IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 9, Issue 3, Ver. IV (May - Jun. 2014), PP 134-140
www.iosrjournals.org

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 UGSsystems is often limited by high false alarm rates, possibly dueto inadequacies of the underlying algorithms and limitationsof onboard computation. In this regard, this paper presents awavelet-based method for target detection and classification. Theproposed method has been validated on data sets of seismic andPassive Infrared sensors (PIR) for target detection and classification,as well as for payload and movement type identification ofthe targets. The proposed method has the advantages of fastexecution in less time and low memory requirements and is potentiallywell-suited for real-time implementation with onboard UGSsystems.*

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

I. Introduction

Unattended ground sensors (UGS) are widely used inindustrial monitoring and military operations. Thesesystems are lightweight devices that automaticallymonitor the local activities *in-situ*, and transfer target detectionand classification reports to the processing centre at a higherlevel. UGS systems makeuse of multiple sensing modalities (e.g., acoustic, seismic,passive infrared, magnetic, electrostatic, and video). Hence, power-efficientsensing 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, thetargets usually include human, vehicles and animals. Forexample, discriminating human footstep signals from othertargets and noise sources is a challenging task, because thesignal-to-noise ratio (SNR) of footsteps decreases rapidlywith 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 andenvironment 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 ontime-frequency domain (e.g. wavelet transform-based) methodsbecause of their denoising and localization properties. PassiveInfrared (PIR) sensors have been widely used in motiondetectors, where the PIR signals are usually quantized into twostates, i.e., “on” and “off”. AlthoughIR sensors have been used for detection and localizationof moving targets.The work reported in this paper makes use of a waveletbasedfeature extraction method, called Symbolic DynamicFiltering (SDF). The SDF-based feature extractionalgorithm mitigates the noise by using wavelet analysis, capturesthe essential signatures of the original signals in thetime-frequency domain, and generates robust low-dimensionalfeature vectors for pattern classification. This paperaddresses the problem of target detection and classificationusing seismic and PIR sensors that monitor the infiltrationof humans, light vehicles and domestic animals for bordersecurity. The major contributions of the paper are as follows:

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

The paper is organized into five sections including thepresent one.
Section II describes and formulates the problemof target detection and classification.
Section III presentsthe procedure of feature extraction from sensor time-series.
Section IV describes the details of the proposed methodand the results of field data analysis.
The paper is concludedin Section V along with recommendations for futureresearch.

II. Problem Description For Target Detection

The main objective is to detect and classify different targets, whereseismic and PIR sensors are used to capture the characteristicsignatures. 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 dueto terrain difficulties). During multiple field tests, sensor datawere collected for several scenarios that consisted of targetswalking along an approximately 150 meters. Figure 1illustrates a typical data collection scenario.The targets consisted of humans,animals, and all-terrainvehicles (ATVs).

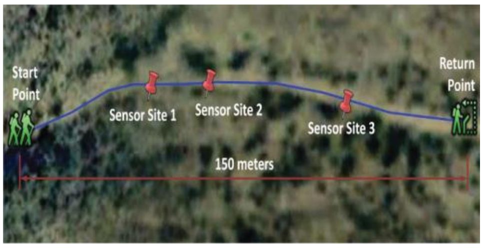

Fig. 1. Illustration of the test scenario with three sensor sites.

Examplesof the test scenarios with different targets are shown in Fig. 2.There were three sensor sites, each equipped with seismic andPIR sensors. The seismic sensors (geophones) were buriedapproximately 15 *cm* deep underneath the soil surface, andthe PIR sensors were collocated with the respective seismicsensors. All targets passed by the sensor sites at a distance ofapproximately 5 *m*. Signals from both sensors were acquiredat a sampling frequency of 10 kHz.

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

The tree structure in Fig. 3 shows how the detection andclassification problem is formulated. In the detection stage,the pattern classifier detects the presence of a moving targetagainst the null hypothesis of no target present; in theclassification stage, the pattern classifiers discriminate amongdifferent targets, and subsequently identify the movement typeand/or payload of the targets. While the detection systemshould be robust to reduce the false alarm rates, the classificationsystem must be sufficiently sensitive to discriminateamong different types of targets with high fidelity. In thiscontext, feature extraction plays an important role in targetdetection and classification because the performance of classifierslargely depends on the quality of the extracted features.

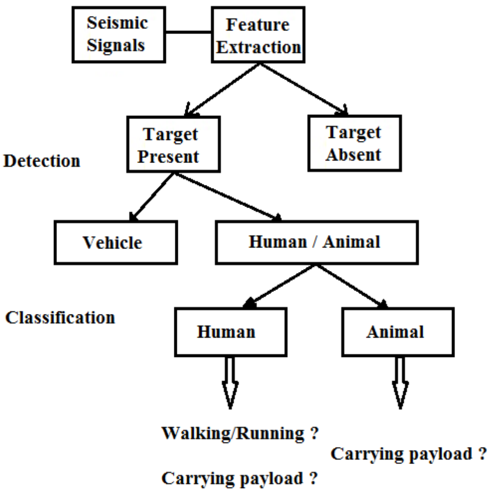

Fig. 3. Tree structure formulation of the detection & classification problem.

In the classification stage, there are multiple classes (i.e.,humans, animals, and vehicles); and the signature of thevehicles is distinct from those of the other two classes. A binary classification is performed to detect thepresence of a target and then to identify whether the target isa vehicle or a human/animal.

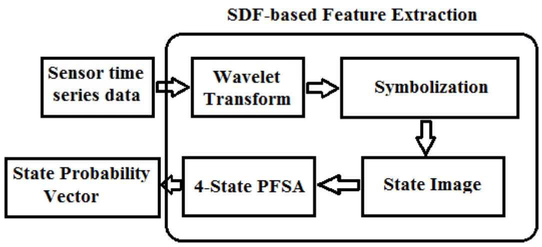

Fig. 4. Overview of the SDF-based feature extraction algorithm.

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 WaveletDomain

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:

$$\alpha^i = \frac{F_c}{f^i_p \Delta t} \qquad (1)$$

whereF_c is the center frequency that has the maximummodulus in the Fourier transform of the signal; and f^i_p's areobtained by choosing the locally dominant frequencies in theFourier transform.Figure 4 shows an illustrative example of transformationof the time series. The amplitudes of the wavelet coefficientsover the scale-shift domain are plotted as a surface. Subsequently,symbolization of this wavelet surface leads to theformation of a symbolic image.

B) Symbolization of Wavelet Surface Profiles

This section presents partitioning of the wavelet surfaceprofile, which is generated by thecoefficients over the two-dimensional scale-shift domain, forconstruction of the symbolic image. The two-dimensional array of symbols,called *symbol image*, is generated from the wavelet surfaceprofile.

The surface profiles can be partitioned by using differentpartitioning methods. If the partitioning planes are separatedby equal-sized intervals, then it is called the *uniform partitioning*(UP). However, the partitioning would be more reasonableif the information-rich regions of a data set are partitionedfiner 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 thegenerated symbols is maximized.

C. Conversion of the Symbol Image to the State Image

This section presents construction of a *probabilistic finitestate automaton* (PFSA) for feature extraction based on thesymbol image generated from a wavelet surface profile.For analysis of (one-dimensional) time series, the states ofa PFSA represent different combinations of blocks of symbolson the symbol sequence and the edges represent the transitionprobabilities between these blocks. Therefore, for analysisof (one dimensional) time series, the "states" denote all possiblesymbol blocks (i.e., words) within a window of certainlength. The notion of "states" is now extended for analysisof wavelet surface profiles via construction of a "*state image*"from a "*symbol image*".In general, the computational requirements increase with thenumber Q of states, which must be constrained for real-timeapplications. As $|Q|$ increases with the window size $|W|$

D. Construction of PFSA and Pattern Generation

A probabilistic finite state automaton (PFSA) is constructedsuch that the states of the PFSA are elements of the compressedstate set O and the edges are transition probabilitiesbetween these states. The transition probabilities aredefined as:

$$\wp(O_k \mid O_l) = \frac{N(O_l, O_k)}{\sum_{K'=1,2,..|O|} N(O_l, O_{k'})} \forall o_l, o_k \in O \qquad (2)$$

where$N(ol\ ,\ ok)$ is the total count of events when ok occursadjacent to olin the direction of motion. The calculation ofthese transition probabilities follows the principle of slidingblock code. A transition from the state $ol$to the stateok occurs if ok lies adjacent to olin the positive directionof motion. Therefore, for every state on the stateimage, 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 allthree classes, i.e., human, vehicle and animal. A brief summaryis 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 × 105 data points that correspond to 10 seconds ofthe experimentation time. In order to test the capability ofthe proposed algorithm for target detection, another data set was

	Day1	Day2	Day3	Total
No Target	50	36	32	118
Vehicle	0	8	0	8
Human	30	22	14	66
Animal	20	6	18	44

Table 1: Number of Feature Vectors for Each Target Class

collected with no target present. The problem of targetdetection is then formulated as a binary pattern classification,where no target present corresponds to one class, and targetpresent (i.e., human, vehicle or animal) corresponds to theother class. The data sets, collected by the channel of seismicsensors that are orthogonal to the ground surface and thePIR sensors that are collocated with the seismic sensors, areused for target detection and classification. For computationalefficiency, the data were downsampled by a factor of 10 withno apparent loss of information.Fig 5 depicts the flow chart of the proposed detectionand classification algorithm that is constructed based on thetheories of symbolic dynamic filtering (SDF) and supportvector machines (SVM). The proposed algorithm consistsof four main steps, namely, signal preprocessing, featureextraction, detection, and classification, as shown in Fig. 5.

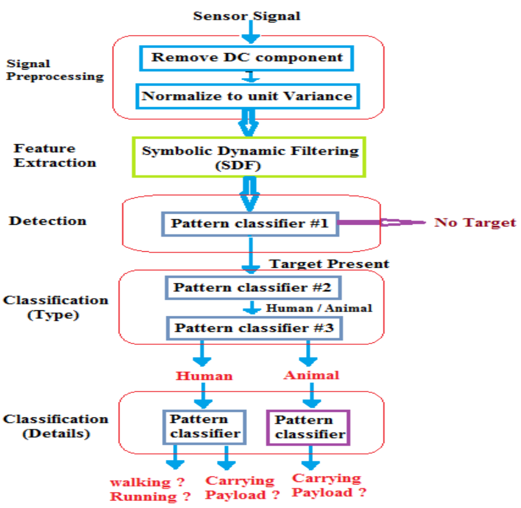

Fig 5. Flow chart of the problem of target detection and classification.

Forexample, the amplitude of the seismic signal of an animal witha heavy payload walking far away could be comparable to thatof a pedestrian passing by at a closer distance, although thesetwo signals are of different texture. However, for PIR signals,only the DC component is removed and the normalization isnot carried out because the range of the PIR signals is notchanged during the field test experiments.Based on the spectral analysisof the ensemble of seismic data at hand, a series of pseudofrequenciesfrom the 1-20 Hz bands have been chosen togenerate the scales for wavelet transform, because these bandscontain a very large part of the footstep energy. Similarly,a series of pseudo-frequencies from the 0.2-2.0 Hz bands havebeen chosen for PIR signals to generate the scales. Upongeneration of the scales, continuous wavelet transforms (CWT)are performed with an appropriate wavelet basis function onthe seismic and PIR signals. The wavelet basis *db*7 is used forseismic signals since it matches the impulsive shape of seismicsignals very well, and *db*1 is used for the PIR case sincePIR 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 leaveone-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:

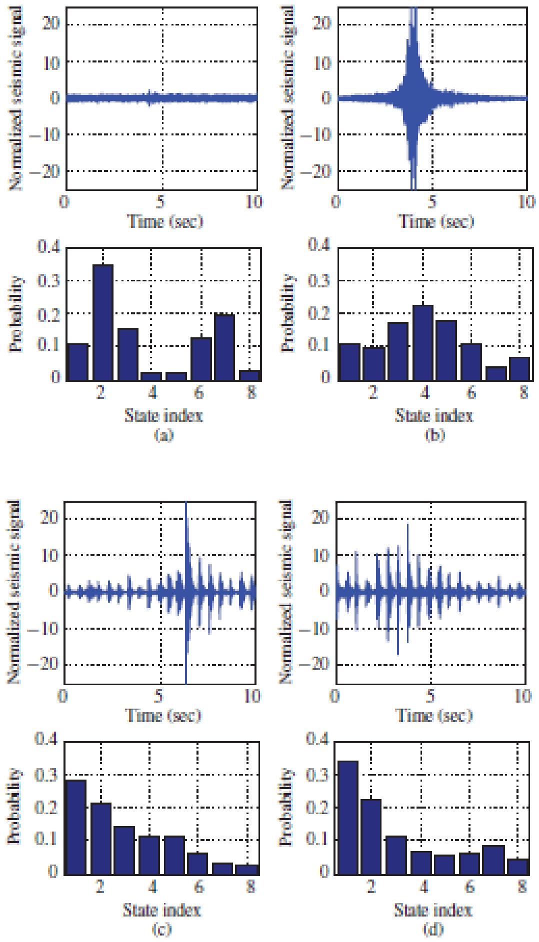

Fig 6 shows the normalized seismic
(a) No Target. (b) Vehicle
(c) Human (d) Animal

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.

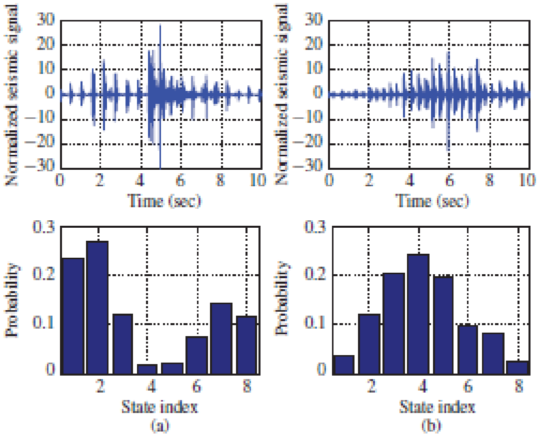

Fig 7: (a) Walking (b) Running

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 aninfrared beam.

C. Field Deployment of Seismic and PIR Sensors

Seismic and PIR sensors have their own advantages and disadvantagesfor target detection and classification. The seismicsensor is omnidirectional and has a long range of detection(up to 70 *m*), whereas a PIR sensor has a typical rangeof less than 6 *m* and has a limited field of view (less than180◦), which restricts the sensor from detecting target movingbehind it. The seismic sensor is not site-independent and isvulnerable 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 thanthose 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 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 differenttypes of deployment (e.g., UGS fencing to secure a region).

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