

[24] M.I. Skolnik, "Radar Handbook", New York: McGraw Hill, 1970.

[25] G. Davidson, 2001, Doppler Filtering and Detection Strategies for Multifunction Radar, PhD Thesis, University College London.

[26] J.S. Lim, Two-Dimensional Signal and Image Processing, Englewood Cliffs, NJ, Prentice Hall, 1990, pp. 469-476.

[27] R. Bracewell. The Fourier Transform and Its Applications. McGraw-Hill Book Company, first edition, 1965.