Application of a continuous wave radar for human gait recognition

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ABSTRACT

A continuous wave (CW) radar has been used for the detection and classification of people based on the Doppler signatures they produce when walking. When humans walk, the motion of various components of the body including the torso, arms, and legs produce a very characteristic Doppler signature. Fourier transform techniques were used to analyze these signatures and key features were identified that are very representative of the human walking motion. Data was collected on a number of human subjects and a simple classifier was developed to recognize people walking. The results of this study could have a wide range of security and perimeter protection applications involving the use of low-cost CW radars as remote sensors.

Keywords: radar, gait recognition, remote sensor, motion sensing

1. INTRODUCTION

Low-cost, low-power microwave motion sensors have long been used for a wide range of applications including intrusion detection and automatic door and light activation. These sensors are CW radars that utilize the Doppler effect to produce a signal that is proportional to the velocity of the target. When humans walk, the motion of various components of the body including the torso, arms, and legs produce a very characteristic Doppler signature. Motivation for this work originated when using this radar for a different application, which was vehicle detection. The output from the CW radar is an audio tone that is proportional to the velocity of the target. When listening to this tone, it was noted that when people walked by the sensor they produced a very distinct and characteristic sound that, upon hearing only a few times, one learns to easily recognize. If a person could easily learn to recognize the Doppler signature of a person walking, then it was logical to assume that a classifier could also be trained to do so. Data collected with a CW radar was analyzed using spectral techniques to extract the motion of the various body components when walking. Key features were extracted from these Doppler signatures and then used to train a classifier to recognize the human gait.

The objective of this study is to explore the potential of using the CW radar as a remote sensor for security and perimeter protection applications. These include detecting intruders approaching a perimeter or at a border crossing. For such applications, sensors need to be low-cost and have low power consumption so that they can be deployed in large numbers for large area surveillance. A common problem, however, with many low-cost sensors, including acoustic, seismic, and passive infrared (IR), is that they are often plagued by high false alarm rates. Environmental noise, wind, and animals can greatly contribute to this. Therefore, a classifier algorithm was developed to process the information from the CW radar to reduce the false alarm rate and improve the probability of detecting humans. There has been extensive research conducted in the area of detecting and recognizing people based on their rhythmical motion of walking [1]. Much of this work has been conducted using video images. The use of CW radar for human gait analysis is being studied at Georgia Tech Research Institute [2]. The advantage radar has over video systems includes operation in poor weather, day or night, and long range. Radar can also penetrate clothing that could fool or obscure optical systems. The radar and classifier algorithm developed here has been incorporated and successfully demonstrated in the Research, Experimentation, and Evaluation Fabric (REEF) project; a program to develop a hardware testbed to evaluate and demonstrate netted sensors for security and perimeter protection applications. In this demonstration the radar was used in conjunction with other sensors to detect and classify people walking.

2. METHODOLOGY

2.1 CW radar

The CW radar used for this work is a low cost, low power, commercially available X-band microwave motion sensing module that is commonly used for automatic door openers and security light actuators, Figure 1. It is a low power unit with an output power of 10 mW, and operates at a center frequency of 10.525 GHz. It uses a dielectric resonant oscillator (DRO) to generate a stable, CW signal for transmit and does direct down-conversion of the receive signal to baseband. Separate pairs of microstrip patch antennas are used for transmit and receive. The output from this device is a tone that corresponds with the Doppler frequency of the moving object. The Doppler frequency shift from a target moving with a velocity *v* along the line-of-sight of the sensor is,

$$f = \frac{2|v|}{\lambda}, \tag{1}$$

where λ is the sensor wavelength. One limitation of this type of device is it cannot distinguish whether the object is moving toward or away from it, hence the absolute value in equation (1). Since this device was low cost (approximately $5) and could provide raw data that could be processed for refinement, it was chosen as the basic module to fabricate the CW Doppler sensors. For velocities typical of people walking and ground vehicles the Doppler frequencies are well within the audio range. This permitted data capture and storage with standard audio equipment.

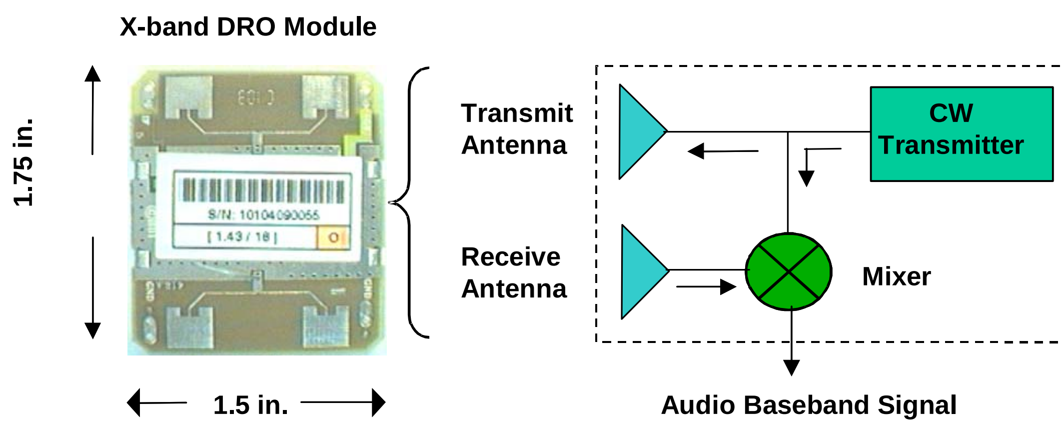

Figure 1. CW Radar Module.

The motion sensor module is packaged in a housing that includes a voltage regulator and a compression amplifier with a noise gate for the audio baseband signal, Figure 2. The unit can be mounted on a standard camera tripod, operates from a 12-volt sealed lead acid battery, and the audio output is provided over a standard microphone jack. A section of PVC tubing is used as a weather-tight radome enclosure.

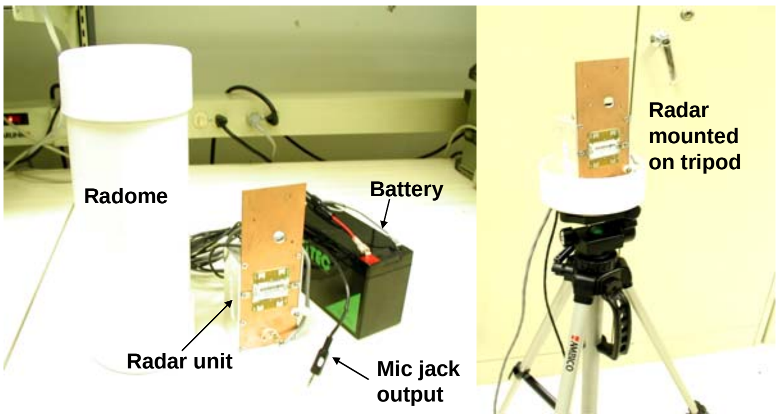

Figure 2. CW radar unit.

2.2 Human walking motion

When a CW RF signal is incident on a person walking towards or away from the radar, the signals reflected from the various components of the body will have a Doppler shift that is proportional to the velocity of those components. Human walking motion is quite complex with contributions to these velocity components from each of the upper and lower parts of the extremities. The primary components of the reflected signal are from the torso, legs, and arms. For a person walking with a constant velocity, v_0, the signal reflected from the torso, $s_0(t)$, will have a constant Doppler shift, Figure 3. The signals reflected from the swinging legs and arms, $s_m(t)$, will be modulated at the cadence frequency, f_m, which is the step or leg swing rate. In general, the arms and legs will have the same periodicity since the arms swing to counterbalance the legs. The analysis conducted in this paper will focus on finding only the periodicity of the gait and not on resolving the biomechanics of the individual arms and legs.

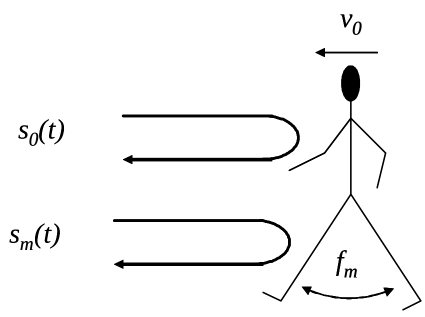

Figure 3. Key signal components from a walking person.

2.3 Signal Processing

To extract the velocity components of the target from the radar's signal, a short-time Fast Fourier Transform (FFT) was used to form spectrograms. The radar's baseband audio signal was recorded onto a laptop, where the data was then saved as digitized WAV files. This allowed for the data to be easily processed using Matlab™. A spectrogram showing a typical Doppler signature of a person walking is shown in Figure 4. These plots are obtained by taking a succession of FFTs, each over a short time window. The integration time in this case was 0.1 seconds and the time spacing between FFT windows is 0.025 seconds. The Doppler frequency is displayed on the vertical axis and time on the horizontal. The amplitude of the reflected signals is color coded with red being the highest intensity and blue the lowest. Forming these short-time FFTs is the first step in processing because it separates the velocities and the amplitudes of the moving body components. In this figure the torso component has a nearly constant Doppler frequency of about 100 Hz indicating the person was moving with a speed, using equation (1), of about 1.4 m/s. The leg swings introduce a nearly sawtooth modulation on top of this torso component. There are about 6 leg swings in the 3 seconds of data shown here indicating a cadence frequency of about 2 Hz. The dominant contribution to the Doppler signature appears to be the motion of the torso and the legs, the contribution of the arms is not as dominant.

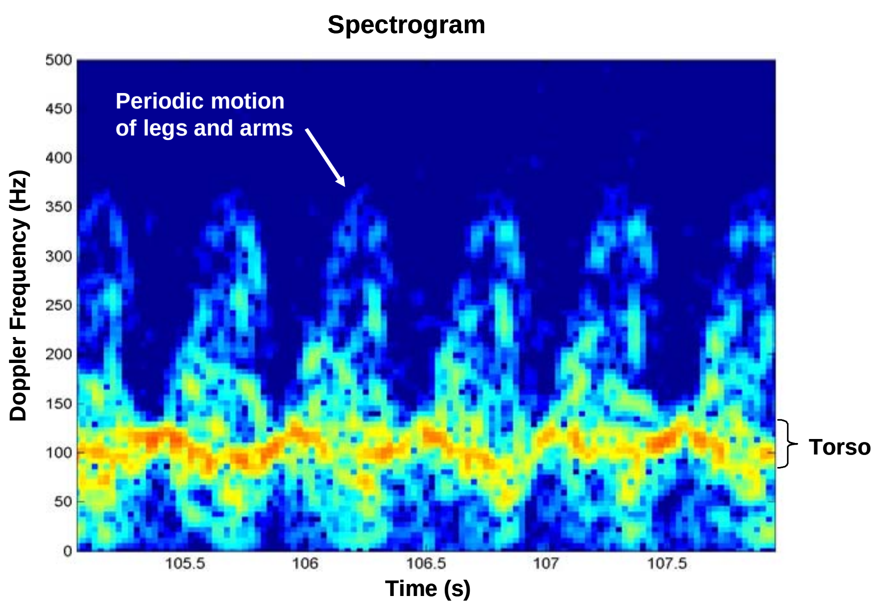

Figure 4. Spectrogram of a person walking.

The Doppler shift from the swinging motion of the legs and arms of a walking person can be modeled as a sum of chirps. The authors of [2] used the continuous chirplet transform [3] to analyze these signals in an attempt to extract information on the biomechanics of walking. They concluded that, although some features extracted using this method may prove useful for identifying individuals or class of individuals, it was difficult to glean useful biomechanical information with it. A simpler approach was used for the work presented in this paper. Since the motion of the legs and arms of a walking person is periodic, it was natural to use the Fourier transform to extract basic information such as the cadence frequency from the spectral image shown in Figure 4. For each Doppler bin on the vertical axis in this figure an FFT was applied over the entire time frame. The length of the time window is chosen to provide enough gait cycles to resolve the cadence frequency for a typical walking subject. The result is that the vertical scale is preserved and the horizontal time axis is transformed to the frequency domain as shown in Figure 5. This image allows for a unique, three-dimensional display of the spectral decomposition of the human gait. The frequency and harmonic content of the individual moving body components are displayed on the horizontal or x-axis, their corresponding velocities on the vertical or y-axis, and their radar cross-section (RCS) on the intensity scale or z-axis. Since the torso is moving with a fairly constant velocity and with little or no modulation, its signal component is the peak that lies near zero on the cadence frequency axis and is offset in Doppler, about 100 Hz, by its velocity (highlighted in Figure 5). From this we obtain the velocity, v_0, and the amplitude of the RCS of the torso. The modulation of the legs has a fundamental cadence frequency, f_m, of about 1.8 Hz.

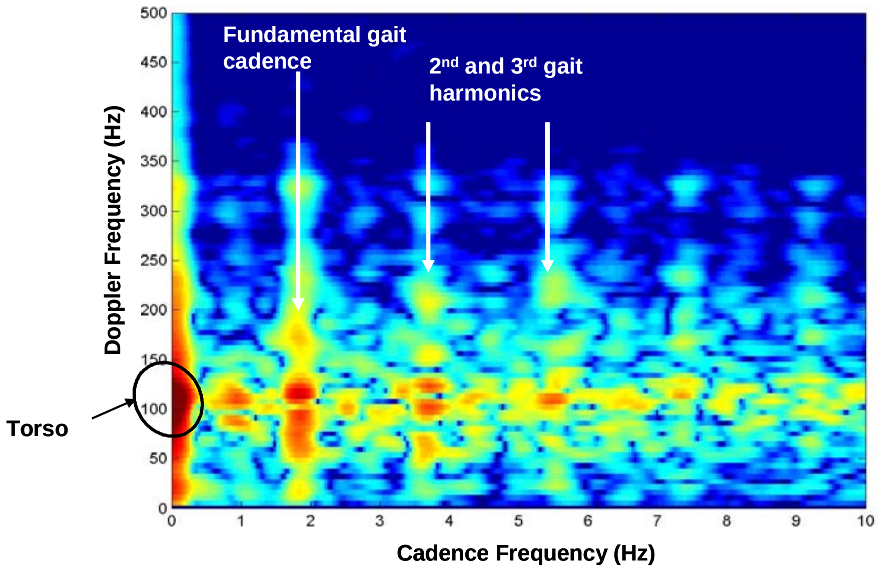

Figure 5. Spectral analysis of figure 4.

By then dividing the velocity by the cadence frequency yields the length of the stride,

$$stride = \frac{v_0}{f_m}, \tag{2}$$

which was chosen as the second feature. In the example of Figure 4, the stride is 0.89 meters. A third feature was chosen that related the ratio of the RCS of the moving appendages (arms and legs) to the torso. It is assumed that this feature would help in discriminating humans from animals, since the ratio of the area of the appendages to the torso is probably unique to each animal. Another advantage of using the spectral decomposition of Figure 5 is that it separates the reflections from the appendages, which move in a periodic manner, from that of the torso. The RCS of the appendages is determined by summing the amplitudes of the peaks of the fundamental and the 2nd and 3rd harmonics that are associated with the periodic motion of the arms and legs. This is then divided by the amplitude of the torso peak in the spectrum. This feature is referred to as the appendage/ torso ratio.

$$appendage/torso = \frac{\sum_{n=1}^{3} RCS_n}{RCS_0}, \tag{3}$$

where RCS_n is the amplitude of the n^{th} peak: n = 0 being the torso, and n = 1, 2, and 3 the fundamental, 2^{nd}, and 3^{rd} gait harmonics, respectively.

3. RESULTS

3.1 Classifier development

A simple, binary classifier was developed that classifies a detection as either a person present or not present. A database of the Doppler signatures of people walking was collected using a CW radar along with a video camera. The system was employed at the entrance to S-building on the MITRE Bedford campus. Data was collected on two consecutive days: during the late afternoon of day one when most people were leaving the building and during the morning of the following day when people were mostly entering. A standard VHS videotape was used to record the video image from the camera, and the output from the radar was recorded onto the audio track. This provided simultaneous recording of the Doppler signatures and imagery of the scene. Later, when the videotape was viewed, the audio channel was fed into the microphone input of a laptop where sections of audio data were saved as WAV files. Having the video available when recording the data files allowed for the subjects to be separated into different categories such as male or female, single person or groups of people, and approaching or receding.

The data was divided into two sets: one used for training and the other for testing. Although the feature space is three-dimensional, for display purposes two features will be plotted at a time. The test set consisted of 49 people walking with only one person within the field of view of the radar at a time. The data consisted of both male and female subjects and people approaching and receding from the sensor. The data was processed in four-second segments. An integration of 0.05 seconds was used for the short-time FFTs to form the spectrograms in Figure 4. There were approximately three looks per subject giving a total number of data points for training of 142. The stride and velocity are correlated since the faster a person is walking or running the longer their stride will tend to be. Therefore a simple linear model was assumed for the stride vs. velocity feature space. A straight line was first fitted to the data shown in Figure 6. The deviation of the stride from the fitted line was then determined and a histogram of these values was taken. A correct classification rate was specified, 95% in this case, which was used to determine the upper and lower classifier bounds. The classifier bounds were then defined by a pair of lines that are parallel to the straight line fit to the data and bounded by the maximum velocity, as shown by the dashed green lines in Figure 6. The bounds were set to accommodate the 95% of the data points in the training set. An upper limit on the velocity of a person was placed at 5.4 m/s, since it was assumed that it would be very rare that a person running faster than a 5 minute/mile.

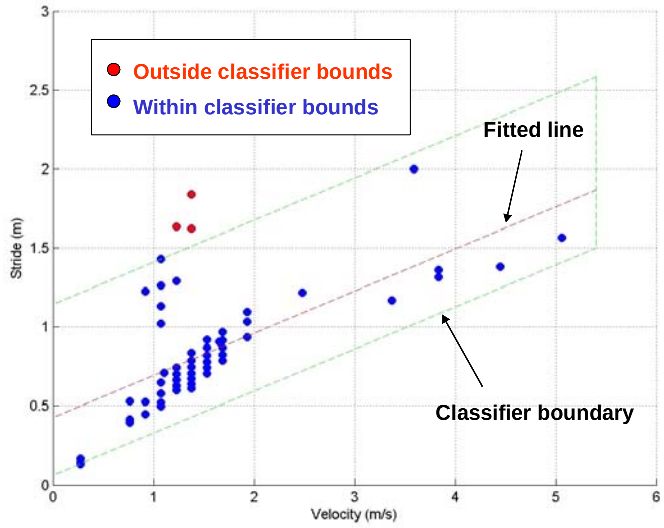

Figure 6. Training set for stride and velocity features.

A similar procedure was used for the appendage/torso ratio feature. A plot for the appendage/torso ratio vs. velocity is shown in Figure 7. In this case, the two features are independent of each other; they are just plotted together for ease of visualization. The resulting classifier bounds define a box in the three-dimensional feature space; if a data point falls within the box, it is declared a person present otherwise no person present.

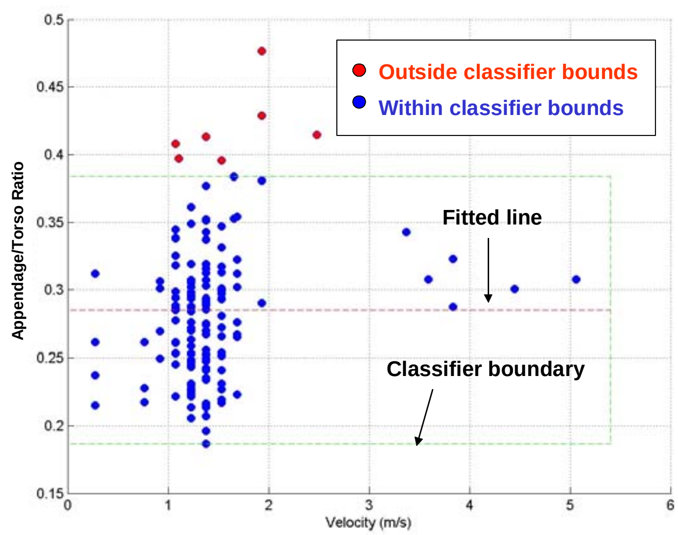

Figure 7. Training set for appendage/torso ratio and velocity features.

The testing data set consisted of approximately half of the data on individual walkers, as well as data for groups of people and recordings of the background environment when no person was present. Data that was retained for testing was not used for training. The results for the classifier testing are shown in Figure 8 and Figure 9 for the stride vs. velocity and torso ratio vs. velocity features, respectively. The classifier results were: correct classification rate (a person classified as a person) = 88 %, false alarm rate = 0, and leakage rate (a person classified as no person present) = 12 %.

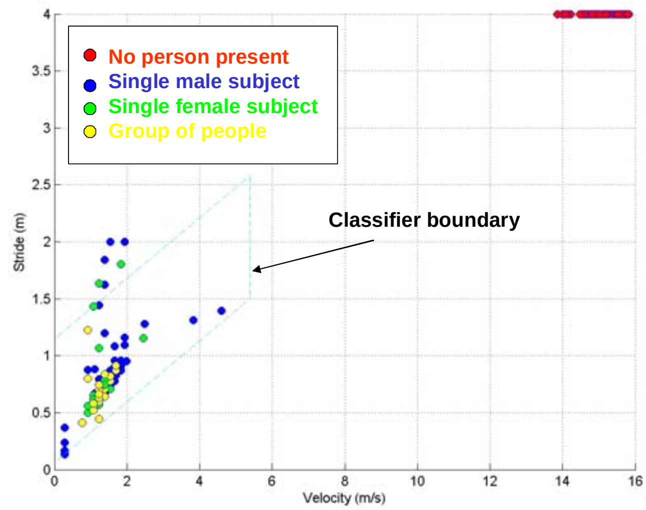

Figure 8. Classifier testing results for stride and velocity features.

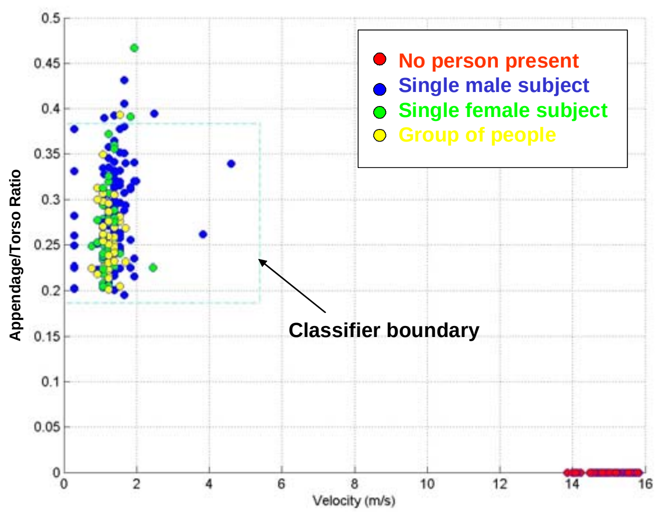

Figure 9. Classifier testing results for appendage/torso ratio and velocity features.

Male and female subjects were given different color markings for visualization purposes only, no attempt was made to discriminate between them with this classifier. From a visual observation of the data it appears that, in general, the male subjects tended to walk slightly faster and have a longer stride, as expected
It is also interesting to note that although the classifier was trained on data for individuals walking it worked well for groups of people.

3.2 Animal signatures

Analysis of radar Doppler signatures may provide a means for discriminating humans from animals. This could be very useful for sensor applications in remote areas, such as border surveillance between the U.S. and Mexico, where false alarms from animals could be a significant problem. A comparison of the Doppler signatures of a human and a dog is shown in Figure 10. The difference in the modulation pattern due to the leg motion between the two is very noticeable. The shorter, thinner legs of the dog have a narrower and sharper Doppler pattern compared to the broader, saw-tooth pattern for the human. The regular motion of the two legs for the human is very discernable whereas it is more complex for the four-legged dog. There may also be a Doppler component due to the wagging tail of the dog. Although the problem of discriminating humans from animals was not addressed in this effort, the signatures appear to be distinct enough that finding features to discern them would be reasonable. Further work would be needed to create a multi-class classifier that can discriminate humans from animals. A database of animal signatures would first need to be acquired and additional features may need to be extracted.

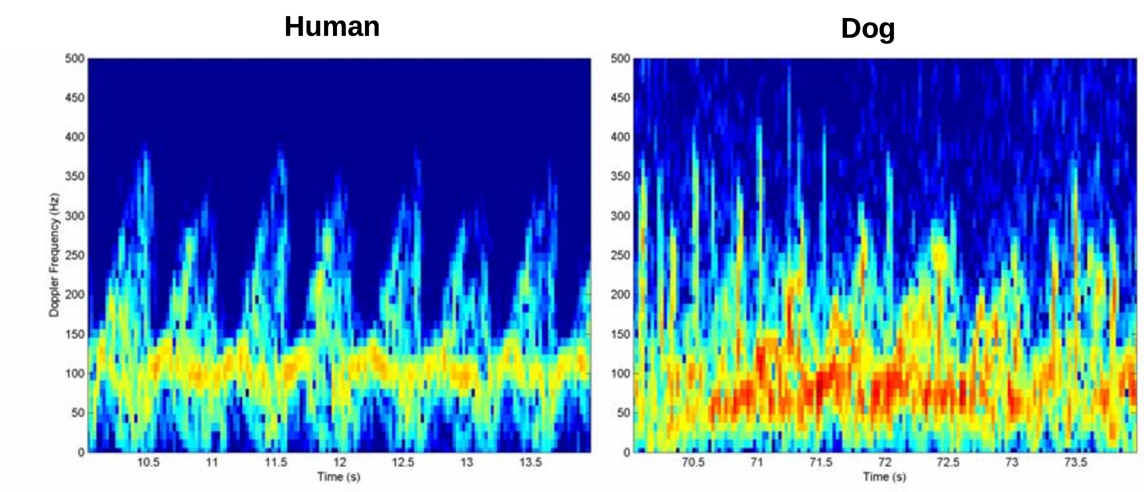

Figure 10. Human and dog Doppler signatures.

4. SUMMARY

The application of a continuous-wave radar for the detection and classification of people based on their walking motion has been demonstrated. The radar are low-cost, low-power commercial motion sensors that have potential remote sensor applications for security, perimeter protection, and border monitoring. Spectral analysis of the output from the radar using a sequence of short-time FFTs is used to extract the time history of the velocities for the major moving components of a person when the are walking. The motion of the torso produces a steady Doppler shifted signal, which is modulated by the motion of the swinging arms and legs that results in a Doppler signature that is very characteristic of humans. Further spectral analysis of this Doppler signature using Fourier transform techniques was used to identify some key features of the human walking motion. To employ Fourier techniques, the observation time of the subject needs to be long enough to cover a few gait cycles in order to resolve the periodicity. In many applications, however, this could be several seconds. If short time windows of observation are needed, high-resolution spectral techniques such as the MUSIC (multiple signal classification) algorithm [4] could be used instead.

The spectral analysis conducted in this paper was only intended to extract very basic information that could be used to determine if a person was present or not. It was not intended to identify individuals or classes of people from their gait. More sophisticated techniques would be needed to resolve the contributions to the gait motion from body parts like the arms, upper leg, lower leg, and foot. The authors in [2] attempted this with the use of the chirplet transform with inconclusive results. The binary classifier developed in the paper demonstrated a basic capability for identifying human walkers while reducing false alarms. With more sophisticated processing and feature extraction techniques, it may be possible to design a multi-class classifier that distinguish humans from various animals. This could have benefits for sensors located in remote areas where false alarms due to animals is a problem.

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