

Classification of people walking and jogging/running using multi-modal sensor signatures

Thyagaraju Damarla and James Sabatier
U.S. Army Research Laboratory, Adelphi, MD 20783, USA

ABSTRACT

In this paper, we address the issues involved in detecting and classifying people walking and jogging/running. When the people are walking, sensors observe the signals for a longer period compared to the case in which people are jogging. To identify fast-moving people, one must make the decision based on the few telltale signals generated by a person jogging: a higher impact of a foot on the ground, which can be monitored by seismic sensors; the panting noise observed through an acoustic sensor; or a higher Doppler from an ultrasonic sensor, to name few. First, we investigate the phenomenology associated with seismic signals generated by a person walking and jogging. Then, we analyze ultrasonic signatures to distinguish the characteristics associated with them. Finally, we develop the algorithms to detect and classify people walking and jogging. These algorithms are tested on data collected in an outdoor environment.

Keywords: Personnel Detection, Seismic, Ultrasonic, micro-Doppler, Cadence

1. INTRODUCTION

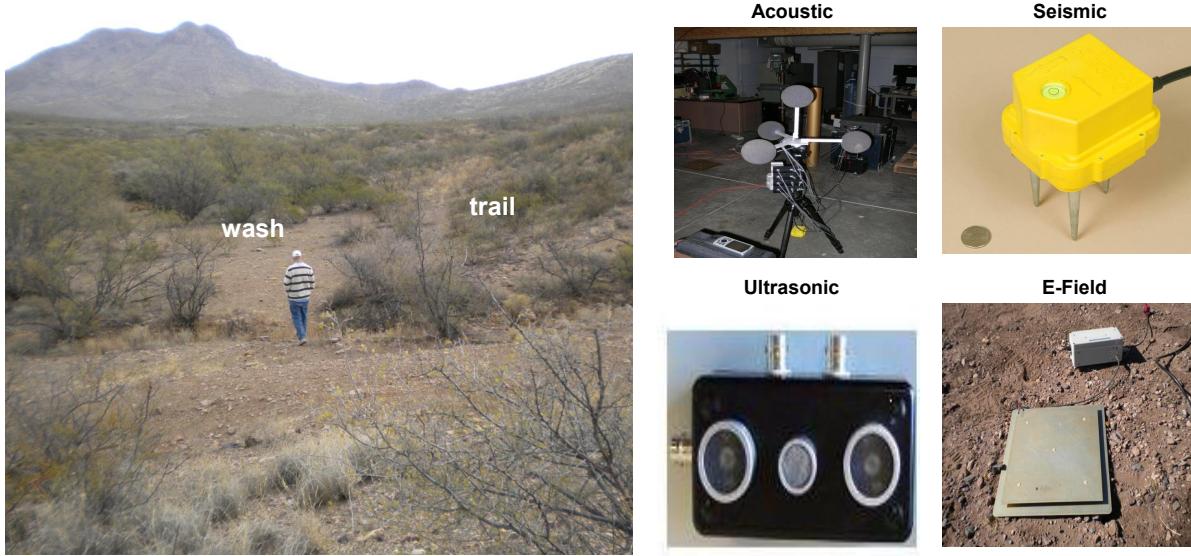
Detection of people is one of the requirements in protecting the perimeter, borders, etc. Detection of people is done primarily by using imaging sensors. However, imaging sensors consume large amounts of power and thus are good for indoor operations or where access to the power is available. In remote operations such as monitoring a border, forward operating bases, perimeter protection, etc., the sensors need to operate day and night for days without requiring any attention. This implies the batteries of the sensors used should last for days, if not weeks and months. Some sensors that consume less power compared to imaging sensors are acoustic, seismic, passive infrared, magnetic, E-field sensors, to name few.

Traditionally, personnel detection is done using seismic sensors,¹⁻³ where the seismic data is analyzed to estimate the cadence of a person walking. The cadence of a person is estimated to be around 1 - 2 Hz. Succi⁴ has used histograms of energy in footstep signals to detect the presence of people. Since footsteps make sounds, some researchers⁵⁻⁷ have also used both acoustic and seismic signals of footsteps to detect people. Iyengar⁵ and Sunderesan⁷ have used the joint probability of distribution of acoustic and seismic signals for better classification of acoustic and seismic signals due to footsteps of people.

Using acoustic and seismic data essentially depends on the estimation of the cadence of a person. When more than one person walks, the estimation of cadence could be difficult, as not all people walking at the same speed. When multiple people walk, the signals could be confused with animals walking and vice versa. In order to clearly distinguish people from animals, it is necessary to look for different characteristics that are unique for people and animals. One such distinguishing feature is micro-Doppler⁸ due to the limb motions of people and animals in the ultrasonic signal returns. In this paper, we analyze the seismic and ultrasonic data to determine the presence of people and animals. Moreover, we also detect people running/jogging using seismic data and ultrasonic signal characteristics.

Section 2 presents the data collection, section 3 presents the algorithms for detecting people walking, running/jogging, and techniques for distinguishing from animals walking. In section 4, we present the conclusions.

Further author information: (Send correspondence to Thyagaraju Damarla;
E-mail: thyagaraju.damarla@us.army.mil, james.sabatier@us.army.mil)



(a) Different terrains: Wash with fine grain of sand and Trail

(b) Sensors: acoustic, seismic, ultrasonic and E-field sensors

Figure 1. Different terrains and some of the sensors deployed

2. DATA COLLECTION

In order to develop algorithms based on real-world environments, we went to the Southwest border and collected data at three different locations, namely, (a) wash, a flash flood river-bed consisting of fine grain sand; (b) a trail, a trail formed by people walking through the thick of bushes, which has a hard surface; and (c) a choke point, a valley between two hills known to be trespassed by illegal aliens, as shown in Figure 1(a). We used a suite of sensors consisting of acoustic, seismic, passive infrared (PIR), magnetic & E-field, ultrasonic, profiling, and radar sensors to collect the data. Some of the sensors used are shown in Figure 1(b).

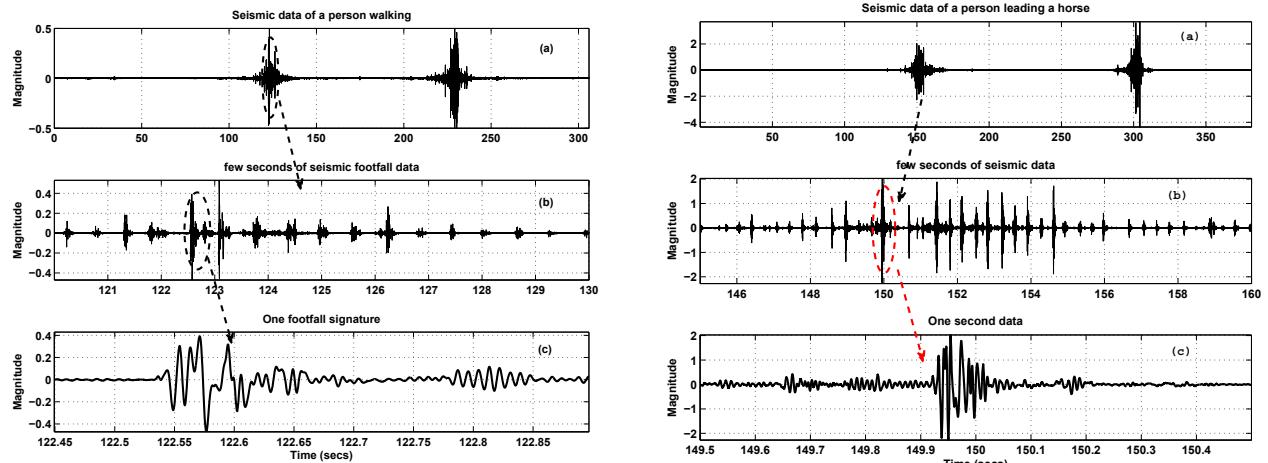
Each sensor suite is placed along the path spaced 40 to 60 meters apart. Some of the scenarios used for data collection include: (a) a single person walking with and without backpack, (b) two people walking, (c) multiple people walking, (d) one person leading an animal, (e) two people leading animals, and (f) three people leading animals with and without payloads. A total of 26 scenarios with various combinations of people, animals, and payloads are enacted and the data are collected at the three sites. The data are collected over a period of four days; each day at a different site and different environment. Sometimes there is wind, sometimes it is quiet. The experiments with animals always involved people; hence, throughout this paper animal detection using seismic and acoustic data analysis for cadence implies an animal with a person leading it.

3. ALGORITHM DEVELOPMENT FOR PEOPLE RUNNING/JOGGING

In this section, we consider two of the sensor modalities shown in Figure 1(b), namely, (a) seismic, and (b) ultrasonic sensors for the detection and classification of targets. As mentioned earlier, each sensor modality offers unique features that other modalities cannot. We present the target phenomenology associated with these modalities and the techniques used to exploit it, while keeping in mind that these algorithms should be low complexity and amenable to implementation on unattended ground sensors (UGSs).

3.1 SEISMIC SENSOR DATA ANALYSIS

The main purpose of seismic sensors is to detect footfalls of humans walking within the receptive field of the sensor. There is a considerable amount of literature¹⁻⁵ on footstep detection. Traditionally, estimation of the cadence of the footsteps is performed for seismic data analysis. However, if multiple people are in the vicinity of the sensor



(A) (a) Seismic data of a person walking, (b) enlarged portion – shows the periodicity of footfalls and (c) signature of one footprint

(B) (a) Seismic data of a person leading a horse, (b) expanded portion – shows the periodicity of hoof signature and (c) enlargement of one impulse due to hoof

Figure 2. Seismic signatures of a person walking and a horse led by a person

and walking, it is difficult to estimate the cadence of an individual person. Moreover, if there are animals, it is difficult to differentiate multiple people and animals walking by observing the footfalls. Figure 2(A) shows the signature of a person walking and Figure 2(B) shows the signature for a person leading a horse. However, the multiple footfalls superimpose one another, resulting in several harmonics of the cadence frequency ‘c’.

Developing an algorithm for personnel detection with multiple people walking, jogging, running, or a combination of them will be extremely difficult. In order to limit the scope of the problem, we assume that the people are walking on a path such as a paved road or a trail in an open field. If there are animals, we assume that these animals are being led by people. We assume if people are running, they are running one behind the other with a 3-4 m separation. Even though this restriction seems artificial, in fact, narrow trails form as people walk and people tend to walk in single file when trails are narrow; similarly, people use paved roads if they exist. If we assume that the people are walking on a path, the seismic signals due to footfalls of humans and animals exhibit a rhythm, and hence, have a cadence. When multiple people walk in single file they tend to synchronize their footsteps with one another for a majority of the time. Frequency analysis of the data would reveal the cadence of the person(s) or animal(s) walking. Since the seismic signals are impulsive in nature, several harmonics of cadence frequency can be observed in the frequency analysis. Since humans and animals have distinct cadences, it is possible to classify the seismic signatures from them. We use the MVG classifier described in references^{2,3} to do seismic signal classification. For the feature set, we first compute the spectrum of the envelope¹⁻³ of the seismic signal accumulated for a period of 6 seconds. Then, the feature set $\{x_1, x_2, \dots, x_n\}$ consists of amplitudes of the frequency bins from 2 to 15 Hz. Then, the MVG algorithm is used to estimate the posterior probability of human or animal footsteps present. The results of the algorithm are shown in Figure 3.

The previously described classification works reasonably well if humans and animals are walking. However, if a person is running, the cadence of the person running is approximately the same as the cadence of a horse walking. In order to determine the presence of humans, it is necessary to determine whether these footsteps belong to a human or an animal. Additional signal processing is done to determine whether the seismic signatures belong to humans or animals. Figure 4 shows some of the processing done on the signatures. Figure 4(A)(a) shows the human footfalls and Figure 4(A)(b) shows the envelope of the magnitudes of the footfalls. The span is computed as the time duration when the magnitudes of the footfalls lie above some threshold. Similarly, Figures 4(B) and 5 show the information for a horse led by a person and for a person running, respectively. Here we assume that the horse hoof signatures dominate the footfalls of a person leading it. The threshold is estimated to be the mean of the absolute values of the peaks ± 5 sec on either side of closest point of approach (CPA) of

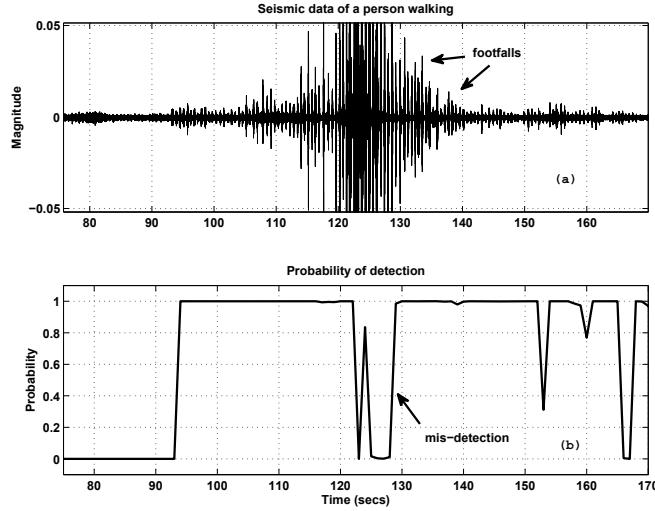
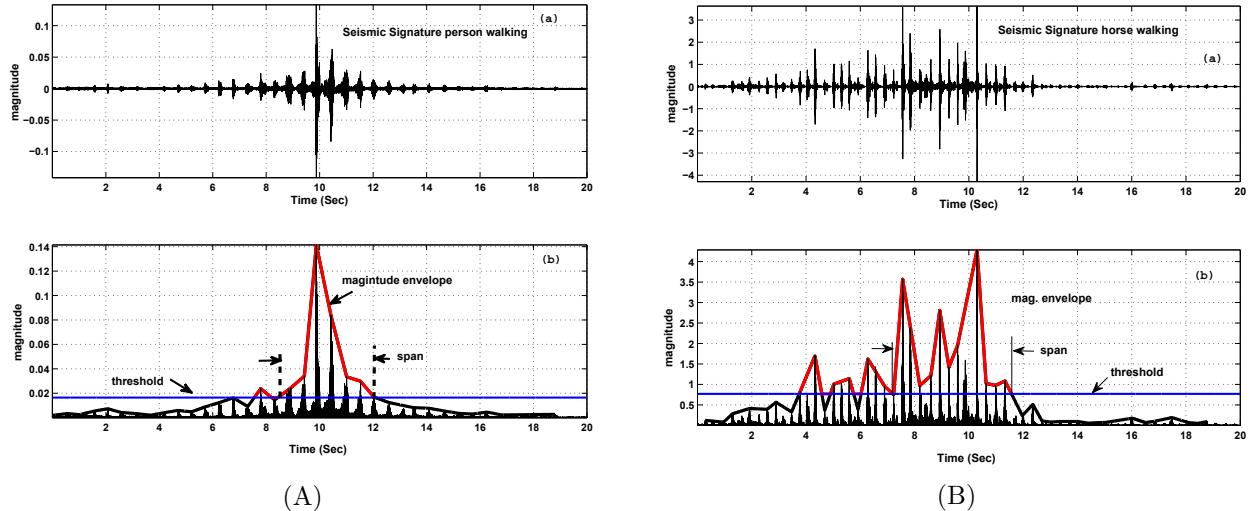


Figure 3. Seismic data of a person walking and (b) probability of detection



(A) (a) Seismic signals generated by a person walking, and (b) signal span for a person walking

(B) (a) Seismic signals generated by horse led by a person, and (b) signal span

Figure 4. Seismic signatures of a person and a horse walking and the signal spans

the target to the sensor. We use the magnitude of the signals along with the span of the signals above a certain threshold as the features to determine the presence of humans or animals. Table 1 shows the features of a person walking and running and a horse walking. These features are used in a MVG classifier to classify the signatures.

Table 1. Distinguishing features for people and animals

	Cadence	Peak Amplitude	Span
Person Walking	1.9 Hz	0.14	3.69 Sec
Person Running	2.9 Hz	0.46	2.6 Sec
Horse Walking	2.71 Hz	3.69	4.34 Sec

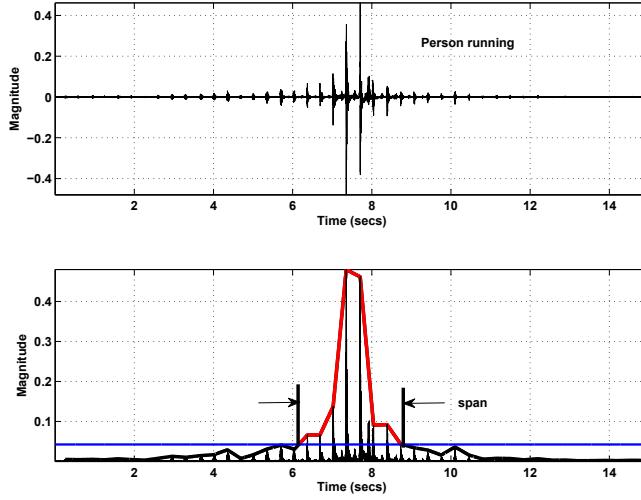


Figure 5. Seismic signals generated by a person running, and (b) signal span

3.1.1 Semantic Data Fusion

Seismic data are particularly sensitive to the soil conditions. Depending on the properties of the soil, the signals propagate at different velocities and the transfer function of the soil affects the signal differently. In order to perform the classification properly, it is necessary to use appropriate training set depending on the type of soil. The semantic tree used for classification is shown in Figure 6. The semantic tree has two branches, namely,

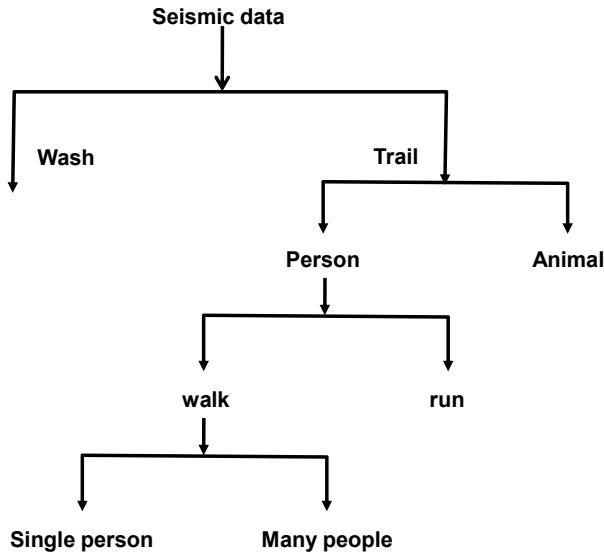
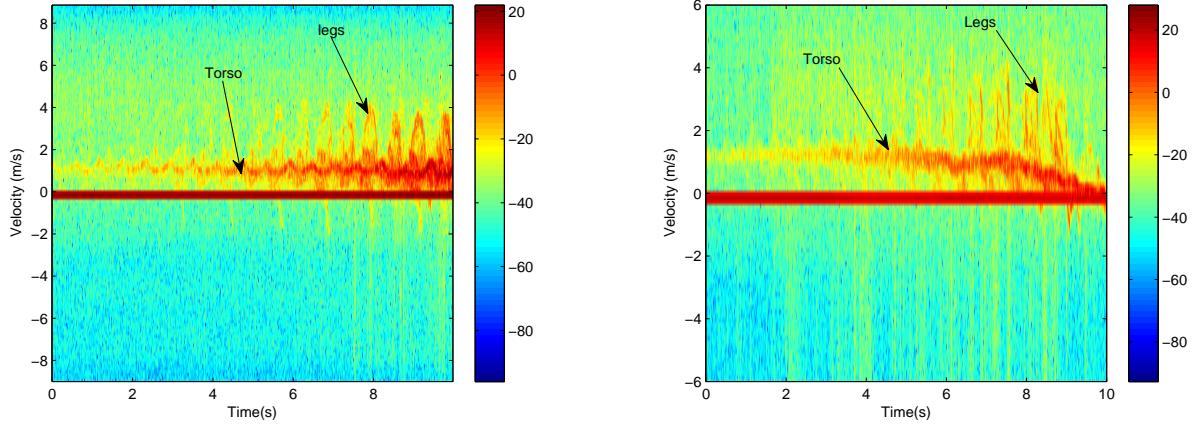


Figure 6. Semantic tree used for classification of seismic data

(a) wash and (b) trail, corresponding to two different soil conditions. The branch corresponding to the trail is expanded where the data are analyzed to determine the presence of personnel and animals. The branch corresponding to the personnel is analyzed to determine if the people are walking or running. Further analysis is done to determine if there is a single person or multiple people are present.



(a) Micro Doppler from various body parts of a walking person

(b) Micro Doppler from various body parts of a walking horse

Figure 7. Micro Doppler for a person walking and a horse walking

3.2 ULTRASONIC SENSOR DATA ANALYSIS

In this section, we discuss the processing of the ultrasonic data. Ultrasonic data are rich in information and embody the Doppler signature of a moving human or an animal such as a horse.⁸ Typical Doppler velocities that are proportional to the Doppler frequencies from various body parts of a walking human and a walking horse are shown in Figure 7. Ideally, the Doppler from the arms, legs, and torso of a person is different from that of animal legs. As mentioned previously, it is important to know the number of people and animals to perform classification. This is due to the reason that information about the number of people and animals has to be included in the training data set. Towards this goal, we processed the ultrasonic data to count the number of targets in the vicinity using the energy content in various bands of the Doppler. Figure 8(a) shows the flowchart for the algorithm used in counting the number of targets. For processing the ultrasonic data, a 1-second interval of the data is considered at a time and the algorithm shown in Figure 8(a) is used to find the energy in each band. Then a sliding window is used, which slides approximately 0.1 second and next segment of data is obtained and processed.

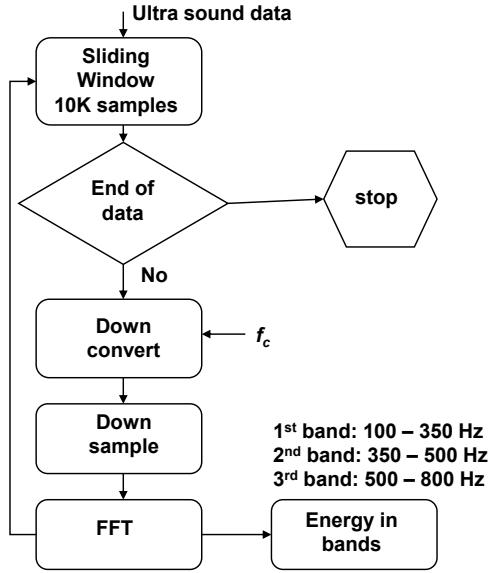
The algorithm results for several runs are shown in Figure 8(b). The scenarios used corresponds to (a) one man walking, (b) one man leading an animal, (c) two men and one woman walking and, (d) four men and three women walking. In the last case, a count of only six targets are realized using the algorithm. The reason is due to a large number of people, one is very close to the other, masking the Doppler returns from one.

3.2.1 Classification of targets using ultrasonic data

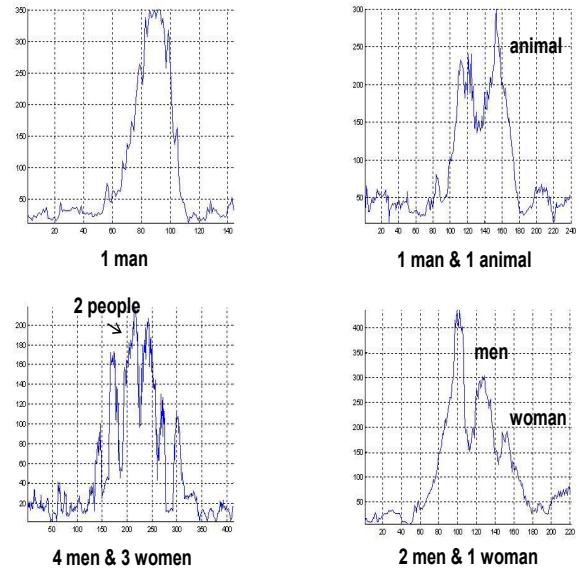
The Doppler returns from animals are quite different compared to those from humans. One distinction is that humans have stronger returns from their torsos while animals have significantly weaker Doppler returns from their torsos, as is evident from Figure 7. The total energy in various bands for the animal is different from that of the humans, as shown in Figure 8. In order to classify, 40 features are selected from each band B_i , $i \in \{1, 2, 3\}$

$$\mathcal{F}^{B_1} = \left\{ F_1^{B_1}, F_2^{B_1}, \dots, F_{40}^{B_1} \right\}$$

where $F_k^{B_i} = \frac{1}{5} \sum_j^{j+4} f_j$ where $j = (k-1)*5 + 1 + C_i$, f_j is the magnitude of the Fourier coefficient j , and $C_i = \{100, 300, 500\}$ for the band B_i . Training data are generated for each point on Figure 8 that correspond to three classes, namely, (a) human, (b) animal, and (c) others. We developed a support vector machine with a polynomial kernel to perform the classification. A correct classification of 95% is achieved. When we used only two classes, humans and everything else (that is, animal plus others), we achieved a correct classification of 98%.



(a) Flowchart showing the ultrasonic signal processing for counting number of targets



(b) Target count using ultrasonic data analysis

Figure 8. (a) Flowchart (b) Target count results

3.2.2 Characterizing a Walking and Running Person

The spectrograms of a walking and running person are shown in Figure 9. Clearly, from these spectrograms, we notice that the average Doppler (corresponding to torso of a person) for a walking person is less compared to that for a running person. In Figure 10 we plot the energy content in several bands, namely, 100-200, 201-500,

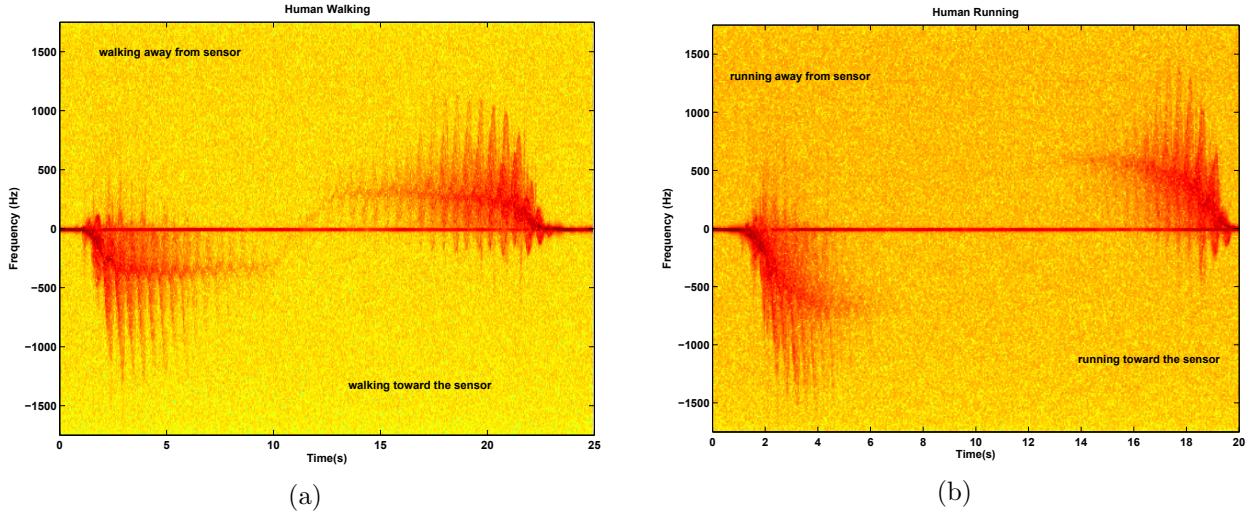


Figure 9. (a) Spectrograms for a person walking and (b) Spectrogram for a person running

501-800, and 801-1000 Hz for a person walking and running. Each iteration corresponds to 0.1-sec shift just as in the case of the counting algorithm. The characteristics of these plots are very different in the 201-500 and 501-800 Hz bands for both a walking and running person. These features can be used to distinguish whether a person is walking or running. Of course, one would also use the Doppler from the torso during classification.

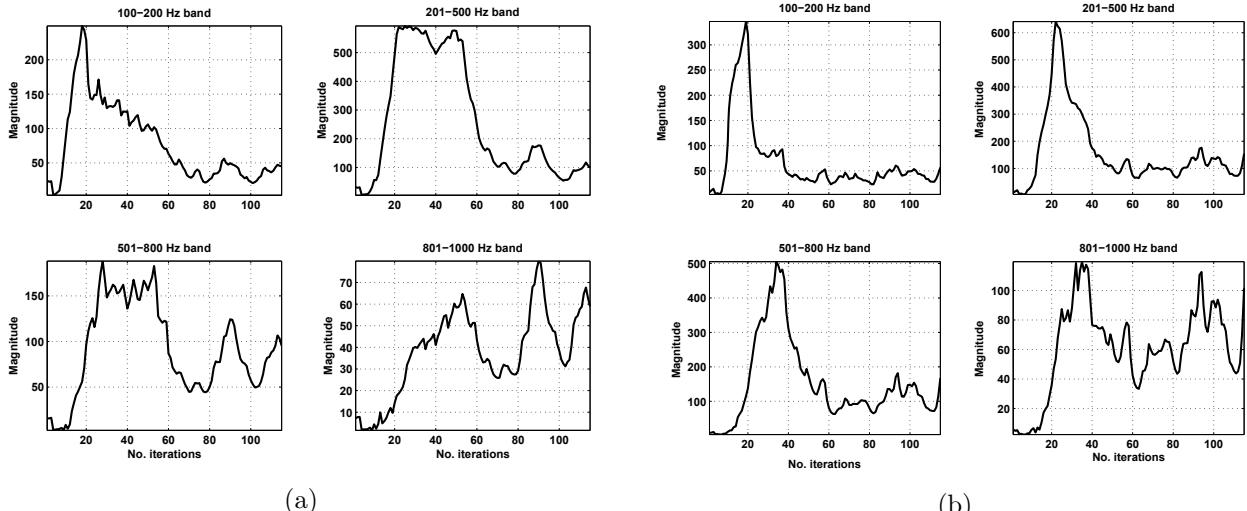


Figure 10. (a) Energy in spectral bands for a person walking and (b) Energy in spectral bands for a person running

4. CONCLUSION

In this paper, we considered the problem of personnel detection, in particular distinguishing whether a person is walking or running, using the seismic and ultrasonic sensor data. We identified several salient features that can be used for characterizing the state of a person in both seismic and ultrasonic data.

REFERENCES

- [1] K. M. Houston and D. P. McGaffigan, "Spectrum analysis techniques for personnel detection using seismic sensors," *Proc. of SPIE*, Vol. 5090, pp. 162–173, 2003.
- [2] R. Damarla and D. Ufford, "Personnel detection using ground sensors," *Proc. of SPIE*, Vol. 6562 - 656205, 2007.
- [3] T. Damarla, J. Sabatier, and A. Ekimov, "Personnel detection at a border crossing," *Military Sensing Symposium - National, Las Vegas, NV*, 2010.
- [4] G. Succi, D. Clapp, and R. Gambert, "Footstep, detection and tracking," *Proc. of SPIE*, Vol. 4393, pp. 22–29, 2001.
- [5] P. V. S. G. Iyengar and T. Damarla, "On the detection of footsteps based on acoustic and seismic sensing," *Conf. Record of the Forty First Asilomar Conference on Signals, Systems and Computers, ACSSC 2007*, pp. 2248–2252, 2007.
- [6] R. E. Bland, "Acoustic and seismic signal processing for footstep detection," Master's thesis, Massachusetts Institute of Technology, Department of Electrical Engineering and Computer Science, Cambridge, Mass., 2006.
- [7] A. Sunderesan, A. Subramanian, P. K. Varshney, and T. Damarla, "A copula based semi-parametric approach for footstep detection using seismic sensor networks," *Proc. of SPIE*, Vol. 7710 - 77100C, 2010.
- [8] A. Mehmood, J. M. Sabatier, M. Bradley, and A. Ekimov, "Extraction of the velocity of walking human's body segments using ultrasonic doppler," *The Journal of the Acoustical Society of America*, Vol. 128, pp. EL316–EL322, October 2010.