Improved Prediction of Dismount Velocity for Tracking

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Abstract—The velocity measurements on moving objects like humans are complicated by the characteristics of bipedal or quadrupedal gait, in contrast to the bulk motion of a vehicle. We utilize the characteristic bipedal motion to recognize and track humans and vehicles. We characterize the moving objects based on its unpredictability and attempt to identify the class. We extract the velocity of the moving human and separate it from the micro-Doppler of the human motion in order to improve the speed of the velocity measurement and thus the extracted acceleration. We describe the detection, tracking, and characterization of moving objects like people and vehicles, as well as the radar sensors used for the measurements, and detail the velocity extraction at millisecond speeds. We discuss the robustness of the approach and potential improvements.

I. INTRODUCTION

Detailed radar processing can reveal many characteristics of human motions and of the human body, including gait characteristics and radar-cross sections (RCS). Micro-Doppler signals refer to Doppler scattering returns produced by the motions of the target other than gross translation. These 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. The human body exhibits micro-Doppler characteristics from the arms, legs, and also from the torso since the bipedal motion of the human body is inherently complex. Vibrations, movement of parts of the target, and natural changes of the target surroundings are unavoidably picked up by the radar. Micro-Doppler phenomena arise from target vibrations like vehicles with their engine idling or running at high rpm’s, rotating parts, moving limbs, and body sway. However, in each single case, the results depend critically on parameters such as clutter level, dwell time, and aspect angle. Modulations of the radar return from arms, legs, and body sway are being investigated by researchers [3, 4, 5]. There are also some tutorials on micro-Doppler phenomena [2, 6, 7].

Micro-Doppler phenomena are created by the Doppler shift produced by target motion and sensed by a Doppler radar. If we denote the target position by \( P(T) \), where the coordinates \( x \) and \( y \) are functions of slowly varying time \( T \) and the origin is the radar:

\[
P(T) = \begin{pmatrix} x(T) \\ y(T) \end{pmatrix}
\]

then the instantaneous radial target speed is given by

\[
v_r(T) = \frac{d}{dT} P(T) \cdot \frac{\vec{r}(T)}{|\vec{r}(T)|}
\]

where \( \vec{r}(T) \) stands for the vector between radar and the target. The resulting Doppler frequency shift \( F_d \) is then:

\[
F_d = \frac{2v_r(T)}{\lambda} = \frac{2F_t v_r(T)}{c}
\]

where \( F_t \) is the frequency of the transmitted signal, \( \lambda \) is the wavelength, and \( c \) is the speed of light. The equation for computing the non-relativistic Doppler frequency shift, \( F_d \), of a simple point scatterer moving with speed \( v \) 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, \( \theta \) 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 (U) 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 motion of a man walking is shown in Figure 1, where the arms and legs swing while the torso and head motions are smaller. The breakdown of the micro-Doppler motions from
different body parts of a simulated man walking is shown in Figure 2, and the measured Micro-Doppler returns are shown in Figure 3. 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].

II. METHODOLOGY

From the measured spectrogram of moving dismounts, we extract the signal presented by the torso (stomach) and try to determine the velocity and acceleration, which can then be used to predict the path for tracking. The mean velocity can be calculated by integrating over a long time period, on the order of several seconds to get the entire stride. In order to determine the mean velocity faster and with less time lag, the micro-Doppler of the moving dismount has to be accounted for.

A vehicle has a single velocity and tends to accelerate linearly, which leads to simple least-squares fitting of the current motion to predict the next few seconds. However, humans do not move at a single velocity, and the ratio of their max acceleration to their mean velocity is much greater than the ratio for vehicles. This acceleration ratio of max acceleration over mean velocity can give a rough estimate of the potential rate of change in the motion, and is given in Equation 1. Radar is particularly suited to highly accurate measurements of velocity from which accelerations can be derived. Humans are a much more unpredictable moving object than vehicles because their acceleration ratio is much greater. We focus on extracting the instantaneous velocity and predicting the mean velocity with minimal time lag from the radar data to use as a predictor of the future motion.

$$A_r = \frac{\text{max}(\text{acceleration})}{\text{mean}(\text{velocity})}$$  \hspace{1cm} (5)

There are several parts to the approach to extract the mean velocity from the radar data on humans: detection and range gating, Doppler filtering to eliminate clutter, torso extraction from the spectrogram, torso filtering to reduce noise, peak period extraction using a Fourier transform [21], then the mean velocity and the sinusoidal micro-Doppler motion can be extracted and used to determine the class of moving obstacle [22]. Target detection was accomplished by taking the standard deviation of the range-gated signal. This method performed well enough for this application by providing a rough distance to the people.
Once the range gates with the target are isolated, the spectrogram is created and then filtering can be done in Doppler, or in velocity, to remove the zero-velocity clutter line. In this case 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. We are also not interested in stationary clutter at this time with the radar. In other cases where the target motion is slow or the clutter line is stronger, more complicated approaches to clutter line suppression are necessary.

III. MEASUREMENTS

The torso line is extracted from the spectrogram shown in Figure 4 and then filtered with a median filter and is shown in Figure 5a. There is an average velocity and a periodic micro-Doppler motion with it. Now that the data has been converted to a 1-D function and filtered to reduce the noise, the average torso velocity can be calculated and tracked as a function of time. The average velocity can be calculated by integrating over time, but this leads to a lag in the responsiveness of the predictor of one or two seconds while the human has already changed direction. In Figure 5a, when the subject begins stopping at 15 seconds there is a reduction in mean velocity but not in the amplitude of the micro-Doppler velocities around the mean velocity. Using a micro-Doppler model [23], the micro-Doppler motion can be removed from the velocities. The mean velocity can then be calculated instantaneously (or integrated for a short time to reduce noise) once the micro-Doppler is removed. The residual mean velocity is shown in Figure 5b. One of the main error sources is the accuracy of the torso extraction, because the error at 14.5 seconds (where the extraction follows the leg instead of the torso) propagates through the analysis. Additionally, the model errors propagate through as well, as can be seen at 15 seconds where the torso motion is not sinusoidal. However, we have shown that the micro-Doppler motion of human bipedal motion can be filtered out, providing a more accurate

![Figure 4](image1.png)

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.

![Figure 5](image2.png)

(a)

(b)

Figure 5. Filtered torso line extracted from the spectrogram of a man walking in (a). The variation of the peak velocity is due to the bipedal motion of the human body. The subject stops at 17 seconds, but the mean velocity started slowing before the subject stopped, but the sinusoidal micro-Doppler motion can mask the change in mean velocity. Shown in (b) is the torso line with the micro-Doppler removed. A micro-Doppler model was fit to amplitude and phase, then removed to give the residuals. There is no filtering of the residuals. The variation of the peak velocity due to bipedal motion is reduced or removed, but the defects in the torso extraction become more pronounced. The phase of the sinusoid varies, but for this person the phase was stable over four seconds. Note that the phase did not change as the subject slows. The subject stops at 17 seconds, but the mean velocity started gradually slowing at 15.25 seconds. The changes in the mean velocity are a leading indicator of a change in motion. One of the main error sources is the accuracy of the torso extraction, because the error at 14.5 seconds (where the extraction follows the leg instead of the torso) propagates through the analysis. Additionally, the model errors propagate through as well, as can be seen at 15 seconds where the torso motion is not sinusoidal. However, most of the 2m/s peak-to-peak micro-Doppler variation is removed.
instantaneous method of determining the mean velocity of a moving dismount.

The prediction of human motion is difficult, but the change in the mean torso velocity (the acceleration) is a leading indicator that the person could be stopping or turning suddenly. Because humans can be so unpredictable, tracking approaches should allow for this when making track associations.

There is a difficulty in the velocity extraction because the motion of a human is periodic, so that the measured velocity is always changing. However, any non-periodic acceleration indicates a change in motion that could include direction. Thus we have determined a leading indicator for path change detection.

IV. DISCUSSION

One of the additional complications that has not been addressed in this paper is the motion perpendicular to the radar beam. The micro-Doppler is affected as is shown in [24], and the radar estimates of motion are not as accurate. However, a video sensor can capture this type of motion and the combined motion can be calculated. The focus of this paper has primarily been on the measurement of an accurate instantaneous velocity and acceleration, but radar also has the capability to determine the accurate range to the moving dismount through time. The prediction of vehicle paths is not discussed in detail because the measurement of the velocity and acceleration is much simpler.

The significant variability of the dismount signatures and the difficulty in extracting a clean torso signature result in glitches as seen in Figure 5.

CONCLUSIONS

The extraction of moving object information from radar data has been shown to be feasible, and a straight-forward approach to determining the mean torso velocity has been demonstrated by removing micro-Doppler signatures. This significantly increases the speed of the measurement. The use of instantaneous velocity did provide a leading indicator for change detection and did allow a faster determination of large accelerations, but there was noise due to an inaccurate torso extraction from the spectrogram due to large micro-Doppler returns. The robustness of this technique can be significantly improved with an improved torso extraction approach that utilizes the micro-Doppler model for the extraction. Additional filtering of the velocities on the time scale of 0.05 to 0.15 seconds could improve the accuracy as well, provided the filtering lag is not a significant factor in reducing the performance.

REFERENCES