Detection of Target and Implemented By Using Seismic and Pir Sensors

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Abstract: To monitor human activities, such as pedestrian motion and detection of intruders in a secure region we are widely using the Unattended ground sensors (UGS). The efficiency of UGS systems is often limited by high false alarm rates, possibly due to inadequacies of the underlying algorithms and limitations of onboard computation. In this regard, this paper presents a wavelet-based method for target detection and classification. The proposed method has been validated on data sets of seismic and Passive Infrared sensors (PIR) for target detection and classification, as well as for payload and movement type identification of the targets. The proposed method has the advantages of fast execution in less time and low memory requirements and is potentially well-suited for real-time implementation with onboard UGS systems.

Keywords: Feature extraction, seismic sensor, passive infrared sensor, symbolic dynamic filtering, target detection.

I. Introduction

Unattended ground sensors (UGS) are widely used in industrial monitoring and military operations. These systems are lightweight devices that automatically monitor the local activities in-situ, and transfer target detection and classification reports to the processing center at a high level. UGS systems make use of multiple sensing modalities (e.g., acoustic, seismic, passive infrared, magnetic, electrostatic, and video). Hence, power-efficient sensing modalities, low-power signal processing algorithms, and efficient methods for exchanging information between the UGS nodes are needed. In the detection and classification problem at hand, the targets usually include humans, vehicles, and animals. For example, discriminating human footstep signals from other targets and noise sources is a challenging task, because the signal-to-noise ratio (SNR) of footsteps decreases rapidly with the distance between the sensor and the pedestrian. Seismic sensors are widely used for personnel detection because they are relatively less sensitive to Doppler effects and environment variations, as compared to acoustic sensors. Current personnel detection methods, based on seismic signals, are classified into three categories, namely, time domain, frequency domain, and time-frequency domain. Recent research has relied on time-frequency domain (e.g., wavelet transform-based) methods because of their denoising and localization properties. Passive Infrared (PIR) sensors have been widely used in motion detectors, where the PIR signals are usually quantized into two states, i.e., “on” and “off”. Although IR sensors have been used for detection and localization of moving targets. The work reported in this paper makes use of a wavelet-based feature extraction method, called Symbolic Dynamic Filtering (SDF). The SDF-based feature extraction algorithm mitigates the noise by using wavelet analysis, captures the essential signatures of the original signals in the time-frequency domain, and generates robust low-dimensional feature vectors for pattern classification. This paper addresses the problem of target detection and classification using seismic and PIR sensors that monitor the infiltration of humans, light vehicles, and domestic animals for border security. The major contributions of the paper are as follows:

1) Formulation of a hierarchical structure for target detection and classification.
2) Experimental validation of the SDF-based feature extraction method on seismic and PIR sensor data.
3) Performance evaluation of using seismic and PIR sensors in target payload and movement type identification.

The paper is organized into five sections including the present one. Section II describes and formulates the problem of target detection and classification. Section III presents the procedure of feature extraction from sensor time-series. Section IV describes the details of the proposed method and the results of field data analysis. The paper is concluded in Section V along with recommendations for future research.

II. Problem Description For Target Detection

The main objective is to detect and classify different targets, whereas seismic and PIR sensors are used to capture the characteristic signatures. The seismic and PIR sensor data, used in this analysis, were collected on
multiple days from test fields on a washand at a chokepoint (i.e., a place where the targets are forced to go due to terrain difficulties). During multiple field tests, sensor data were collected for several scenarios that consisted of targets walking along an approximately 150 meters. Figure 1 illustrates a typical data collection scenario. The targets consisted of humans, animals, and all-terrain vehicles (ATVs).

![Fig. 1. Illustration of the test scenario with three sensor sites.](image1)

Examples of the test scenarios with different targets are shown in Fig. 2. There were three sensor sites, each equipped with seismic and PIR sensors. The seismic sensors (geophones) were buried approximately 15 cm deep underneath the soil surface, and the PIR sensors were collocated with the respective seismic sensors. All targets passed by the sensor sites at a distance of approximately 5 m. Signals from both sensors were acquired at a sampling frequency of 10 kHz.

![Fig. 2. Examples of test scenarios with different targets. (a) Human. (b) Vehicle. (c) Animal led by human.](image2)

The tree structure in Fig. 3 shows how the detection and classification problem is formulated. In the detection stage, the pattern classifier detects the presence of a moving target against the null hypothesis of no target present; in the classification stage, the pattern classifiers discriminate among different targets, and subsequently identify the movement type and/or payload of the targets. While the detection system should be robust to reduce the false alarm rates, the classification system must be sufficiently sensitive to discriminate among different types of targets with high fidelity. In this context, feature extraction plays an important role in target detection and classification because the performance of classifiers largely depends on the quality of the extracted features.

![Fig. 3. Tree structure formulation of the detection & classification problem.](image3)
In the classification stage, there are multiple classes (i.e., humans, animals, and vehicles); and the signature of the vehicles is distinct from those of the other two classes. A binary classification is performed to detect the presence of a target and then to identify whether the target is a vehicle or a human/animal.

For example, if the target is recognized as a human, then further binary classifications are performed to identify if the human is running or walking, and if the human is carrying a payload or not.

III. Symbolic Dynamics-Based Feature Extraction

The details of SDF briefly reviews the underlying concepts of feature extraction from sensor time series for completeness of this paper.

A) Transformation of Time Series to Wavelet Domain

A crucial step in SDF is partitioning of the transformed data space for symbol sequence generation. In wavelet-based partitioning, the time series is first transformed as a set of wavelet coefficients at different time shifts and scales, where the choice of the wavelet basis function depends on the time frequency characteristics of the underlying signal, and the (finitely many) wavelet scales are calculated as follows:

\[ a^i = \frac{F_c}{f^i p \Delta t} \]  

where \( F_c \) is the center frequency that has the maximum modulus in the Fourier transform of the signal; and \( f^i \)’s are obtained by choosing the locally dominant frequencies in the Fourier transform. Figure 4 shows an illustrative example of transformation of the time series. The amplitudes of the wavelet coefficients over the scale-shift domain are plotted as a surface. Subsequently, symbolization of this wavelet surface leads to the formation of a symbolic image.

B) Symbolization of Wavelet Surface Profiles

This section presents partitioning of the wavelet surface profile, which is generated by the coefficients over the two-dimensional scale-shift domain, for construction of the symbolic image. The two-dimensional array of symbols, called symbol image, is generated from the wavelet surface profile.

The surface profiles can be partitioned by using different partitioning methods. If the partitioning planes are separated by equal-sized intervals, then it is called the uniform partitioning (UP). However, the partitioning would be more reasonable if the information-rich regions of a data set are partitioned finer and those with sparse information are partitioned coarser. To achieve this objective, the maximum entropy partitioning (MEP), has been adopted such that the entropy of the generated symbols is maximized.

C. Conversion of the Symbol Image to the State Image

This section presents construction of a probabilistic finite state automaton (PFSA) for feature extraction based on the symbol image generated from a wavelet surface profile. For analysis of (one-dimensional) time series, the states of PFSA represent different combinations of blocks of symbolon the sequence and the edges represent the transition probabilities between these blocks. Therefore, for analysis of (one-dimensional) time series, the “states” denote all possible symbol blocks (i.e., words) within a window of certain length. The notion of “states” is now extended for analysis of wavelet surface profiles via construction of a “state image” from a “symbol image”. In general, the computational requirements increase with the number \( Q \) of states, which must be constrained for real-time applications. As \( |Q| \) increases with the window size \( |W| \).
A probabilistic finite state automaton (PFSA) is constructed such that the states of the PFSA are elements of the compressed state set $O$ and the edges are transition probabilities between these states. The transition probabilities are defined as:

$$
\varphi(O_k | O_l) = \frac{N(O_l, O_k)}{\sum_{l'=1,2,..,k} N(O_l, O_k')} \forall O_l, O_k \in O
$$

where $N(o_l, o_k)$ is the total count of events when $o_k$ occurs adjacent to $o_l$ in the direction of motion. The calculation of these transition probabilities follows the principle of sliding block code. A transition from the state $o_l$ to the state $o_k$ occurs if $o_k$ lies adjacent to $o_l$ in the positive direction of motion. Therefore, for every state on the state image, all state-to-state transitions are counted.

### IV. Results Of Field Data Analysis

Field data were collected in the scenario illustrated in Fig. 1. Multiple experiments were made to collect data sets of all three classes, i.e., human, vehicle, and animal. A brief summary is given in Table I showing the number of runs of each class. Each data set, acquired at a sampling frequency of 10 kHz, has $1 \times 10^5$ data points that correspond to 10 seconds of the experimentation time. In order to test the capability of the proposed algorithm for target detection, another data set was collected with no target present. The problem of target detection is then formulated as a binary pattern classification, where no target present corresponds to one class, and target present (i.e., human, vehicle or animal) corresponds to the other class. The data sets, collected by the channel of seismic sensors that are orthogonal to the ground surface and the PIR sensors that are collocated with the seismic sensors, are used for target detection and classification. For computational efficiency, the data were downsampled by a factor of 10 with no apparent loss of information. Fig 5 depicts the flow chart of the proposed detection and classification algorithm that is constructed based on the theories of symbolic dynamic filtering (SDF) and support vector machines (SVM). The proposed algorithm consists of four main steps, namely, signal preprocessing, feature extraction, detection, and classification, as shown in Fig. 5.

<table>
<thead>
<tr>
<th>Day1</th>
<th>Day2</th>
<th>Day3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Target</td>
<td>50</td>
<td>36</td>
<td>32</td>
</tr>
<tr>
<td>Vehicle</td>
<td>0</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>Human</td>
<td>30</td>
<td>22</td>
<td>14</td>
</tr>
<tr>
<td>Animal</td>
<td>20</td>
<td>6</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 1: Number of Feature Vectors for Each Target Class

Fig 5. Flow chart of the problem of target detection and classification.
For example, the amplitude of the seismic signal of an animal with a heavy payload walking far away could be comparable to that of a pedestrian passing by at a closer distance, although these two signals are of different texture. However, for PIR signals, only the DC component is removed and the normalization is not carried out because the range of the PIR signals is not changed during the field test experiments. Based on the spectral analysis of the ensemble of seismic data at hand, a series of pseudo-frequencies from the 1-20 Hz bands have been chosen to generate the scales for wavelet transforms, because these bands contain a very large part of the footstep energy. Similarly, a series of pseudo-frequencies from the 0.2-2.0 Hz bands have been chosen for PIR signals to generate the scales. Upon generation of the scales, continuous wavelet transforms (CWT) are performed with an appropriate wavelet basis function on the seismic and PIR signals. The wavelet basis $db7$ is used for seismic signals since it matches the impulsive shape of seismic signals very well, and $db1$ is used for the PIR case since PIR signals are close to square waves.

A. Performance Assessment Using Seismic Data

This section presents the classification results using the patterns extracted from seismic signals using SDF. The leave-one-out cross-validation method has been used in the performance assessment of seismic data. Since the seismic sensors are not site-independent, they require partial information of the test site, which is obtained from the training set in the cross-validation. Results of target detection and classification, movement type and target payload identification are reported in this section.

1) Target Detection and Classification:

Fig 6 shows the normalized seismic sensor signals (top row) and the corresponding feature vectors (bottom row) extracted by SDF of the three classes of targets and the no target case. The original data were recorded in the unit of volt by microphones for storage in a digitized format. It is observed that the feature vectors are quite different among no target, vehicle...
and human/animal case. The feature vectors of human and animal are similar and yet still distinguishable. For the purpose of comparative evaluation, kurtosis analysis, a benchmarking technique of footstep detection, is also used for target detection and classification. Kurtosis analysis is useful for footstep detection because the kurtosis value is much higher in the presence of impulsive events (i.e., target present) than the case of no target. The results of SDF and kurtosis analysis. It is observed kurtosis analysis has slightly worse but comparable performance with SDF in target detection and vehicle classification, whereas SDF outperforms kurtosis analysis in distinguishing human from animal.

![Fig 7: (a) Walking (b) Running](image)

2) Movement Type Identification: Upon recognition of human, more information can be derived by performing another binary classification to identify whether the human is running or walking. The physical explanations are: i) the cadence (i.e., interval between events) of human walking is usually larger than the cadence of human running; ii) the impact of running on the ground is much stronger than that of walking, and it takes longer for the oscillation to decay.

Figure 7 shows the seismic signal and corresponding feature vectors of human walking and running.

Target Payload Identification: Similar with the movement type identification shown above, the target payload information can also be derived by performing another binary classification for both animal and human targets. Figure 8 shows the seismic signals and feature vectors of human/animal with and without payload examples.

B. Performance Assessment Using PIR Data

PIR sensors are widely used for motion detection. In most applications, the signals from PIR sensors are used as discrete variables (i.e., on or off). This may work for target detection, but will not work well for target classification because the time-frequency information is lost in the discretization. In this paper, the PIR signals are considered to be continuous signals, and continuous wavelet transform (CWT) is used to reveal the distinction among different types of targets in the time-frequency domain. Since a PIR sensor does not emit an infrared beam.

C. Field Deployment of Seismic and PIR Sensors

Seismic and PIR sensors have their own advantages and disadvantages for target detection and classification. The seismic sensor is omnidirectional and has a long range of detection (up to 70 m), whereas a PIR sensor has a typical range of less than 6 m and has a limited field of view (less than 180°), which restricts the sensor from detecting target moving behind it. The seismic sensor is not site-independent and is vulnerable to variations in sensor sites, whereas a PIR sensor merely passively accepts the incoming infrared radiation and is independent of the sensor site. In order to improve the detection and classification accuracy while reducing the false alarm rate, it is recommended that the seismic and PIR sensor should be used together to provide complementary information to each other. Information fusion techniques are needed to combine the outputs of the two sensing modalities, and this is a topic of future research. Field deployment of sensors largely depends on the tasks and terrains. To ensure intruder detection, the maximum sensor spacing should be less than the effective range of the sensor. Therefore, sensor deployment could be very expensive, because the detection range of PIR sensors is less than 6 m.
V. Conclusion

This paper presents a symbolic feature extraction method for target detection and classification, where the features are extracted as statistical patterns by symbolic dynamic modeling of the wavelet coefficients generated from time series of seismic and PIR sensors. By appropriate selection of wavelet basis and scale range, the wavelet-transformed signal is denoised relative to the original time-domain signal. In this way, the symbolic images generated from wavelet coefficients capture the signal characteristics with larger fidelity than those obtained directly from the time domain signal. The symbolic images are then modeled using probabilistic finite state automata (PFSA) that, in turn, generate low-dimensional statistical patterns, also called feature vectors. A distinct advantage of the proposed feature extraction method is that the low-dimensional feature vectors can be computed in-situ and communicated in real time over a limited-bandwidth wireless sensor network with limited-memory nodes. The proposed method has been validated on a set of field data collected from different locations on multiple days. Results show that SDF has superior performance over kurtosis analysis, especially in the human/animal classification.

A three-way cross-validation has been used to assess the performance of PIR sensors for target detection and classification. Results show that PIR sensors are very good for target detection, and has comparable performance with seismic sensors for target classification and movement type identification. While there are many research issues that need to be resolved before exploring commercial applications of the proposed method, the following topics are under active research: 1) Enhancement of target detection and classification performance by fusion of seismic and PIR sensor signals. 2) Real-time field implementation of the proposed method on low-cost low-power microprocessors for different types of deployment (e.g., UGS fencing to secure a region).

References


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