# Applying matching pursuit decomposition time-frequency processing to UGS footstep classification

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## ABSTRACT

The challenge of rapid footstep detection and classification in remote locations has long been an important area of study for defense technology and national security. Also, as the military seeks to create effective and disposable unattended ground sensors (UGS), computational complexity and power consumption have become essential considerations in the development of classification techniques. In response to these issues, a research project at the Flexible Display Center at Arizona State University (ASU) has experimented with footstep classification using the matching pursuit decomposition (MPD) time-frequency analysis method. The MPD provides a parsimonious signal representation by iteratively selecting matched signal components from a pre-determined dictionary. The resulting time-frequency representation of the decomposed signal provides distinctive features for different types of footsteps, including footsteps during walking or running activities. The MPD features were used in a Bayesian classification method to successfully distinguish between the different activities. The computational cost of the iterative MPD algorithm was reduced, without significant loss in performance, using a modified MPD with a dictionary consisting of signals matched to cadence temporal gait patterns obtained from real seismic measurements. The classification results were demonstrated with real data from footsteps under various conditions recorded using a low-cost seismic sensor.

**Keywords:** Footstep classification, matching pursuit decomposition, time-frequency analysis, feature extraction, Bayesian classification, unattended ground sensor, seismic sensing.

## 1. INTRODUCTION

In many areas of security, footstep detection and classification continues to be an important need, particularly along the nation's borders and around forward operating bases and nuclear power plants. The need to detect people passing by a sensor, with minimum number of false alarms caused by animals or friendly military personnel, requires effective signal processing and classification algorithms, that can sort through the sensor data and accurately classify individuals that pass by the sensor. Another dimension of difficulty is added when the classification uses data from unattended ground sensors.[1–3] These sensors are often placed in difficult-to-reach or hostile locations. As their power supplies cannot be changed often, such devices necessitate low power consumption in order to continue to operate for months, even years.

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Footstep classification has been at the forefront of research for the past few years in response to the aforementioned needs.[2–7] In 2011, Damarla and Sabatier, from the U.S. Army Research Laboratory, presented work on classifying people walking and jogging/running using data from several different sensors, including seismic, acoustic, and ultrasonic sensors.[3] The paper discussed how cadence frequency (or walking rate) can be used as a key feature in footstep classification, although difficult to calculate when multiple people are walking or a person is leading an animal. It also considered other distinctive features of seismic data that can be used to distinguish between a person walking, a person running, and a horse walking. These features included peak amplitude and span, where span is the amount of time the magnitude of the footstep signal remains above a given threshold. Cadence analysis of temporal gait patterns was also used to obtain information features on the temporal distribution of gait beats; the features were modeled and classified using Gaussian mixture models.[4] Recently published work sought to distinguish between human and horse footsteps using independent component analysis of the footstep signatures.[5] In another work, the authors focused on classifying the seismic signatures produced by animals and humans using the short time Fourier transform and non-negative matrix factoring analysis techniques.[6] Differences in the signatures were found due to the fact that humans typically walk with their heel striking the ground first followed by their toes whereas animals walk on their toes or hooves. Thus, a different part of the foot generates the primary impulse of the footstep, resulting in a different seismic signature. A similar analysis can also be conducted for men and women walking, due to their different gaits and weights. Overall, these papers demonstrate that successful footstep classification requires the use of distinctive features to distinguish between different classes of footsteps.

This clear emphasis on distinctive features on footstep classification in previous literature has led us to investigate the use of the matching pursuit decomposition (MPD) time-frequency technique[8] to footstep signal analysis. The MPD is a signal processing algorithm that can be used to approximate a signal in terms of a basic element or atom, stored in a time-frequency dictionary. The dictionary is often set to consist of a standard library of mathematical functions with high time-frequency resolution properties such as Gaussian signals. The dictionary elements can also be user-specified and chosen to match the characteristics of the analysis signal.[9,10]

In this paper, we investigate the performance of the MPD using a dictionary comprised of time-frequency shifted and scaled versions of a basic Gaussian signal. We use this MPD for footstep signal analysis and classification. Specifically, we classify footsteps based on distinctive features obtained from the MPD time-frequency approximation of seismic sensor measurements and a Bayesian classifier. We also consider a modified MPD whose dictionary elements consist of signal segments that are matched to cadence temporal gait patterns obtained from real seismic measurements. As we are using features directly from measurements, the modified MPD requires a substantially smaller number of dictionary elements and results in a smaller number of components in its signal decomposition. As the MPD is an iterative algorithm, the smaller number of iterations required by the modified MPD results in a lower computational complexity and thus a lower power consumption. This is because each MPD iteration computes an inner product between the signal or its residue (after a component is extracted) and each element of the dictionary. With a reduced dictionary size and a reduced number of iterations required for decomposition accuracy, the modified MPD can provide a power-efficient way to analyze footsteps.

This paper is organized as follows. In Section 2, we summarize the MPD and the modified MPD for time-frequency feature extraction. We apply the MPD to footstep signals in Section 3, and we discuss features for cadence temporal gait patterns in Section 4. The classification results for real seismic measurements are presented in Section 5.

## 2. MPD FEATURE EXTRACTION

Mallat and Zhang proposed the matching pursuit decomposition (MPD) algorithm in.[8] The goal of the MPD algorithm is to obtain an approximation of a signal in terms of atoms from a predetermined time-frequency dictionary.[8,11,12] This dictionary is designed using time-frequency Gaussian signal elements or atoms which are the most highly-concentrated signals in both time and frequency. Gaussian atoms are selected from the dictionary in an iterative manner to match the signal components of interest. The quality of the resulting approximation can be controlled by fixing the number of iterations or by fixing the energy of the residual signal. Based on this convergence criterion, the MPD approximation can result in a signal expansion consisting mainly of useful signal components with reduced noise components.

### 2.1 MPD with Gaussian Dictionary

The MPD constructs an approximation of a signal by iteratively subtracting weighted elementary basis elements or atoms that are predefined in a user-defined time-frequency dictionary. The original signal can then be represented as a linear combination of these weighted atoms. If the original (finite energy) signal is represented as $s(t)$ and the weighted expansion coefficient and the Gaussian basis function at the $i$th MPD iteration are represented as $\kappa_i$ and $g_i(t)$ respectively, the complete signal expansion is given by

$$s(t) = \sum_{i=0}^{\infty} \kappa_i \, g_i(t).$$

It can be shown that the representation preserves signal energy for an infinite number of iterations.[8] That is, the total energy of the signal can be shown to be equal to the sum of squares of the expansion coefficients when the energy of the basis elements is normalized.

The MPD algorithm computes the signal expansion in an iterative manner. The algorithm starts by initializing the residual signal as the original signal, $r_0(t) = s(t)$. At the $i$th iteration, the element that best matches the $i$th residue is found by calculating and maximizing the inner product of the signal with all of the elements in the dictionary. The contribution of this element is then subtracted from the $i$th residue to obtain the residue for the next iteration as

$$r_{i+1}(t) = r_i(t) - \kappa_i \, g_i(t).$$

After $N$ iterations, the MPD expansion can be approximated as

$$s(t) = \sum_{i=0}^{N-1} \kappa_i \, g_i(t) + r_N(t).$$

The iterations are terminated when the residue signal energy is smaller than a predetermined threshold.

In the construction of the dictionary of time-frequency Gaussian atoms, three parameters are specified: the scale $\alpha$, the frequency-shift $\nu$, and the time-shift $\tau$. The time-frequency shifted and scaled Gaussian element chosen during the $i$th iteration is given by

$$g_i(t) = \left(\frac{8\,\alpha_i}{\pi}\right)^{1/4} \exp\left(-\alpha_i \, (t - \tau_i)^2\right) \cos(2\pi\nu_i t). \tag{1}$$

These atoms have high resolving capability in both time and frequency. The upper and lower bounds of the parameters, as well as their resolutions, are selected to construct an overcomplete dictionary. With this time-frequency dictionary, the computational cost of the inner-products can be decreased from $O(N_s^2)$ to $O(N_s \log N_s)$, where $N_s$ is the signal length, using the fast Fourier transform to efficiently perform convolutions.[11, 12]

The MPD time-frequency representation (TFR) of the signal $s(t)$ is defined as

$$M_s(t, f) \equiv \sum_{i=0}^{N-1} |\kappa_i|^2 \, \mathrm{WD}_{g_i}(t, f),$$

where $\mathrm{WD}_{g_i}(t, f)$ is the Wigner distribution of $g_i(t)$, given for the time-frequency shifted and scaled Gaussian atom in (1) as

$$\mathrm{WD}_{g_i}(t, f) = 2 \exp(-2\alpha_i \, (t - \tau_i)^2) \exp\left(-\frac{2\pi^2 (f - \nu_i)^2}{\alpha_i}\right).$$

The MPD TFR of the approximation (i.e., linear combination of the WD of the MPD selected elements) can provide a visual analysis of the main time-frequency components of the signal, captured in the MPD approximation. This is particularly useful for the application in this experiment as it provides a means to differentiate actual seismic signal components from noise components.

## 2.2 Modified MPD with Dictionary Based on Real Measurements

When the analysis signal has components with different time-frequency structures, the MPD uses many dictionary atoms to accurately decompose the signal; this can cause it to become very computationally intensive. The modified MPD is an MPD whose dictionary is chosen to include waveforms that have similar time-frequency signatures or features as the signal to be analyzed.[9, 10] The advantage of using the mod-MPD with a dictionary matched to the analysis data is that a signal expansion can be achieved with only a small number of elements, and hence a fewer number of MPD iterations, resulting in a parsimonious representation. This is important for an application such as ours since computational power needs to be kept as low as possible.

For the modified MPD, a dictionary is thus created in order to approximate running and walking signal segments that include multiple footsteps. These modified dictionary elements are constructed to be representative of sequences of multiple footstep impulses, as observed in real seismic data in order to better match true cadence temporal gait patterns. As a result, for the modified MPD, each dictionary element consists of the sum of five time-frequency shifted and scaled Gaussian signals and is of the form

$$c_i(t) = \sum_{\ell=0}^{4} \beta_\ell \, \exp(-\alpha_{\ell,i} \, (t - \gamma_{\ell,i})^2) \, \cos(2\pi\nu_i t). \tag{2}$$

The footstep cadence, represented by the time intervals between the five Gaussian signals, is allowed to vary by varying the time-shift parameter $\gamma_{\ell,i}$. The signal segment in (2) represents the (strongest) footstep impulses of a walking and running signal. Also, a simple amplitude profile was developed to approximate the profile observed in most signals in order to represent the five impulses closest to the sensor; the amplitude profile was used to define $\beta_\ell$ in (2). Although we considered multiple amplitude profiles, a single profile proved to be most effective in matching the cadence values to those found using the Gaussian dictionary MPD. Note that, in order to reduce the number of dictionary atoms, the signal being analyzed was shifted such that its peak amplitude in the time domain occurred in the center of the graph. This eliminated the need to time-shift the dictionary elements in order to find the footstep with the largest intensity, corresponding to the one closest to the sensor.

The advantage of the modified MPD dictionary is twofold. First, this method reduces the number of dictionary elements necessary in the expansion. This saves greatly on power consumption as well as memory required for the classification algorithm. Second, the system greatly reduces the number of MPD iterations required to match the signal. If only one person is walking/running, the classifier requires only one iteration and outputs a feature vector containing the estimated cadence of the signal as well as the coefficient used to match the dictionary element, analogous to the largest MPD coefficient obtained using Gaussian dictionary elements. As will be shown in the following sections, the gain in power efficiency results in only a small loss in classification performance. Thus, it would be effective to implement on an unattended ground sensor or other devices that necessitate low power consumption.

## 3. APPLICATION OF MPD TO SEISMIC SIGNALS

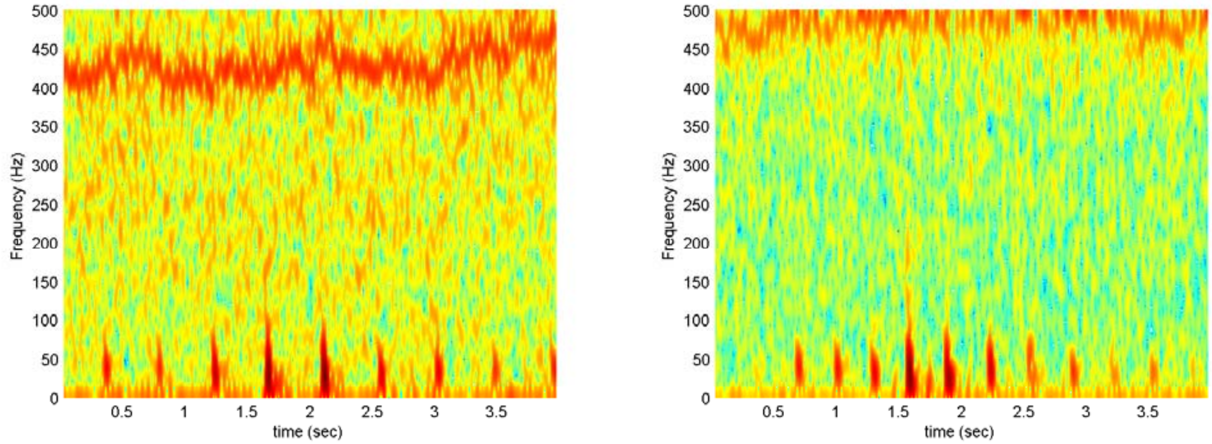
### 3.1 Seismic Footstep Data Collection

Seismic footstep data was collected in two locations using a OYO-2400 geophone. This is a relatively low cost and compact sensor; it is a good representation of a sensor that could be used on a UGS. The two locations used were a stretch of sidewalk away from the main road and a wash in unused land behind the Flexible Display Center at ASU. The sidewalk was chosen to give a clear picture of what data should be expected from individuals walking and running. The wash was used to simulate a real life situation in which a ground sensor would be used, perhaps along a border or outside a forward operating base. The data from both locations was similar, and at each location, data was recorded for two individuals walking and running.

### 3.2 Preprocessing

Several preprocessing steps were performed before applying the MPD to the seismic signals, as demonstrated in Figure 2. The spectrogram time-frequency representation of the data was first obtained in order to identify approximate bounds on the time-frequency location of the main signal components. Sample spectrograms of walking and running activities signals are shown in Figures 1(a) and 1(b), respectively. Note that the spectrogram is only used for preprocessing since, in general, it does not provide high resolution time-frequency representations due to its use of windowing.[13] Using the spectrogram plots, the footstep signals caused by an individual's can be clearly seen at the lower frequencies; also present is high frequency environmental noise. Because of the large difference in frequency of the signal and noise components, the noise can be easily removed using a lowpass filter with a cutoff frequency of around 150 Hz.

The appropriate range of the MPD Gaussian dictionary parameters was chosen based on the time and frequency location and spread of the footstep signal spectrogram representation. Specifically, we chose the range of the frequency shift to be from 1 to 150 Hz; the range of the scale parameter was chosen to be from $3\sqrt{2}$ to $30\sqrt{2}$ Hz$^2$. The time shift parameter ranged over the duration of the signal. For the modified MPD dictionary elements, the only parameter required is the time interval between each footstep component to be represented by the time interval between the Gaussian components. This range was determined by examining the real data for both walking and running activities.




(a) (b)

Figure 1. Example of spectrogram time-frequency representations of footstep signals of a person: (a) walking and (b) running.

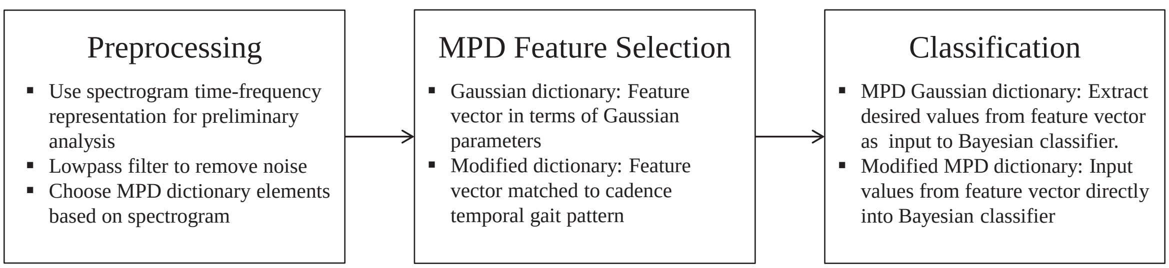
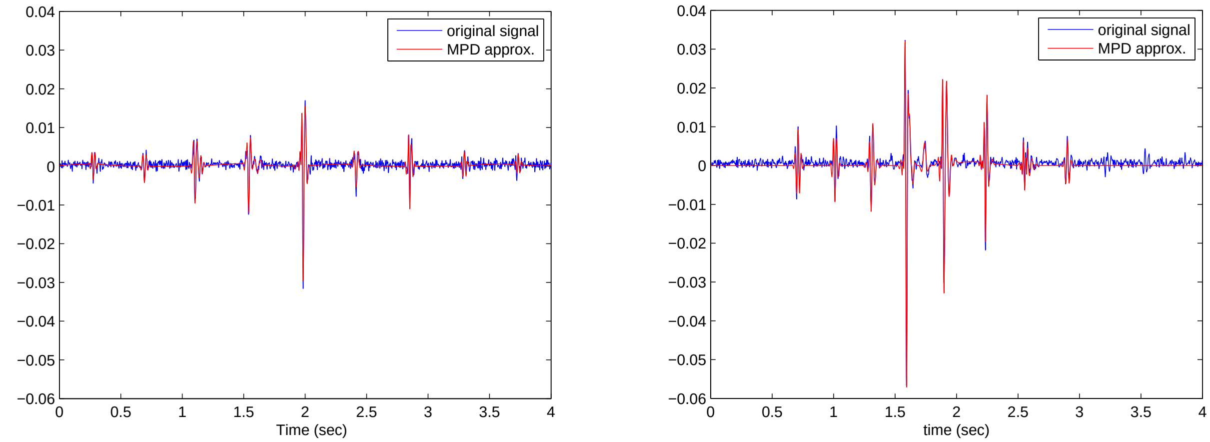



Figure 2. Block diagram summarizing the steps used for preprocessing, MPD analyzing, and classifying seismic signals.

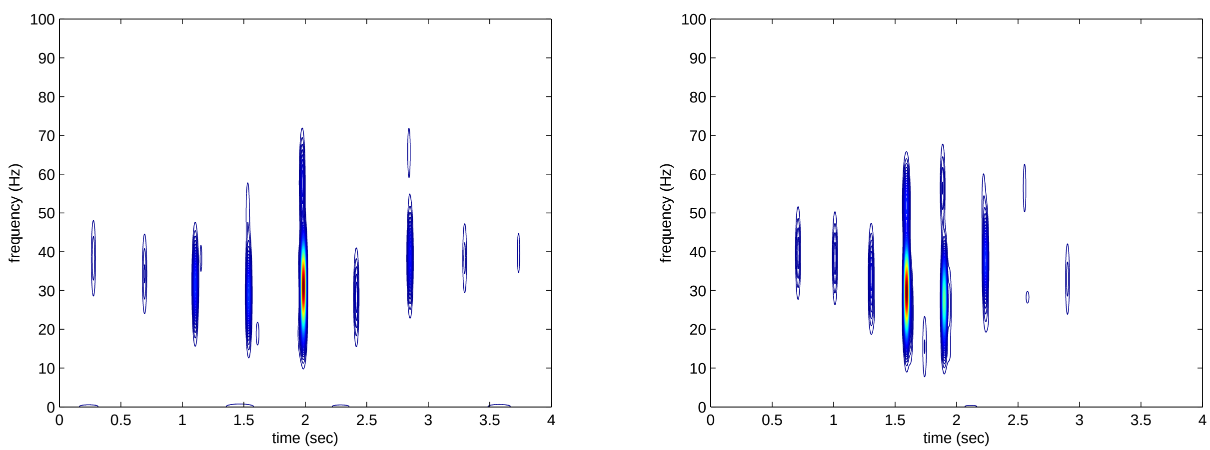
### 3.3 MPD of Seismic Signals

After preprocessing using a Butterworth lowpass filter with a 150 Hz cutoff frequency (see Figure 2), the MPD algorithm was applied to each of the seismic signals using a Gaussian signal dictionary; the range of the parameters of the Gaussian signals was determined from preprocessing, as discussed above. In order to demonstrate the MPD signal expansion, Figures 3(a), 4(a) and 5(a) are all obtained from the same MPD simulation. The number of MPD iterations used in calculating the approximation was chosen such that the residual signal remaining had only about 10% of the original signal energy, with mostly noise remaining. The majority of tests were adequately categorized to have approximately 10% residual energy remaining after at most 25 iterations of the MPD algorithm, as confirmed by Figure 5(a) and Figure 5(b). Figure 3(a) and Figure 3(b) show the signal and the well-matched superimposed MPD approximation of the signal in the time domain. Figure 4(a) and Figure 4(b) show contour plots of the cross-term free MPD time-frequency representation of the signals. The Gaussian components shown in these figures demonstrate the relative presence of a frequency at a particular time in the matched signal. From the time-domain plots, the number of footstep pulses that were matched and the calculation of the remaining residual energy can provide an evaluation of the quality of the approximation. If several footstep pulses are missed (not matched), this can be resolved by performing additional MPD iterations, a strategy that is less successful as noise components start to also get decomposed. In the example shown here, the MPD approximation is seen to provide a slightly better match for the walking activity as compared to the corresponding one for the running activity.




(a) (b)

Figure 3. Seismic signal in the time domain with superimposed MPD approximation: footsteps from (a) walking and (b) running activities.

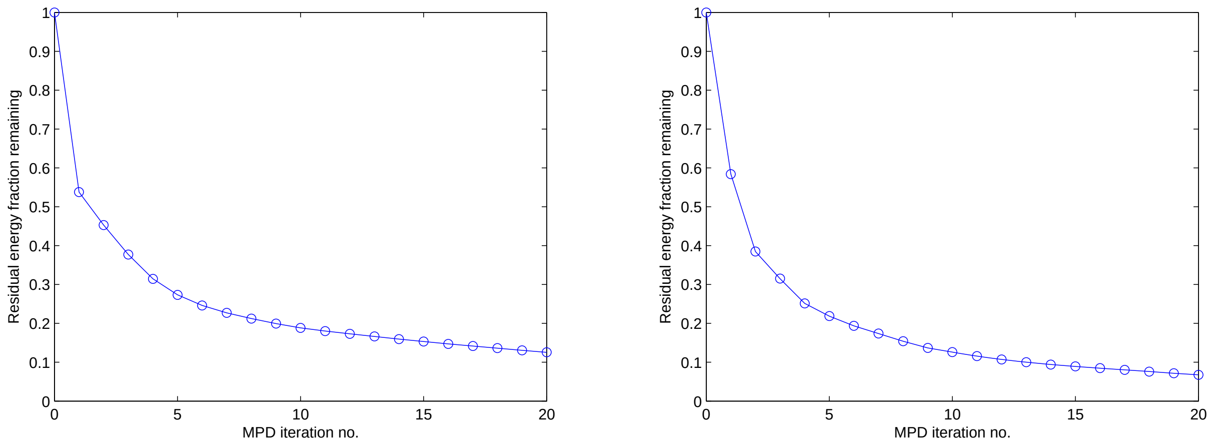



(a) (b)

Figure 4. MPD time-frequency representations of decomposed signals: (a) walking and (b) running activities.

## 4. DISTINCTIVE FEATURES

In the previous section, the method for obtaining the MPD approximation of a seismic signal was demonstrated for both the walking and running activities. The method yielded a time-frequency approximation of the signal in terms of Gaussian atoms, typically approximating the pulse component corresponding to different footsteps. From this approximation, two different routes were pursued. The first approach calculates distinctive features from the MPD signal approximation parameters. Distinctive features used for classification in the literature, such as cadence and peak amplitude, were straightforward to extract from the MPD approximations. In addition,




(a) (b)

Figure 5. Residual energy remaining in the original signal after 20 successive MPD iterations: (a) walking and (b) running activities.

from the time-frequency plot, other features such as frequency spread and amplitude profile were extracted and analyzed. Using this method on some of the real data records, thresholds for the walking and running activities within each of these features were derived in order to train the Bayesian classifier.

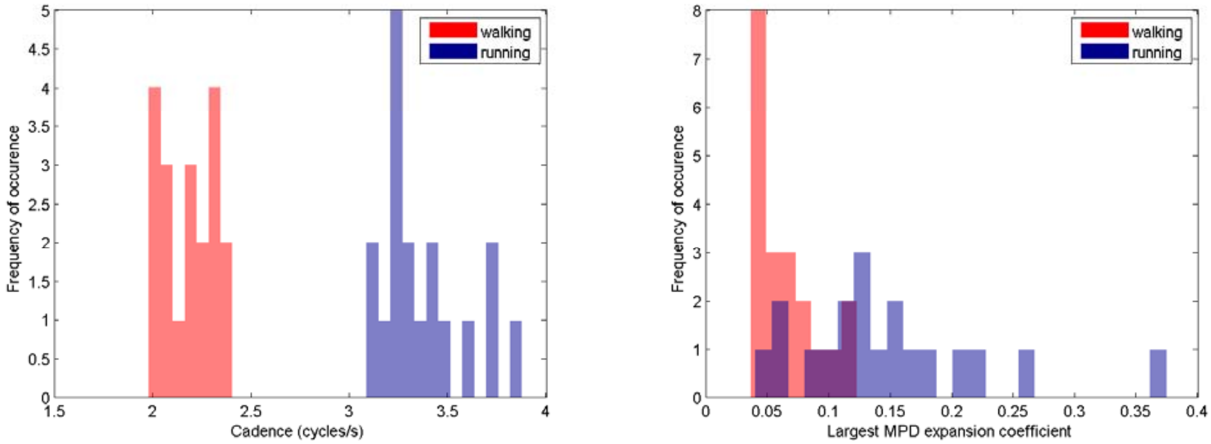
The second approach uses real seismic data to construct the modified MPD dictionary based on distinctive features as described above. The MPD is applied to the signals using the modified dictionary, producing a feature vector in terms of these distinctive features. Although this method does not provide the same exact level of classification accuracy as that from the features obtained using the Gaussian dictionary, it provides a low-power alternative approach that utilizes a much smaller dictionary and can match the signals in only a few iterations.

## 4.1 Gaussian Dictionary

### 4.1.1 Cadence Frequency

The first feature extracted from the MPD approximation was the footstep cadence corresponding to each activity. Cadence has been almost universally used to classify footsteps, although its limitations have been demonstrated when trying to distinguish between animals and humans walking. This was demonstrated on features of seismic data, showing that the cadence of a horse walking is clearly different from that of a human walking, but is very similar to the cadence of a human running.[3] Thus, while other features are necessary for broader classification, cadence is an essential tool for distinguishing between walking and running.

The cadence value for each signal was computed from the feature vector comprised of the expansion coefficients, time shifts, frequency shifts, and scales used in the Gaussian MPD approximation. First, noise was eliminated by removing the Gaussian atoms with small amplitude and large time spread. The time spread of the dictionary elements approximating the noise were typically much wider than those approximating the footstep pulses, allowing the algorithm to easily distinguish between the two. This left only the atoms needed to construct each main footstep pulse signal. In order to effectively calculate the time interval between each pulse, multiple Gaussian signals representing a single pulse had to be combined. This was achieved by evaluating the time differences between successive elements and eliminating those that fell below a particular threshold.




(a) (b)

Figure 6. Distribution of: (a) cadence values and (b) largest MPD expansion coefficients.

The difference between the center of successive Gaussians was used to calculate the period and cadence. Figure 6(a) shows a plot of the histogram of the cadence values for all the seismic signals. As it can be clearly seen from the histogram, the margin between the walking and running activity signals was over 0.5 Hz, making it an excellent feature for classification between walking and running. It is important to note however that this method of determining cadence would be relatively ineffective when dealing with multiple individuals walking.

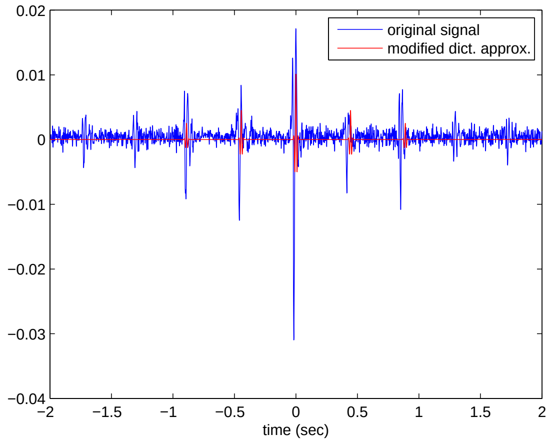
### 4.1.2 Largest MPD Expansion Coefficient

The second feature used for classification is the expansion coefficient with the largest magnitude from each MPD approximation. The largest MPD coefficient represents the signal's peak amplitude in the time domain. Peak amplitude has been demonstrated to be effective in footstep classification, even when including animals walking.[3] As shown in the histogram in Figure 6(b), the largest MPD coefficients for the walking activity signals are overall lower than those of the running activity. This is expected, as the impact of the foot when running is almost always stronger than that when walking. Since the distance between the activity and the sensor is approximately constant in our experiments, the difference in the largest MPD coefficient can be attributed to the difference between features of the walking and running activities.

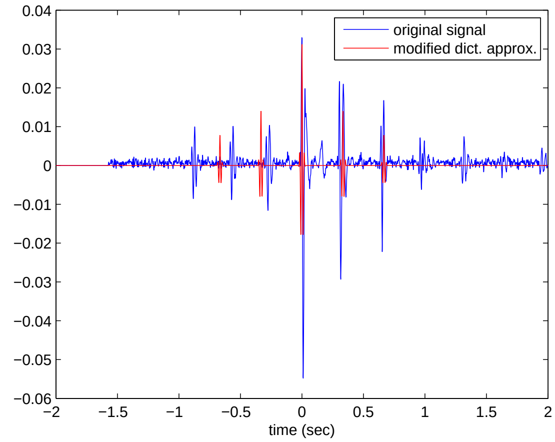
## 4.2 Modified MPD Dictionary

For our application, we design the modified MPD dictionary atom to consist of a combination of five scaled Gaussians to represent a set of five consecutive pulses generated from footsteps. This longer segment of an atom can also undergo time-frequency changes to form the modified MPD dictionary, if needed. We use the amplitude profile to represent how the pulses increase in intensity as a person walks closer to the sensor and then decreases as the person walks away from the sensor. This amplitude profile does not currently serve as a distinctive feature, but it enables the atoms to match the signal better in order to obtain an accurate value for the scaling coefficient.

With the modified MPD dictionary, the MPD algorithm estimated the desired distinctive features in just one iteration. The distribution of the cadence values is shown in Figure 4.2. This method works well for estimating cadence because the five Gaussians tend to align themselves with the strongest seismic signal pulses by finding the best match in the dictionary elements. In addition, one of the main differences between the modified dictionary and the standard Gaussian dictionary is the fact that the feature vector for the former case gives the signal in terms of distinctive features such as cadence rather than the parameters of Gaussians as in the latter case. This eliminates any extra processing steps in the classification process.




(a)




(b)

Figure 7. Signal approximation using the MPD with the modified dictionary: (a) walking and (b) running activities.

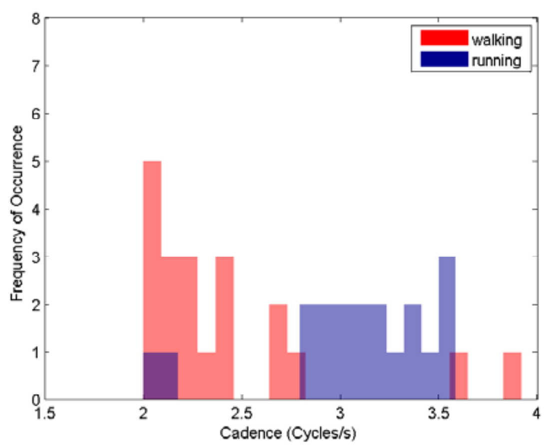



Figure 8. Distribution of cadence using MPD with modified dictionary.

## 5. FOOTSTEP CLASSIFICATION

### 5.1 Bayesian Classifier

The aforementioned distinctive features for the walking and running activities were classified using a Bayesian classifier.[14,15] For this two-class walking activity (Class 0 or Hypothesis $H_0$) and running activity (Class 1 or Hypothesis $H_1$), the Bayesian classifier utilizes the posterior probabilities to decide on Class $j$, where

$$j = \arg\max_m p(H_m|\mathbf{x}) = \arg\max_m p(\mathbf{x}|H_m) \Pr(H_m).$$

Here, $\mathbf{x}$ denotes the feature vector being classified (comprised of cadence, MPD expansion coefficient, etc. extracted from the measured seismic signals using the MPD algorithm), and $\Pr(H_m)$ is the *a priori* probability of Class $m$. Assuming equal prior probability for the walking and running activities, $\Pr(H_0) = \Pr(H_1)$, and modeling the class-conditional probability distributions using Gaussian probability density functions (PDFs), we classify to Class $j$, where

$$j = \arg\max_m \, p(\mathbf{x}|H_m) = \arg\max_m \, \mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m).$$

Here, $\mathcal{N}(\cdot; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes a multivariate Gaussian PDF with mean $\boldsymbol{\mu}$ and covariance $\boldsymbol{\Sigma}$. The mean $\boldsymbol{\mu}_m$ and covariance $\boldsymbol{\Sigma}_m$ of the Gaussian for the $m$ class, $m = 0, 1$, are obtained using maximum likelihood estimation as the sample mean and covariance of the training feature vectors from that class.

### 5.2 Classification Results

Using the Bayesian classifier, the seismic signals were first classified using the Gaussian dictionary MPD. Using part of the data for training, the means and covariances of the Gaussian models for the walking and running activity features were determined. Following this training stage, the remainder of the data was used for classification and the assigned class labels were evaluated against the actual class labels. Three classification trials were conducted, using a different set of features each time. The first used only the cadence feature, the next only the largest MPD coefficient, and finally both of these features were used together. As seen from the results given in Tables 1, accurate classification results were obtained for all three cases (average correct classification of 98.7%). Because both cadence and the largest MPD coefficient were used, the algorithm can be later expanded to include other categories such as animals walking.

Table 1. Footstep classification results using the MPD with Gaussian dictionary.

| **Feature** | **Number of correctly classified walking activity signals** | **Number of correctly classified running activity signals** |
|---|---|---|
| Largest MPD coefficient | 13/13 | 11/12 |
| Cadence | 13/13 | 12/12 |
| Largest MPD coefficient and cadence | 13/13 | 12/12 |

Table 2. Footstep classification results using the modified dictionary MPD.

| **Feature** | **Number of correctly classified walking activity signals** | **Number of correctly classified running activity signals** |
|---|---|---|
| Cadence | 11/13 | 11/12 |

The Bayesian classifier was also used to classify between walking and running activities using the MPD with the modified dictionary, using only cadence as a feature. The results, shown in Table 2, are promising but the classification accuracy is slightly lower than that obtained using the Gaussian dictionary MPD (88% correct classification). The ability of the modified dictionary MPD to match the signal is dependent on the amplitude profile used. Because only a single generic profile was used in these simulations, whereas the relative strengths of the footstep pulses can vary significantly in the real data, the MPD matches were not always very accurate. Nevertheless, the MPD with the modified dictionary can be attractive as a low-power footstep classification method.

## 6. CONCLUSION

Effective footstep classification continues to be vital for our national security. This necessitates that a device can detect and classify the footstep of individuals passing by with low percentage of false alarms and low-power hardware. This paper has demonstrated an effective way to incorporate distinctive features of different walking and running activity signals into an effective Bayesian classification algorithm using matching pursuit decomposition (MPD) time-frequency processing. The MPD provides an iterative approximation of seismic signals using a combination of time-frequency dictionary elements. This method was shown to be effective in extracting distinctive features for footstep classification using two different approaches. In the first approach, an MPD dictionary of time-frequency shifted and scaled Gaussian signals was used to match the signal. This required a large dictionary and typically needed 10-20 iterations to match the signal up to 10% residue energy. The MPD with the Gaussian dictionary worked very well for extracting the cadence and largest MPD expansion coefficient features, which were subsequently used with a Bayesian classifier to successfully classify signals collected for walking and running activities.

The second approach was proposed with low-power needs of unattended ground sensors in mind using a modified MPD dictionary based on features observed in real seismic data. This modified dictionary imposes upon MPD the assumption that the time interval between the footstep pulses of an individual is roughly constant, and represents the signal using atoms that are a linear combination of five Gaussians. The period between these Gaussians is varied in the dictionary based on the range of time intervals observed in real seismic data, and the amplitude profile of the Gaussians was also designed to represent the values observed in real data. Applying the MPD with this dictionary to the recorded data resulted in the algorithm estimating the cadence in a single iteration. This algorithm uses a vastly smaller dictionary and operates faster than the Gaussian dictionary MPD. Simulations show that is a small loss in classification accuracy, likely caused by mismatching amplitude profiles, but the significant amount of power and run-time saved using this dictionary makes it a promising footstep classification method for unattended ground sensors.

We analyzed and processed the data using MATLAB; at a later stage, the analysis will be transferred to a field-programmable gate array (FPGA) and possibly a small micro-controller. For the FPGA implementation, the advanced signal processing MPD algorithm can be modified for power-aware processing. This combination of low-power hardware design and advanced signal processing has the potential to result in practical and disposable unattended ground sensors. Future research will also test our proposed techniques with a more expansive set of data, considering more detailed amplitude profiles to further improve classification performance. Finally, additional cases such as animals or multiple individuals passing by a sensor will be added to the classification tests. By expanding the dictionary of signals used for classification in order to represent distinctive features for these additional classes, the MPD algorithm has the potential to perform increasingly more complex classification operations.

## REFERENCES


[1] Damarla, T., Pham, T., and Lake, D., "Algorithm for classifying multiple targets using acoustic signatures," in [*Proceedings of SPIE*], **5429**, 421–427 (2004).

[2] Damarla, R. and Ufford, D., "Personnel detection using ground sensors," in [*Proceedings of SPIE*], **6562**, 656205 (2007).

[3] Damarla, T. and Sabatier, J., "Classification of people walking and jogging/running using multinodal sensor signatures," in [*Proceedings of SPIE*], **8019**, 80190N (2011).

[4] Park, H. O., Dibazar, A. A., and Berger, T. W., "Cadence analysis of temporal gait patterns for seismic discrimination between human and quadruped footsteps," in [*IEEE International Conference on Acoustics, Speech and Signal Processing*], 1749–1752 (2009).

[5] Mehmood, A. and Damarla, T., "Blind separation of human and horse footstep signatures using independent component analysis," in [*Proceedings of SPIE*], **8382**, 83620L (2012).

[6] Damarla, T., "Seismic and ultrasonic data analysis for characterizing people and animals," in [*Proceedings of SPIE*], **8388**, 83880K (2012).

[7] Succi, G. P., Clapp, D., Gampert, R., and Prado, G., "Footstep detection and tracking," in [*Proceedings of the SPIE, Unattended Ground Sensor Technologies and Applications III*], **4393**, 22–29 (September 2001).

[8] Mallat, S. and Zhang, Z., "Mathcing pursuits with time-frequency dictionaries," *IEEE Transactions on Signal Processing* **41**, 3397–3415 (1993).

[9] Papandreou-Suppappola, A. and Suppappola, S. B., "Analysis and classification of time-varying signals with multiple time-frequency structures," *IEEE Signal Processing Letters* **9**(3), 92–95 (2002).

[10] Ebenezer, S. P., Papandreou-Suppappola, A., and Suppappola, S., "Classification of acoustic emissions using modified matching pursuit," *EURASIP Journal on Applied Signal Processing* **3**, 347–357 (March 2004).

[11] Chakraborty, D., Kovvali, N., Wei, J., Papandreou-Suppappola, A., Cochran, D., and Chattopadhyay, A., "Damage classification structural health monitoring in bolted structures using time-frequency techniques," *Journal of Intelligent Material Systems and Structures* **20**, 1289–1305 (July 2009).

[12] Chakraborty, D., *Time-Frequency Based Adaptive Learning for Structural Health Management*, PhD thesis, Arizona State University (2010).

[13] Hlawatsch, F. and Boudreaux-Bartels, G. F., "Linear and quadratic time-frequency signal representations," *IEEE Signal Processing Magazine* **9**, 21–67 (1992).

[14] Van Trees, H. L., [*Detection, Estimation, and Modulation Theory, Part I*], Wiley-Interscience (2001).

[15] Duda, R. O., Hart, P. E., and Stork, D. G., [*Pattern Classification*], Wiley-Interscience, 2 ed. (2000).