ARMY RESEARCH LABORATORY

Personnel Detection at a Border Crossing—An Exercise

by Thyagaraju Damarla, Ronald A. Frankel, Hao Vu, Matthew Thielke, Asif Mehmood, James M. Sabatier, and Gary Chatters

ARL-TR-6699 **October 2013**

NOTICES

Disclaimers

Army Research Laboratory
Adelphi, MD 20783-1197

ARL-TR-6699 **October 2013**

Personnel Detection at a Border Crossing—An Exercise

Thyagaraju Damarla, Ronald A. Frankel, Hao Vu, Matthew Thielke,
Asif Mehmood, James M. Sabatier, and Gary Chatters
Sensors and Electron Devices Directorate, ARL

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED (From - To)
October 2013	Final	

4. TITLE AND SUBTITLE
Personnel Detection at a Border Crossing—An Exercise

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Thyagaraju Damarla, Ronald A. Frankel, Hao Vu, Matthew Thielke,
Asif Mehmood, James M. Sabatier, and Gary Chatters

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Army Research Laboratory
ATTN: RDRL-SES-A
2800 Powder Mill Road
Adelphi, MD 20783-1197

8. PERFORMING ORGANIZATION REPORT NUMBER
ARL-TR-6699

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
In March 2012, an international team of scientists, engineers, and technicians gathered at the southwest border of the United States with specialized equipment to collect data on people, animals, and vehicles travelling in the rugged terrain. The goal of the effort is to collect data in the natural environment and develop robust algorithms to detect people, animals, and vehicles with fewer false alarms and high confidence. The Canadian team used SASNet; the Israeli team used Pearls of Wisdom; University of Memphis brought a Profiling sensor; and the University of Mississippi, Night Vision and Electronic Sensors Directorate, the Space & Naval Warfare Systems Command (SPAWAR), and U.S. Army Research Laboratory brought their equipment to collect the data. Representatives from Finnish Defense participated in observing the team. Some of the sensor modalities used are acoustic, seismic, passive infrared (IR), profiling sensor, sonar, and visible and IR imaging sensors. Some description of the sensors and their data analysis is presented. In this report, we present the data collection effort and some of the algorithms developed for various sensor modalities along with the results on the field data.

15. SUBJECT TERMS
Personnel detection, border patrol, acoustic, seismic, PIR, ultrasonic, profiling sensor, SASNET, Pearls of Wisdom, non-negative matrix factorization, single channel source separation

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					Thyagaraju Damarla
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER (*Include area code*)
Unclassified	Unclassified	Unclassified	UU	28	(301) 394-1266

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

1. Introduction

Detection of people is one of the important tasks in intelligence, surveillance, and reconnaissance (ISR) requirements. For example, in perimeter protection, one would like to detect any intruders during day and night so that proper authorities can be alerted for appropriate action. In urban operations, one would like to make sure once a building is evacuated nobody entered the building—this implies, sensors should detect people entering the building. Homeland Security often requires detection of illegal aliens crossing the border. There are numerous other applications where personnel detection is important.

Detection of people is a challenging problem. For example, acoustic sensors may analyze the sound and determine if there is any human voice present. However, if the people are not talking, the acoustic sensors may not be able to detect people based on the voice analysis. So, other sensors such as seismic, passive infrared (PIR), sonar, ultrasound, radar, magnetic, and electric field (E-field) sensors should be used for detection of people, since no single sensor will be able to detect in every situation and circumstance. Notice that the emphasis is on non-imaging sensors, since they tend to be low power and long lasting. Video sensors are often high power consuming and require frequent replacement of batteries; hence, there is a higher chance of compromising the mission. As such, the sensors used should consume little power and last long on batteries. For these reasons, majority of the sensors used for personnel detection tend to be acoustic, seismic, PIR, magnetic, E-field sensors, to name few. However, when one is collecting the data for development of algorithms, truth data are vital. For this purpose, we use video cameras to capture the truth data.

The people participated in this data collection are listed below:

1. U.S. Army Research Laboratory (ARL), Adelphi, MD, USA
2. Night Vision and Electronic Sensors Directorate (NVESD), Ft. Belvoir, VA, USA
3. Space & Naval Warfare Systems Command (SPAWAR), San Diego, CA, USA
4. University of Mississippi, Oxford, MS, USA
5. University of Memphis, Memphis, TN, USA
6. Canadian Defense Organization
7. Israeli Team
8. Finnish Defense Organization

We now present some descriptions of the equipment used by various parties.

1.1 ARL Data Collection System

ARL has brought three sensor systems, which are used to collect the data for the choreographed scenarios. It also brought another three sensors systems to collect the data of animals in their natural habitat— and the data are collected day and night.

One of the commercially available data collection systems, namely, "Wavebook," is primarily used for data collection for choreographed scenarios where people and animals walked along the trails in an orderly fashion. It has eight channels for data acquisition. The sampling rate, and the aliasing filters can be preprogrammed as desired. The following sensors are used on the Wavebook:

- Acoustic, seismic, PIR and ultrasonic sensor suite

An automatic data collection unit (ADCU) is used at remote sites to collect the data around the clock for animals in their natural habitat. The system is capable of collecting data on eight channels at 4 k samples per second. The sensor suite consists of the following:

- Acoustic, seismic, PIR and ultrasonic sensor suite

The sensors, namely, acoustic, seismic, PIR and ultrasonic sensors, used for data collection are same as the ones used during the 2009 data collection effort and thus have been described previously (*36*). The Wavebook data collection system with sensor suite deployed near trail is shown in figures 1 and 2, the latter of which shows one of the scenarios being enacted during the data collection. Figure 2 clearly shows several people and animals walking the trail.

(a) (b)

Figure 1. (a) ARL sensor deployment and (b) new profiling sensor.

Figure 2. People and animals walking on the trail.

1.2 Night Vision Data Collection System

NVESD brought a high-resolution camera to the field to collect data. The camera system is shown in figure 3. The system included a fish-eye lens to see the targets coming from all around.

Figure 3. NVESD camera system.

1.3 SPAWAR Data Collection System

SPAWAR brought two magnetic sensors and deployed them along the trail. The sensor is sensitive enough to detect people passing by carrying some ferrous material (e.g., keys). The sensors are shown in figure 4.

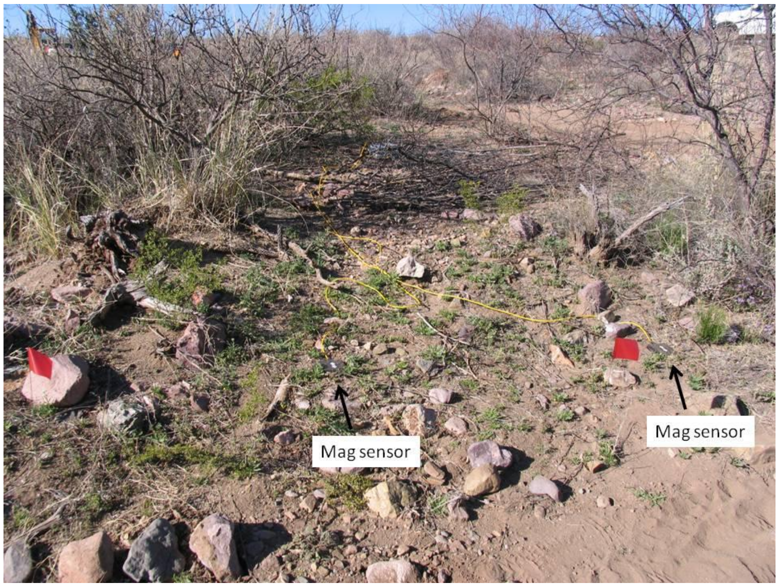

Figure 4. SPAWAR's magnetic sensors.

1.4 University of Mississippi Data Collection System

University of Mississippi deployed a similar system to ARL's system with acoustic, seismic and ultrasonic sensors. The deployed system is shown in figure 5.

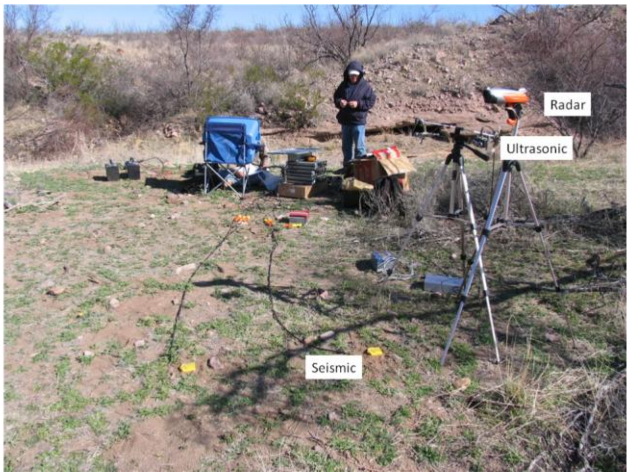

Figure 5. University of Mississippi sensors.

1.5 University of Memphis Data Collection System

University of Memphis have been working on developing new sensor system to replace high power consuming, high bandwidth requiring imaging sensors such as a camera. They developed a pyroelectric array profiling sensor with fewer pixels to capture the essence of an image. The deployed sensor is shown in figure 6.

Figure 6. Profiling sensor by University of Memphis.

1.6 Defense Research and Development Canada SASNet

The Canadian Defense Organization has developed a low-cost network called Self-healing Autonomous Sensor Networks (SASNet) for detecting and tracking targets. Each sensor node in the SASNet consists of acoustic, seismic, and magnetic sensors. Figure 7 shows some elements of SASNet.

Figure 7. SASNet.

1.7 Israeli Team

The Israeli team has deployed their system called "Pearls of Wisdom," which consists of acoustic, seismic, magnetic, and imaging sensors. Their system is shown in figure 8.

Figure 8. Pearls of Wisdom system.

2. Signal Processing

In this section, we present some of the advances made in seismic and ultrasonic signal processing for personnel detection. Most of the advances in signal processing concentrated on acoustic (ultrasound) and seismic sensors as they offer high fidelity to distinguish people from animals.

2.1 Seismic Signal Processing

The main purpose of a seismic sensor is to detect footfalls of humans walking within the receptive field of the sensor. There is a considerable amount of literature (*1–6*) in footstep detection. Traditionally, researchers have focused on estimating the cadence. However, if multiple people are in the vicinity of the sensor 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 walking and animals walking by observing the footfalls. However, multiple footfalls superimpose on one another, resulting in a frequency of 'c' Hz (where 'c' is an effective cadence of multiple walkers). So, a seismic algorithm can look for harmonics of cadence or several strong frequency components between 2 to 15 Hz to distinguish single and multiple walkers.

The seismic algorithm used is a multivariate Gaussian classifier (*1–7*) with the feature set consisting of amplitudes of the frequency bins from 2 to 15 Hz. Then, an algorithm is used to estimate the posterior probability of footsteps present.

The algorithm only determines whether there are footsteps present. In order to detect the presence of humans, it is necessary to determine whether these footsteps belong to a human or an animal. For this, we invariably turn to acoustics. If there is voice, it can be detected and identified as a human voice based on the formants. In order to distinguish people and animals

when no voice is present, we analyze the sound generated by the animals walking. When a single hoof of a horse strikes the ground, it produces a sound pattern that is distinct from that of a human foot. Figure 9 shows the signature of horse walking (for a period of 6 s) before and after noise removal. The noise removal is performed using empirical mode decomposition (*4, 6*) of the original signal into various component signals. From figure 9, it is clear that there are three peaks uniformly distributed in each time interval of 1 s. This indicates the cadence of the horse to be approximately 2.8 to 3 Hz. Since the cadence of a person is around 1.5 to 2 Hz, one can infer the presence of animals.

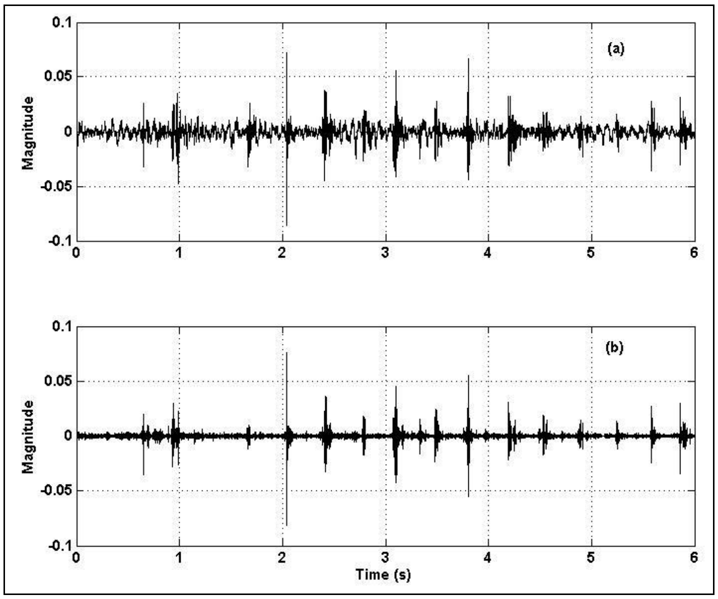

Figure 9. (a) Hoof signature and (b) hoof signature after noise removal.

When a person walks, the heel of the foot strikes first and then the toe end of the foot strikes, rubbing against the ground, creating a unique seismic signature compared to that of an animal (figure 10). Animals, in general, walk on their hoof or "toe" (the horse ankle and heel or fetlock do not strike the ground), which strikes the ground producing signatures that are different from those of people. Both the signatures have different frequency response on the same ground. In section 2.1.1, we present a technique that uses the differences in frequency responses to distinguish both types of footfalls.

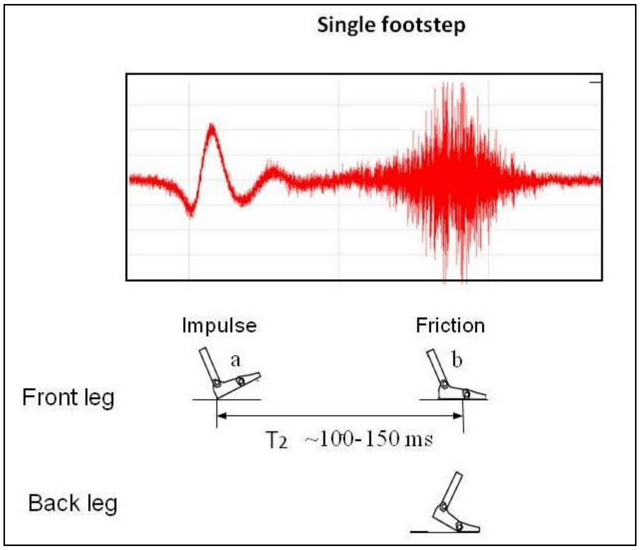

Figure 10. Seismic signature of a single footstep of a person.

2.1.1 Discrimination of Animal and Human Seismic Signatures

For a single walking person, detection of cadence and human footstep signature is relatively easy. However, when animals and people are walking in the vicinity of a seismic sensor, the detection of human foot signature is not as straightforward. If there are multiple sensors collecting the same signatures, one can use principal component analysis (PCA) or independent component analysis (ICA) (*9*) to separate the human footstep signatures from the animal footsteps depending whether the noise is Gaussian or not. Most of unattended ground sensor (UGS) systems consist of only one sensor per modality, that is, one acoustic, one seismic, etc., so it is not possible to use the PCA or ICA technique for blind signal separation, since PCA or ICA require at least *n* number of sensors to separate *n* sources. In acoustics, several researchers (*10–14*, *37*) have developed techniques for single channel source separation where they attempted to separate signals from two human speakers from a single microphone. In almost all the cases, they used short time Fourier transform (STFT) and non-negative matrix factorization (NMF) techniques.

The NMF technique was first introduced by Lee and Seung (*15*, *16*) and was adopted by others to minimize the cost function

$$\frac{1}{2}\sum_{\omega,t}\left\| X_{\omega,t}\right| - \sum_{k} H_{\omega,k}W_{k,t}\Big|^{2} + \lambda\sum\left|W_{k,t}\right|^{1}, \tag{1}$$

where X is the STFT with variables in frequency ω and time t; H and W are the basis and weight matrices; and λ controls the sparcity of the weights, that is, fewer weights, hence fewer basis functions, will be used. The fact that the elements of $X_{\omega,t}$, H, and W are all non-negative gives the algorithm the name non-negative matrix factorization. We use discrete cosine transform (DCT) instead of STFT to avoid the problems arising due to complex signals. Let

$$X_i = dct(x_i(t)) \tag{2}$$

be the DCT of the signal $x_i(t)$. It is found that first 500 of the DCT coefficients are sufficient to reconstruct the time domain signal with negligible distortion. It is worth noting that earlier versions of JPEG compression schemes used DCT. So X_i denotes the first 500 DCT coefficients. Let B_i and β_i denote the positive and negative DCT coefficients such that $X_i = B_i - \beta_i$. Let the matrix $X_p = \{X_i\}; \quad \forall i$ be the set of DCT coefficients for all the training data corresponding to the people. Then, the matrix $[X_p]$ can be written as

$$[X_p] = [X_p^+] - [X_p^-] \tag{3}$$

with matrix $[X_p^+] = \{B_i\}$ representing the positive DCT coefficients and matrix $[X_p^-] = \{\beta_i\}$ representing the negative DCT coefficients of X_p. Similarly, X_a represents the set for animals. After performing the NMF on the matrices, we get

$$\left[X_p^+\right] \approx W_p H_p; \quad \left[X_p^-\right] \approx \mathcal{W}_p \mathcal{H}_p \tag{4}$$

$$\left[X_a^-\right] \approx W_a H_a; \quad \left[X_a^-\right] \approx \mathcal{W}_a \mathcal{H}_a \tag{5}$$

The matrices W and $\mathcal{W}$ represent the weight matrices and the matrices H and $\mathcal{H}$ correspond to the bases. Once the basis matrices are available, they can be used to represent the DCT coefficients X_t of a test signal $x(t)$ as weighted sum of their components. The algorithm to estimate the weights and bases (subset of H and $\mathcal{H}$) is given below:

Algorithm 1:

- Step 1: Normalize the test signal $x(t)$ after removing the mean. Compute X_t = dct ($x(t)$). Let $X_t = B_t - \beta_t$, where B_t and β_t denote the positive and negative DCT coefficients.
- Step 2: Estimate the weights $W = \{w_1, w_2, \cdots, w_r\}$ and $V = \{v_1, v_2, \cdots, v_r\}$ such that

  $$|B_t - WH|^2 + |\beta_t - V\mathcal{H}|^2 \text{; such that } 0 \le w_i, v_i \le u_b; \forall i \in \{1, 2, \cdots, r\} \tag{6}$$

  is minimum, u_b is typically 1. One may use any constrained nonlinear optimization program such as the "*fmincon*" function in MATLAB to determine the weights.
- Step 3: Non-zero weights w and v give the bases used to represent X_t.
- Step 4: Reconstruct the signal $\hat{x}(t)$ by taking the inverse DCT of the difference ($WH - V\mathcal{H}$).

We used NMF technique (*18*) to separate human and animal signatures from a single seismic channel data. In order to verify the technique, we took two seismic signals, one from a person and another from a horse walking, and mixed them, as shown in figure 11. Then the NMF technique is used on the mixture to separate the signals. The results of NMF technique is shown

in figures 12 and 13. From these figures, we notice the reconstruction (separation) of the signals is good except in the places where there is noise. The NMF algorithm is further used on several sets of data collected on a single person, single horse, and both a horse and a person walking. The sum of the weights corresponding to the bases of horse S_h and a person S_p determine whether the extracted signature belongs to a horse (animal) or a person depending on whether $S_h > S_p$. The values of S_h and S_p are plotted in figure 14 as 'o' and '*', respectively. From the figure, we find that the NMF algorithm provided $S_p > S_h$ and is higher than the threshold shown by a solid line at 0.7 for the data with one person walking majority of times and $S_h > S_p$ for the case when a horse was walking. When both a person and a horse walked, both S_h and S_p are above the threshold, indicating that both the targets are present. So we can detect and classify the footprint signatures of people and animals even when both are present at the same time. Traditional classification algorithms classify only any one of the targets present but not both simultaneously. They fail if both targets are present. Several results using NMF techniques are presented in the literature (*39, 40, 43, 44*).

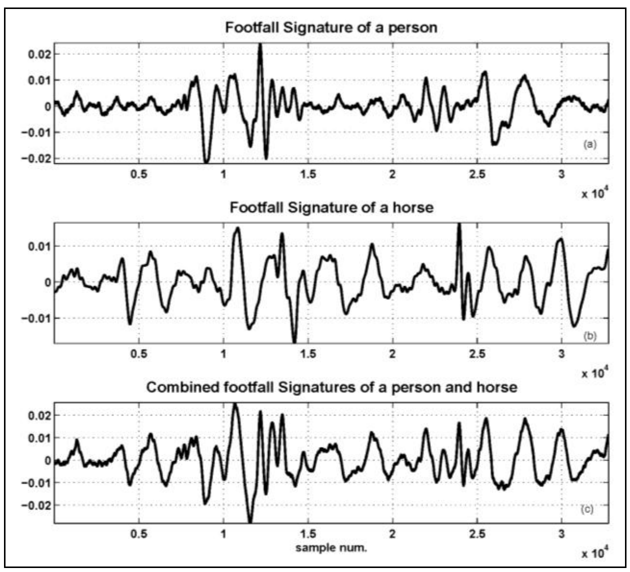

Figure 11. Mixture of a signature from a person and a horse.

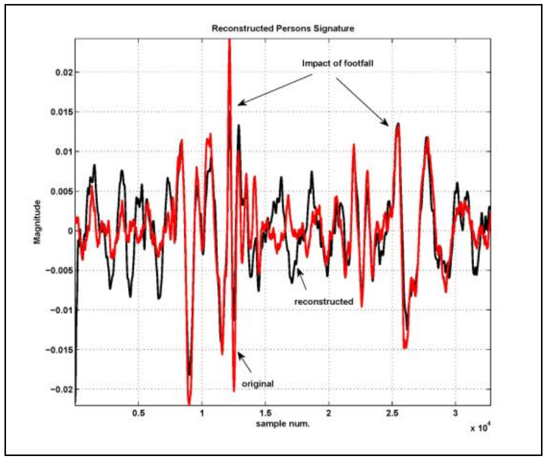

Figure 12. Extraction of human signature.

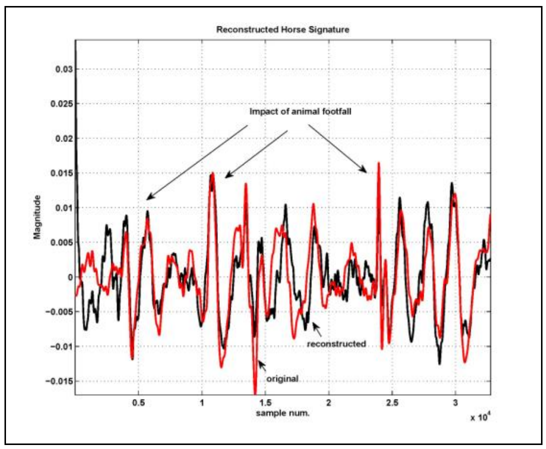

Figure 13. Extraction of horse signature.

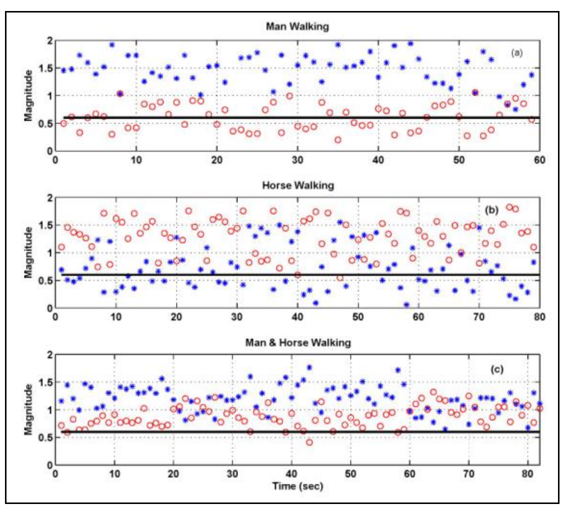

Figure 14. Results of NMF algorithm on signature data of (a) man, (b) horse, and (c) man and horse walking.

2.2 Ultrasonic Sensor Modeling and Ultrasonic Signal Processing

In this section, we present the analysis of ultrasonic sensor data to characterize and discriminate both people and animals. The ultrasonic sensor is an active sensor that radiates a 40-kHz ultrasonic signal and captures the signals that are bounced back by the target in its beam. The principle of operation is same as radar (*19*). The micro-Doppler returns due to the swinging of the arms, legs, and torso of a person or an animal are analyzed. We take advantage of these Doppler returns from the limbs to classify the targets. However, in order to understand the type of Doppler signatures that would be generated by the swinging of arms, legs, and torso of various targets, it is necessary to model these parts and compute the Doppler values.

Our University of Mississippi partners Bradley and Sabatier (*20, 21*) have explained the observed human-gait features in Doppler sonar grams by using the Boulic-Thalmann (BT) (*22*) model, shown in figure 15, to predict joint angle time histories and the temporal displacements of the body's center of mass. In the BT model, body segments are represented as ellipsoids. Temporally dependent velocities at the proximal and distal end of key body segments are determined from the BT model, as shown in figure 16. Doppler sonar grams are computed by mapping velocity-time dependent spectral acoustic cross sections for the body segments onto time-velocity space, mimicking the STFT used in Doppler sonar processing. Figure 17a shows the estimated velocities using the model for various parts of the body for a 6-ft-tall person. The Doppler is related to the radial velocity v_r of the target and is given by $f_d = \frac{2v_r}{c} f_c$, where c is the propagation velocity of sound and f_c is the radiated carrier frequency. The detailed computation of velocities of various limbs can be found in reference 20. Similar, models are developed (*21*) for a quadruped, such as a horse. Figure 17b shows the estimated velocities for a horse. The models are validated using experimental results and have been reported previously (*41*, *42*, *45*, *47*).

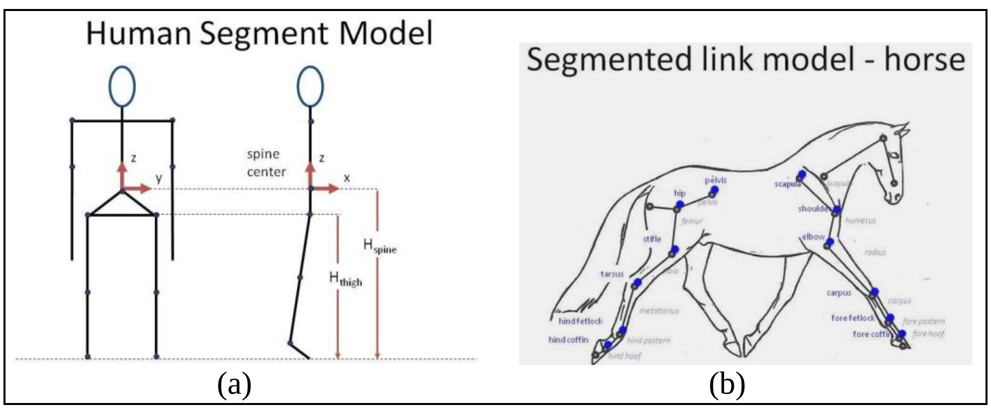

Figure 15. (a) Human model as a stick figure and (b) horse model.

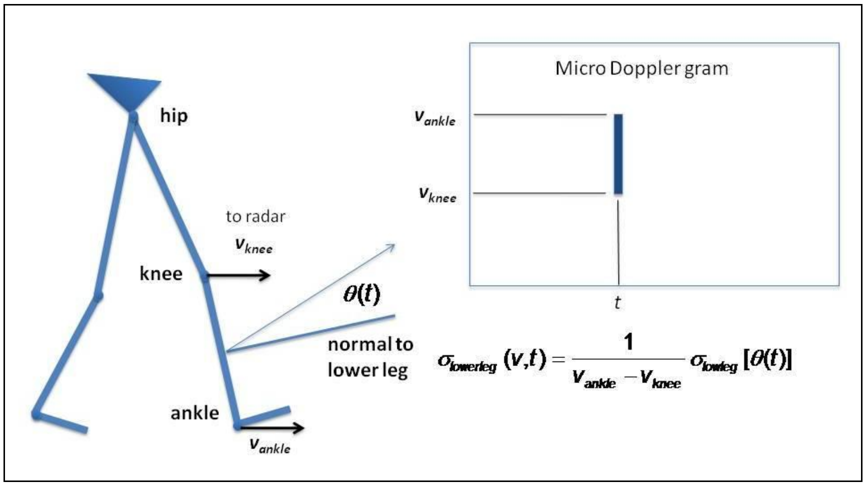

Figure 16. Estimation of velocities of various parts of body.

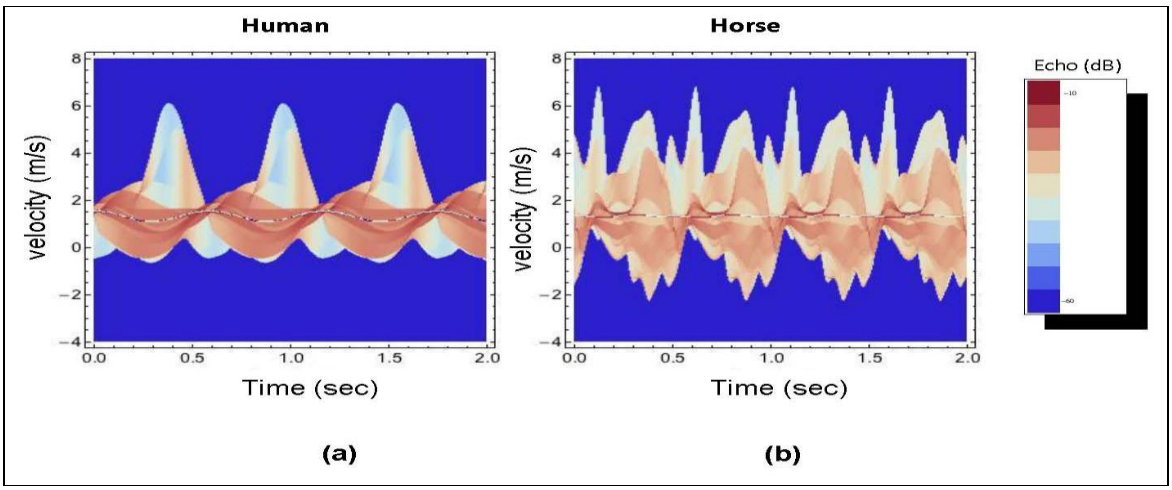

Figure 17. Estimated velocity (Doppler) for (a) a person walking and (b) a horse walking.

Figure 18 shows the Doppler signature collected for a person walking in one of the scenarios. Each sensor records the data when the person walks by the sensor. The data collection is done when a person (or a horse) walks toward the sensor at close range (figure 18b) and when the person (or a horse walks away from the sensor at a distance and to one side of the sensor [figure 18c]). In the first case, the signal strength is high and the Doppler returns from the various parts are clearly visible, while in the latter case the Doppler returns are weak and the features are not clearly visible. Hence, we developed two algorithms to classify the targets, namely, (1) when the signal-to-noise ratio (SNR) is high (>6 dB) and (2) when the SNR is low.

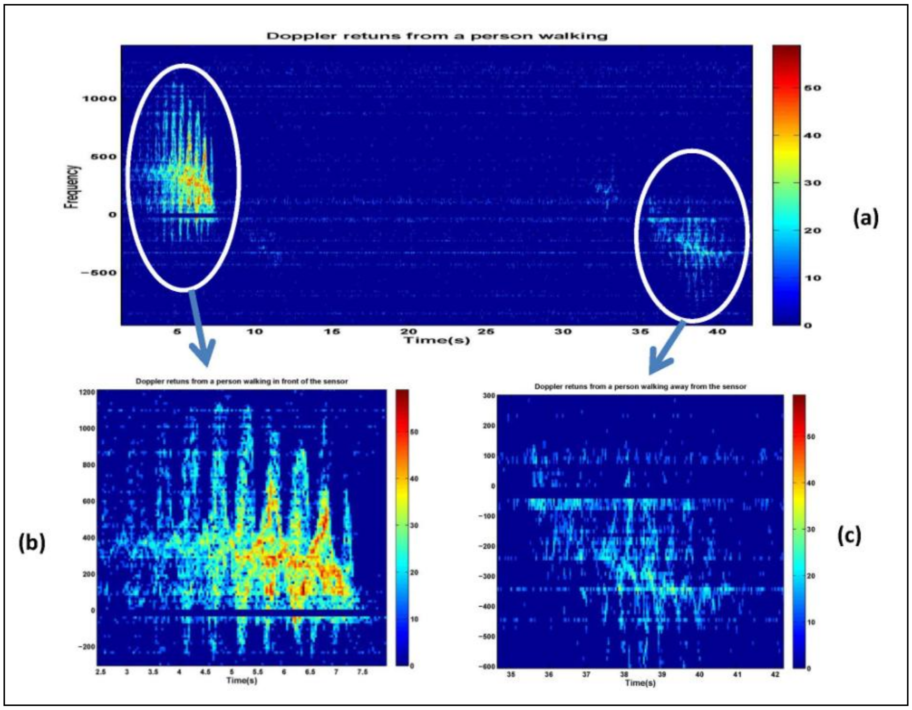

Figure 18. (a) Doppler returns for a person walking, (b) measured Doppler when a person walks towards the sensor, and (c) Doppler returns when a person walks away from the sensor.

2.2.1 Case 1: High Signal-To-Noise Ratio (SNR)

In this case, the targets walk in front of the sensor at a close proximity, and the atmospheric (wind) effects on the received signal are minimal. This is the case where some model features can be clearly identified, and the classification can be made based on the model. An example of high SNR is shown in figure 18b. In order to characterize the target either as a person or an animal, we look for (a) cadence, (b) maximum and minimum variation in the Doppler frequency due to limbs, and (c) the sequential nature of limb movements. Figure 19 shows the enlarged version of figure 18b. It shows the average Doppler of the torso (average velocity of a person walking) and the Doppler due to arms and legs. When the arms and legs swing forward/backward, we get a Doppler above/below the average (the sinusoidal line above/below the average line). The cadence is estimated as $1/t$, where t is the time between two peaks of a sinusoidal curve. The cadence is estimated to be 1.8 Hz for the person. The maximum and minimum Doppler frequency of limbs with respect to the average is found to be ±800 Hz, and this will be contrasted with the values for an animal. The vertical lines on figure 19 are drawn to show the lag (sequential nature of limb movement) between the top and lower sinusoidal curves. The lag is ~0.1 s.

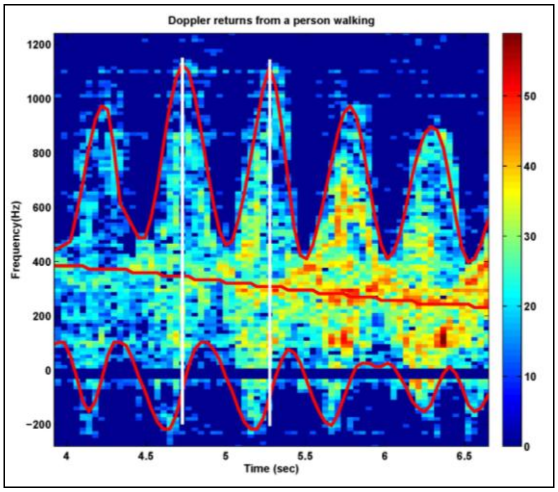

Figure 19. Measured Doppler output for a person.

Figure 20 shows the ultrasonic returns from a horse walking. One clear distinction between the Doppler signatures for a person and a horse walking is that the signature for a person is sinusoidal in nature. Horse motion is much more complex, as there are many more moving parts for a horse than a person. Another distinct feature for the horse is that the Doppler returns below the "average torso Doppler" are significantly less. The maximum variation of Doppler for the horse (~1500 Hz) is higher compared than that for a person (~1100 Hz). Figure 21 shows the Doppler energy plot for a horse walking. The peaks in figure 21 show the periodic nature of a horse walking; the cadence can be estimated from it. The cadence of the horse is estimated to be around ~1.7 Hz. This cadence value is significantly low for a horse; this is due to the fact that the horse is made to walk slowly on purpose. This is also verified using the seismic data. The cadence of the horse is found to be close to the cadence of a person walking. Hence, cadence alone cannot be used to distinguish a person from a horse or any other quadruped. From figure 21, we notice that each peak has an adjacent smaller peak marked by ellipses in the figure. This double peaked result is characteristic of a quadruped walking and is also seen in the model shown in figure 17b. The time difference between two adjacent peaks is ~0.12 s. The algorithm to distinguish people and animals using the features described earlier is given in the flowchart shown in figure 22.

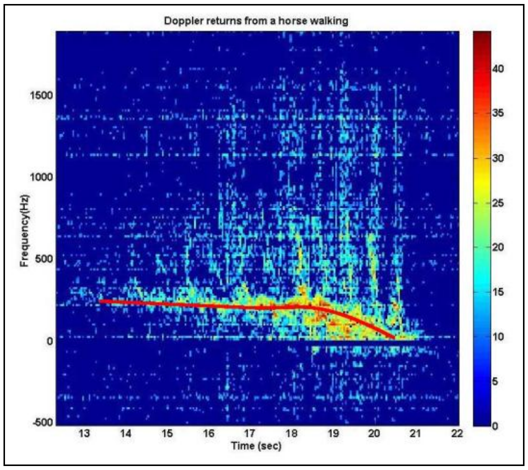

Figure 20. Measured Doppler for a horse.

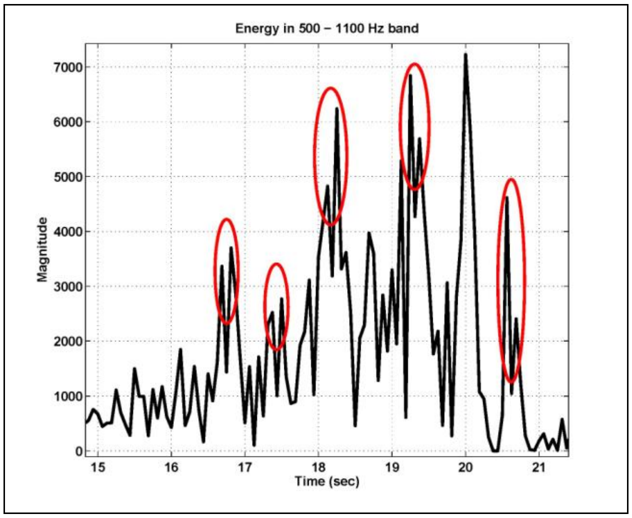

Figure 21. Doppler energy in 500–1100 Hz band for a horse walking.

Figure 22. Classification of ultrasonic data.

2.2.2 Case 2: Low Signal-To-Noise Ratio

In the event the signal returns are weak for any reason (such as prevailing winds, the target being farther than optimal distance, the target being illuminated by the ultrasonic transducer at an angle, etc.), the features observed in the case of high SNR may not be present, as seen in figure 18c. For low SNR data, it is appropriate to use classical signal processing techniques to classify the targets. We used a support vector machine (SVM) for classification, as shown in figure 22.

3. Conclusions

In this report, we presented the data collection done at the southwest border of United States during March 2012. We also presented the advances made in signal processing for personnel detection. The main focus had been on acoustic, seismic, and ultrasonic data processing. Acoustic data are processed to determine the presence of a human voice and the sounds due to footsteps. If the human voice is detected reliably, the cadence of the footsteps is ~1.5 Hz, and the energy distribution in the spectral bands determines it belongs to a person, the sensor fusion algorithm classifies the target as being a person with high confidence.

The seismic sensor data are analyzed for cadence and the distribution of its harmonics are analyzed to determine if they belong to a person or an animal. Furthermore, the seismic signatures are classified using NMF to confirm whether they belong to a person or an animal. We can determine even if both people and animals are present at the same time since we separate their signals. A fusion algorithm combines both the results to assign an overall classification rating. Integration of the results over a period of time results in higher confidence in the classification.

The ultrasonic sensor provides high fidelity Doppler data of arm, leg, and torso movements of people and animals. These Doppler returns are processed with the algorithms developed using physics-based phenomenological models to determine the classification of the targets. When the SNR is >6 dB, the classification is very accurate (within the 95% range.)

4. References

1. Houston, K. M.; McGaffigan, D. P. Spectrum Analysis Techniques for Personnel Detection Using Seismic Sensors. *Proc. of SPIE* **2003**, *5090*, 162–173.

2. Sabatier, James M.; Ekimov, Alexander. Range Limitation for Seismic Footstep Detection. *Proc. of SPIE* **2008**, *6963*, 69630V-1.

3. Ekimov, Alexander; Sabatier, James M. Passive Ultrasonic Method for Human Footstep Detection. *Proc. of SPIE* **2007**, *6562*, 656203.

4. Sunderesan, A.; Subramanian, A.; Varshney, P. K.; Damarla, T. A Copula Based Semi-Parametric Approach for Footstep Detection Using Seismic Sensor Networks. *Proc. of SPIE* **2010**, *7710*, 77100C.

5. Bland, R. E. *Acoustic and Seismic Signal Processing for Footstep Detection*; Master's Thesis, Massachusetts Institute of Technology, Department of Electrical Engineering and Computer Science, 2006.

6. Iyengar, S. G.; Varshney, P. K.; Damarla, T. On the Detection of Footsteps Based on Acoustic and Seismic Sensing. in *Conference Record of the Forty First Asilomar Conference on Signals, Systems and Computers*, ACSSC 2007, pp. 2248-2252, 4–7 November 2007.

7. Damarla, T.; Ufford, David. Personnel Detection Using Ground Sensors. *Proc. of SPIE* **2007**, *6562*, 656205.

8. *Encyclopedia of Acoustics*; Vol. 4, Edited by Malcolm J. Crocker, Published by John Wiley & Sons, Inc. New York, NY, 1997.

9. Hyvarinen, A.; Karhunen, J.; Oja, E. *Independent Component Analysis*; John Wiley & Sons, New York, NY 10158, 2001.

10. Schmidt, M. N.; Morup, M. Nonnegative Matrix Factor 2-d Deconvolution for Blind Single Channel Source Separation. in *Independent Component Analysis* **2006**, 700–707.

11. Schmidt, M. N.; Olsson, R. K. Single-Channel Speech Separation Using Sparse Non-Negative Matrix Factorization. in *International Conference on Spoken Language Processing (INTERSPEECH* **2006**.

12. Roweis, S. T. One Microphone Source Separation. *In Advances in Neural Information Processing Systems* **2000**, *13*, 793–799 (MIT Press).

13. Jang, G.; won Lee, T.; Cardoso, J. Franois; Oja, E.; Amari, S. I. A Maximum Likelihood Approach to Single-Channel Source Separation. *Journal of Machine Learning Research* **2003**, *4*, 1365–1392.

14. King, B.; Atlas, L. Single-Channel Source Separation Using Simplified-Training Complex Matrix Factorization. in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, 4206–4209, 2010.

15. Lee, D. D.; Seung, H. Learning the Parts of Objects by Non-Negative Matrix Factorization. in *Nature* **1999**, *401*, 788–791.

16. Lee, D. D.; Seung, H. Algorithm for Non-Negative Matrix Factorization. in *NIPS* **2001**, *13*, 556–562.

17. King, B.; Atlas, L. Single-Channel Source Separation Using Simplified-Training Complex Matrix Factorization. in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, 4206–4209, 2010.

18. Mehmood, A.; Damarla, T.; Sabatier, J. Discrimination of People From Animals Using Non-Negative Matrix Factorization in Seismic Signatures. under 2nd review *Journal of Acoustical Society of America*.

19. Geisheimer, J. L.; Marshall, W. S.; Greneker, E. A Continuous-Wave (cw) Radar for Gait Analysis. in *Proc. of* 35*th Asilomar conference on Signals, Systems and Computers*, 2001, pp. 834–838.

20. Bradley, M.; Sabatier, J. M. Applications of Fresnel-Kirchhoff Diffraction Theory in the Analysis of Human-Motion Doppler Sonar Grams. *Journal Acoustical Society of America Express Letters* **Nov 2010**, *128*, 1–10.

21. Bradley, M.; Sabatier, J. M. Using Acoustic Micro-Doppler Sonar to Distinguish Between Human and Equine Motion. in *NATO Workshop on Autonomous Sensing and Multi-Sensor Integration SET-176 RSM*, Cardiff, UK, October 2011.

22. Boulic, T. R.; Thalmann, D. A Global Human Walking Model with Real-Time Kinematic Personification. *The Visual Computer* **1990**, *6*, 344–358.

23. Mehmood, A.; Sabatier, J. M.; Bradley, M.; Ekimov, A. Extraction of Walking Human's Body Segments Using Ultrasonic Doppler. *Acoustical Society of America Journal* **2010**, *128*, 316.

24. Damarla, T.; Sabatier, J. Sensor Fusion for Personnel Detection. *Proc. NATO SET-176 Specialists Meeting on Autonomous Sensing and Multi-Sensor Integration for ISR Applications*, Oct. 24-25, 2011, Cardiff, UK.

25. Mitchell, H. B. *An Introduction to Multi-Sensor Data Fusion*; Springer-Verlag, New York, 2007.

26. Hall, D. L.; McMullen, S.A.H. *Mathematical Techniques in Multisensor Data Fusion*; Artech House, Norwood, MA, 2004.

27. Damarla, T.; Mehmood, A.; Sabatier, J. Detection of People and Animals Using Non-Imaging Sensors. in *14th Intl. Conference on Information Fusion*, Chicago, IL, pp. 429–436, July 5–8, 2011.

28. Sen, P.; Damarla, T.; Hasegawa-Johnson, M. Multi-Sensory Features for Personnel Detection at Border Crossings. in *14th Intl. Conference on Information Fusion*, Chicago, IL, pp. 421–428, July 5–8, 2011.

29. Rabiner, L. R.; Juang, B.-H.; Levinson, S. E.; Sondhi, M. M. Recognition of Isolated Digits Using Hidden Markov Models with Continuous Mixture Densities. *AT&Technical Journal* **1985**, *64* (6 pt 1), 1211–1234.

30. Jin, X.; Gupta, S.; Ray, A.; Damarla, T. Multimodal Sensor Fusion for Personnel Detection. in *Proc. 14th International Conference on Information Fusion*, Chicago, IL, July 5-8, 2011, pp. 437–444.

31. Iyengar, Satish G.; Varshney, Pramod K.; Damarla, Thyagaraju. A Parametric Copula-based Framework for Hypothesis Testing using Heterogeneous Data. *IEEE Trans. on Signal Processing* **May 2011**, *59* (5), 2308–2319.

32. Jin, Xin; Sarkar, S.; Ray, A.; Gupta, S.; Damarla, T. Target Detection and Classification Using Seismic and PIR Sensors. *IEEE Sensors Journal* **2011**.

33. Ray, A. Symbolic Dynamic Analysis of Complex Systems for Anomaly Detection. *Signal Processing* **2004**, *84* (7), 1115–1130.

34. Gupta, S.; Ray, A. *Symbolic Dynamic Filtering for Data-Driven Pattern Recognition*; in Pattern Recognition: Theory and Application. Nova Science Publishers, Hauppage, NY, 2007, ch. 2, pp. 17–71.

35. Vidal, E.; Thollard, F.; Higuera, C.; Casacuberta, F.; Carrasco, R. C. Probabilistic Finite-State Machines–Part I. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **July 2005**, *27* (7), 1013–1025.

36. Damarla, T.; Walker, T.; Sartain, R. *Data Collection and Analysis for Personnel Detection at a Border Crossing*; ARL-TR-5426; U.S. Army Research Laboratory: Adelphi, MD, 2011.

37. Mehmood; Damarla, T. Kernel Non-Negative Matrix Factorization for Seismic Signature Separation. *Journal of Pattern Recognition Research* **June 2013**, *8* (1), 13–25.

38. Damarla, T.; Bradley, M.; Mehmood, A.; Sabatier, J. M. Classification of Animals and People Ultrasonic Signatures. *IEEE Sensors Journal* **May 2013**, *13* (5), 1464–1472.

39. Damarla, T.; Mehmood, A.; Sabatier, J. M. Seismic Signature Analysis for Discrimination of People From Animals. *Proc. of SPIE* **Apr. 2013**, *8745*, 874518-1.

40. Mehmood, A.; Damarla, T.; Sabatier, J. M. Separation of Human and Animal Seismic Signatures Using Non-Negative Matrix Factorization. *Pattern Recognition Letters* **December 2012**, *33* (16), 2085–2093.

41. Mehmood, A.; Sabatier, J. M.; Damarla, T. Ultrasonic Doppler Methods to Extract Signatures of a Walking Human. *J. Acoust. Soc. Am.* **September 2012**, *132* (3), pp. EL243-EL249.

42. Mehmood, A.; Sabatier, J. M. Extraction of the Velocity of Walking Human's Body Segments Using Ultrasonic Doppler. *The Journal of the Acoustical Society of America* **Nov. 2010**, *128* (5), EL316-EL322.

43. Mehmood, A.; Patel, V. M.; Damarla, T. Discrimination of Bipeds from Quadrupeds using Seismic Footstep Signatures. *IEEE IGARSS* **22–27 July 2012**, 6920–6923.

44. Mehmood, A.; Damarla, T. Blind Separation of Human and Horse Footstep Signatures Using Independent Component Analysis. *Proc. SPIE* **2012**, *8382*, 83820L.

45. Mehmood, A.; Sabatier, J. M; Damarla, T. Review of Ultrasonic Doppler Measurements. *NATO Workshop on Autonomous Sensing and Multi-Sensor Integration SET-176 RSM,* October 2011.

46. Damarla, T.; Mehmood, A.; Sabatier, J. M. Detection of People and Animals using Non-Imaging Sensors. *14th International IEEE Conf. on Information Fusion*, pp. 429–436, 2011.

47. Damarla, T.; Mehmood, A.; Sabatier, J. M. Personnel Detection using Acoustic, Seismic & Ultrasonic Signatures. *8th NATO Symposium on Military Sensing SET-169 RSY-025 MSS*, 2011.

48. Mehmood, A.; Sabatier, J. M. Video Validation of Human Leg Velocities from Doppler Ultrasound. *Proc. Military Sensing Symposium on Battlefield Acoustic and Magnetic Sensors*, August 2010.

NO. OF COPIES	ORGANIZATION
1 (PDF)	DEFENSE TECHNICAL INFORMATION CTR DTIC OCA
2 (PDFS)	DIRECTOR US ARMY RESEARCH LAB RDRL CIO LL IMAL HRA MAIL & RECORDS MGMT
1 (PDF)	GOVT PRINTG OFC A MALHOTRA
7 (PDFS)	DIRECTOR US ARMY RESEARCH LAB RDRL SES A THYAGARAJU DAMARLA RONALD A. FRANKEL ASIF MEHMOOD JAMES M. SABATIER GARY CHATTERS ATTN RDRL SES P HAO VU ATTN RDRL SES E MATTHEW THIELKE,