Human Motion Animation Using MicroDoppler Signatures from Multiple Doppler Sensors

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Introduction

Monitoring and tracking of humans have important applications in security and surveillance operations. Radars, in particular, have been researched since they are capable of operating 24/7 and in non-line-of-sight environments. However, one of the limitations of radar sensors when compared to optical sensors is that human movements cannot be directly visualized from the radar signatures. Hence, there is interest in developing techniques that will convert radar data to a visual animation of the human undergoing movements. Particular interest has been paid to the human microDoppler data derived from the non-rigid motions of human torso, arms and legs [1]. In [2, 3], human walking motion parameters were extracted from the microDoppler data and were successfully used to animate the Thalmann model for human gait [4]. .

In this paper, we propose an alternate approach to visualize the human motion based on microDoppler signatures collected from multiple Doppler radars. Several previous works have shown that it is possible to estimate the location and velocity of a single point scatterer (such as a baseball or the human torso) from the Doppler-only data collected from multiple sensors [5, 6]. In this paper, we examine the detailed human microDoppler spectrogram to estimate the time-varying position and velocity coordinates of five point scatterers on the human body (torso, two arms and two feet). Feature extraction of the microDoppler spectrogram is first performed to isolate the Dopplers from different body parts. Estimation of the velocity and position is then performed using a local search. Finally, Kalman filtering is performed to denoise the resulting data. Simulated microDoppler signatures derived from computer-animated human walking motions are used to demonstrate the approach.

Methodology

We consider the following radar geometry: 16 monostatic Doppler radars ($i = 1{:}16$) operating at 2.4GHz symmetrically span the perimeter of a 8m x 8m space (X, Y) with 4 sensors on each side of the square. The sensors are spaced 0.13m apart along the height dimension Z to span a 2m elevation. Computer animation data from Sony Computer Entertainment America are used to describe a 3-second duration walking motion of a human within this space. The human radar returns are simulated using the primitive based prediction technique described in [7], where all the body parts are modeled as simple ellipsoids whose radar cross-section (RCS) are known in closed form. The Doppler spectrogram at each radar is generated by applying the short-time Fourier transform (STFT) on the time-domain radar data.

1. Feature extraction from the Doppler data and correspondence across sensors:

Fig. 1a shows the Doppler spectrogram generated at a radar sensor located at (-4, -3,2)m. The following features are extracted from each of the 16 spectrograms. At any time instant t, the Doppler corresponding to the strongest returns is extracted. Usually, this Doppler f_i^{torso}, arises from the motion of the human torso. Next, the highest, second highest, lowest and second lowest Doppler features are also extracted. These features

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arise from the motion of the human limbs. Fig. 1b shows the 5 features extracted from the Doppler spectrogram shown in Fig. 1a. The key challenge is to correctly correspond each Doppler feature across multiple sensors. We use some model based reasoning to address this correspondence problem. For the human walking motion, at any time instant one foot always moves with the highest speed of all the body parts, while the other foot remains almost still. Hence, the highest absolute Dopplers $|f_i^{foot1}|$ extracted from all the spectrograms correspond to one foot while the lowest absolute Dopplers $|f_i^{foot2}|$, to the other foot. It is important to note that if the torso is moving away from the radar, that is if $f_i^{torso} < 0$, then $f_i^{foot1} < 0$. Next, the second highest and second lowest absolute Dopplers, $|f_i^{arm1}|$ and $|f_i^{arm2}|$, are identified to arise from the motion of the arms.

2. Inversion of Doppler data to obtain position and velocity:

The Doppler of any of the 5 body parts, $f_i^b(t)$, extracted from the spectrogram of radar i, is a function of the time-varying position $\boldsymbol{r}^b(t)$ and velocity $\boldsymbol{v}^b(t)$ of the body part, and the position of the radar $\boldsymbol{r}_i$, as shown in equation (1):

$$f_i^b = g(\boldsymbol{r}^b, \boldsymbol{v}^b, \boldsymbol{r}_i) = \frac{2f_c}{c}\boldsymbol{v}^b \cdot \frac{\boldsymbol{r}_i - \boldsymbol{r}^b}{|\boldsymbol{r}_i - \boldsymbol{r}^b|} \tag{1}$$

where f_c and c are the carrier frequency and the speed of light, respectively. In [6], the position $\boldsymbol{r}_e^b$, and velocity $\boldsymbol{v}_e^b$, of the torso were estimated by using an artificial neural network. Here, we use the fminsearch routine in MATLAB to minimize the mean square error between the extracted and estimated Dopplers from all the sensors:

$$error = min_{\boldsymbol{r}_e^b, \boldsymbol{v}_e^b} \left\{ \frac{1}{16} \sum_{i=1}^{16} [f_i^b - g(\boldsymbol{r}_e^b, \boldsymbol{v}_e^b, \boldsymbol{r}_i)]^2 \right\} \tag{2}$$

To avoid being trapped in a local minimum, multiple initial guesses with random position and velocity vectors are used in the nonlinear solver at $t = 0$. Subsequently, $\boldsymbol{r}_e^b(t-1)$ and $\boldsymbol{v}_e^b(t-1)$ are used as the initial guess for estimating $\boldsymbol{r}_e^b(t)$ and $\boldsymbol{v}_e^b(t)$. With no errors in the input Dopplers, the algorithm was found to be quite robust in estimating the correct position and velocity of the different body parts. Otherwise, the estimation error in this step is affected by the input errors from the feature extraction. This inversion procedure is carried out for all the five body parts: torso, two feet and two arms.

3. Post processing of the position and velocity estimates of the body parts:

Next, some model-based post processing is carried out to distinguish the right and left limbs. The human walking motion is characterized by periodic swinging motion of the arms and legs. If T is the time interval of one human stride, then the highest Doppler extracted, f_i^{foot1}, corresponds to the Doppler of the right foot over $(t : t+T/2)$ and to the left foot over $(t+T/2 : t+T)$. Similarly, the other extracted Dopplers (f_i^{foot2}, f_i^{arm1} and f_i^{arm2}) also alternate between the right and left limbs. Hence the positions and velocity estimates of the two limbs are switched every $T/2$ to correctly account for the trajectory of the right or left limb. Finally, a second-order linear Kalman filter is implemented on the time-domain position and velocity results of each body part. We use the Kalman filter since it models the state of the motion of the body part accurately by incorporating both the position and velocity data of each body part to reduce the error in the position estimates.

Simulation Results

Based on the methodology described in the previous section, the time-varying position and velocity of the 5 body parts (torso, two feet and two arms) are estimated.

The error of the position and velocity along the Z coordinate v_z was found to be high. This is likely due to the limited elevation extent of the sensors along the Z dimension, which is only 2m. Any increase in the aperture extent along the Z dimension would, however, result in a more challenging correspondence problem across sensors since at higher elevations, the Dopplers of the arms are higher than the Dopplers of the feet. Also, the velocity of the body parts along the X and Y dimensions, v_x and v_y, are much higher than v_z. Hence, the extracted Dopplers in (1) are dominated by v_x and v_y. Fig. 2a shows the true and estimated position of the human torso corresponding to the top view of the human motion. Figs. 2b and 2c show the true and estimated positions of the left and right feet respectively. It is observed that the error is slightly higher in this case when compared to the torso results. This is because while walking, each human foot remains still for approximately half the time period of the motion. Hence, the foot Doppler is near zero, which makes it impossible to accurately estimate its position. Figs. 2d and 2e show the true and estimated positions of the left and right arms respectively. Here, the error is even higher than that of the feet. This error is mostly caused by the poor feature extraction as the Dopplers from the arms coincide closely with the Dopplers of the lower legs.

Conclusion

A technique for imaging five prominent point scatterers on the human (torso, two legs and two feet) using the microDoppler data collected from multiple Doppler sensors is presented along with some preliminary results. The accuracy of the estimation of the position of the body parts is mainly limited by errors in the feature extraction. The method is potentially applicable for visualizing more complex human motions, provided the correspondence issue of extracted Doppler features across multiple sensors could be properly addressed.

Acknowledgments

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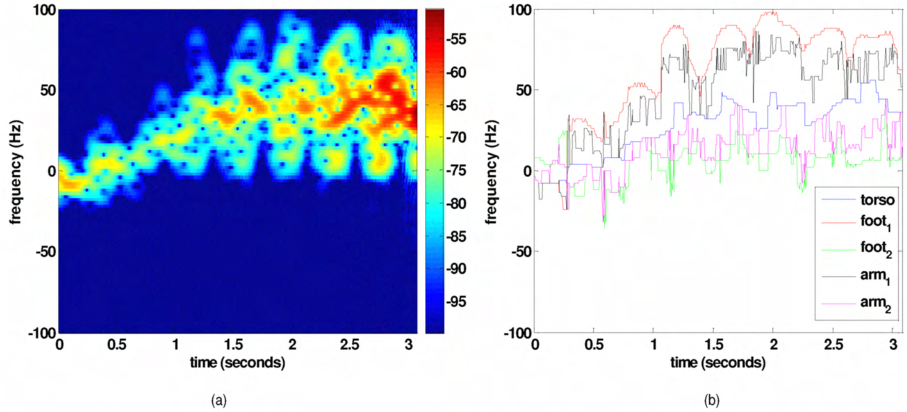

Fig. 1 (a) Doppler spectrogram of human walking motion at 2.4 GHz for a radar located at (-4, -3, 2) m. (b) Extracted Doppler features from five body parts.

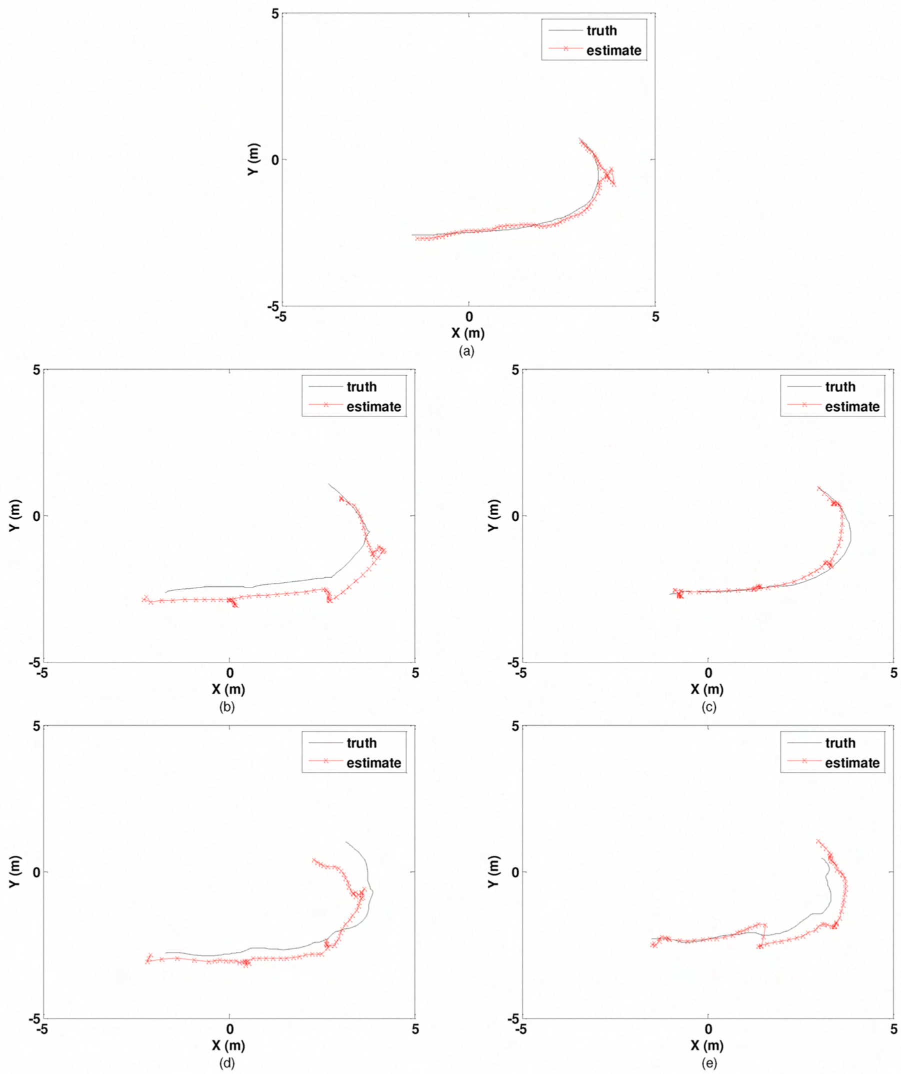

Fig. 2. Estimated positions of (a) torso, (b) left leg, (c) right leg, (d) left arm, and (e) right arm.