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Poignant ground target recognition with Smooth Pseudo Wigner-Ville Distribution by Analysis of Time-Frequency Techniques

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***Abstract*—Humans have had the ability to recognise items for hundreds of years, possibly even since they first appeared on Earth. All of the senses sight, smell, hearing, taste, and touch play a role in helping humans determine what is in their immediate vicinity. In order to integrate and make sense of the information picked up by the senses, the brain receives signals from those organs. Repetition of an experience has been shown to improve cognition. The learned knowledge is put to use in a wide variety of ways, from the mundane to the crucial, such as in the areas of security, surveillance, traffic monitoring, and so on. Human senses are limited to a relatively small range, and it could be dangerous or even fatal to work in some settings. This study provides a comprehensive evaluation of the many time-frequency methods now in use for finding targets. Furthermore, a unique method for detecting targets utilising an improved time-frequency representation of the seismic data is outlined in this research paper. When compared to solely time-domain or frequency-domain methods, time-frequency domain analyses do better. Because traditional time domain and frequency domain analysis methods only reveal one aspect of a signal at a time, time-frequency methods reveal both aspects at once.**

Keywords: EWT; STFT; Seismic Signal; SPWV.

I. Introduction

Humans have had the ability to recognise items for hundreds of years, possibly even since they first appeared on Earth. Humans use their senses of sight, smell, hearing, taste, and touch to determine the identities of things in their immediate surroundings. Transmission of sensory organ impulses to the brain allows for the latter's processing and interpretation of the data. That's why repetition is so important for learning [1]. The learned knowledge is put to use in a wide variety of ways, from the mundane to the crucial, such as in the areas of security, surveillance, traffic monitoring, etc. Due to the short range of the human senses and the potential dangers of working in some environments, this approach has spatial and temporal constraints. Technology's rise has also led to the development of increasingly sophisticated sensors that can detect subtle shifts in their respective environments, such as cameras, microphones, geophones, and other devices. The processor module's computing skills also contribute to the processing work at hand [2]. Moreover, machine learning methods and processing on a highly computational framework can accomplish automation. High-powered computers have made automation a no-brainer, and this has spawned innovations like automatic target identification and recognition. Without any help from a human operator, automatic target detection and classification attempts to identify the target. Meaningful information about the target must be extracted from complex data. The following are some of the main drivers in the evolution of autonomous target recognition algorithms:

The method used to recognise targets, be it for detection, tracking, or classification, varies from one application to the next [3]. The complexity of target recognition algorithms is increased by the fact that target recognition consists of multiple stages, beginning with detection and progressing through tracking and finally classification. The technique's efficacy and practicality are both modified by the dimensions of the target. Sizes can range from those of aeroplanes to those of tractors, buses, humans, and animals. Also, target size variation adds another layer of difficulty.

Target identification and classification is a difficult task that is heavily influenced by the surrounding environment. A forest, city, or wide field, for example, would all work as potential backdrops. As atmospheric obscuration increases, it becomes more difficult to identify the target and more variables are required to learn about it.

More than that, there are both military and civilian uses for automatic target detection and categorization techniques, such as in intelligent traffic systems, perimeter monitoring, incursion detection, force protection, mediating animal-human conflicts, etc. The gender of a person's footfall can be predicted using target recognition techniques [4]. Feature extraction from sensor data is the basis for automatic target detection and classification methods. Active detection techniques include sending out a signal into the environment and then using the reflected signal to identify a target.

Over the course of more than a decade, research has been conducted on sensing technologies for use in surveillance applications, namely in the field of automatic target recognition (ATR). Unmanned border area monitoring and the early detection of suspicious movement are of the utmost importance in vulnerable and restricted regions such as the perimeter fencing of key installations. Other examples include other sensitive and prohibited locations. Researchers have spent a significant amount of time labouring over the creation of ATR systems. In the grand scheme of things, we want to evaluate sensory input with digital computers in order to automatically discover, localise, and recognise target signatures. In other words, we want to do this with as little help from humans as we possibly can [5]. The detection of any movement in the surveillance area, whether that be of people or vehicles, is the primary focus of this function. The sensory data that has to be processed could have been generated by any one of a wide variety of sensors, such as seismic, acoustic, radar, or infrared sensors, amongst others. Within the scope of this study, we will investigate the application of seismic and auditory sensors for the purpose of identifying human activities and moving vehicles. ATR would play a significant part not just in lowering the cost of man-hours but also in offering round-the-clock aided security without causing employees tiredness and requiring nothing in the way of upkeep. ATR systems place a premium on efficient data gathering and encourage researchers to investigate a wide variety of target signatures [6]. As a consequence of this, the target signatures, regardless of whether they are seismic, acoustic, optical, or magnetic, need to be processed automatically in a manner that is both highly effective and very inexpensive. As a result, the topic of autonomous target detection is one that is not only interesting but also demanding. One of the most important criteria is that the system should generate a low number of false alerts while maintaining a high detection rate. It has a wide range of applications, including military surveillance as well as civilian usage such as perimeter protection, remote sensing, traffic monitoring, intelligent transportation systems, person identification, and animal detection systems [7].

II. Related Work Done

Processing the seismic time-series signal in the time-domain allows for the extraction of target information. In order to locate and categorise the target, many time-domain methods have been explored in the literature.

Target identification and categorization utilising the root-mean-square (RMS) of the auditory and seismic signal was proposed by the authors. The military base at Mappin, Germany served as the test site for the experiment. In order to generate train and test data, the five tracked and five wheeled vehicles operate on the track at seven different speeds on four lanes. Its root-mean-square (RMS) value is calculated using a 0.25-second timeframe. If the acoustic and seismic signal's root-mean-square maxima exceed the threshold set by the background noise, then tracked and wheeled vehicles are detected [8]. After then, LVQ separates vehicles with wheels from those with tracks. Combining auditory and seismic modalities successfully distinguishes tracked from wheeled vehicles in 94% of trials.

To do this, they suggested a time-domain feature extraction method known as time encoded signal processing and recognition [9]. TESPAR is used to convert a signal in the time domain into a symbol stream. To begin, each epoch of the time domain symbol stands alone. After that, we employ two more characteristics: epoch shape (S) and duration (D). The epoch's shape (S) reveals the occurrence of either local minimums (in a positive epoch) or local maximums (in a negative epoch). A standard icon is used to denote this specific combination of shape and duration (D/S). As such, the symbol stream serves as a representation of the signal in the time-domain. By counting how often each symbol appears in the stream, we may create a matrix. The ANN receives this matrix as input and uses it to identify different types of moving ground vehicles. The proposed method has been used in an offline setting; authors have not performed any real-time analysis [10]. Classification of AAV and DW vehicles has been implemented using the suggested technique on the sitex02 dataset of DARPA.

Both the AAV and the DW can be accurately recognised 81% of the time by their respective auditory signals. When using the seismic signal dataset, findings are not as promising, although the AAV achieves 76% accuracy and the DW vehicle achieves 72% accuracy [11].

The authors classified the ground target in motion using seismic and acoustic sensors with the help of CART (Classification and regression tree) and Gaussian mixture model (GMM) as classifier. Sensor fusion is utilised to determine the difference between wheeled and tracked vehicles, and the likelihood acquired by GMM is fed into decision trees of classification and regression tree (CART). The algorithm's performance has been analysed, and a comparison made with a previously published method, using the accuracy metric [12]. To be more precise, GMM has been shown to be more accurate than KNN and SVM classifiers. The proposed approach yields an accuracy of roughly 94.10%. When compared to using random nodes, accuracy improves by 4.17 percentage points when employing group-level fusion. When compared to other classifiers, the GMM's complexity is lower [13].

Another method for extracting features in the time domain, temporal domain harmonics' amplitude (TDHA) was developed by the authors and published in the literature to detect and categorise military vehicles. When classifying cars, TDHA makes use of the signal's energy, harmonic frequencies, and amplitude harmonics as attributes. In order to test the efficacy of the suggested technique, it has been applied to the BVP (Bochum Verification Project) dataset [14]. The authors have characterised the effectiveness of their algorithm by means of two metrics: detection and false alarm rate. The proposed method has been analysed side-by-side with the spectral method. It has been demonstrated that TDHA requires less computer power than spectral analysis. The proposed algorithm has a classification accuracy of 90.38 percent [15].

The researchers used the dynamic data driven application system as the classifier and symbolic dynamic filtering (SDF) as the feature extraction technique to categorise the ground target as it moved. Different types of moving ground targets, including humans, animals, and vehicles, have been utilised by the writers. It's important to keep in mind that sensor readings might be influenced by things like weather, time of day, and daylight. As a result of factors such as temperature and mechanical stiffness, the geophysical sensors are affected by what is referred to as context [16]. The static classifiers may underperform because of the varying contexts. Therefore, authors employed context knowledge as feedback to adaptively select the classifier to boost system performance. The authors calculated the algorithm's effectiveness using accuracy as the metric to measure success, and they've utilised a box plot to display the correlation between the amount of symbols in each modality and the algorithm's success in classifying them. The authors demonstrate an accuracy of 80% for a seven-letter alphabet. Using accuracy as a metric, we have compared the algorithm's performance both in and out of context [17].

One of the most important responsibilities for UGS systems is the selection of sensor modalities. On military battlefields, UGS has been utilised for the purposes of remote target detection, localisation, and recognition. The signal data that has to be processed could have been generated by any one of a wide variety of sensors, including seismometers, acoustic sensors, magnetometers, radar, electro-optical sensors, passive infrared sensors, and infrared imaging sensors, to name just a few [18]. Because they don't rely on line of sight, omnidirectional sensors, such as seismic and acoustic based sensors, have a significant advantage.

Recent research has shown that one of the most essential topics to investigate is the monitoring of places that have seismic activity. For the purpose of passively sensing vibrations that are transmitted via the ground, seismic sensors that convert mechanical ground waves into electrical voltages are utilised. Rayleigh surface waves are the form in which seismic waves that are propagated within the ground when they are caused by anthropogenic activities or the movement of vehicles. The displacement of the earth medium caused by the wave's propagation is what the seismic sensor picks up on. Geophones and accelerometers are the two types of seismic sensors that are utilised most frequently for applications of this nature [19]. Accelerometers and geophones have been utilised in the process of identifying various sorts of heavy civilian vehicles as well as military vehicles. They can be utilised as a cue in conjunction with other sensors that are either auditory or electro-optical to detect or categorise targets.

One variety of seismic sensor, known as a geophone, is one that is totally buried in the earth and is therefore less susceptible to being impacted by the weather. A moving coil is supported by a spring and encircled by a magnet in this design. The coil moves whenever there is a vibration, which causes it to create a voltage that is proportionate to the speed at which the ground is vibrating. The geophones that are most frequently utilised have resonance frequencies of 10 Hz, 28 Hz, and 40 Hz respectively. Research based on geophone sensors had previously been put to use in a variety of applications, including the identification of approaching vehicles and people in seismic signals. General Sensing Systems (GSS) has conducted research and developed methods for the detection of seismic footstep utilising geophone sensors as part of an intrusion detection system [20]. Research has been carried out while taking into account a wide variety of factors, including the weather, the time of day, and the various categories of targets.

Microphones, which are a type of acoustic sensing device, are most generally known for their ability to convert pressure waves into electrical voltage. The speed at which acoustic waves travel through air is roughly 345 metres per second. It is also common knowledge that when there is a windy condition, acoustic waves lose the coherency of their wave propagation beyond a few tens of feet, which results in a degradation of the coherent processing of data [21]. In the case of seismic sources, the speed of propagation can change, and this change is determined by the geology of the surface. As a result of the proximity of the sensors to the source of the sound, two situations are created.

In recent years, there has been an increase in the utilisation of the joint time-frequency domain for the processing of signals. This is due to the fact that the TFDs contain more information regarding non-stationary signals [22]. These can also be modelled as different kinds of probability distribution functions.

The Wigner-Ville Distribution is used for the decomposition and characterization of seismic signals (WVD). On temporal frequency diagrams (TFDs) of biomedical and seismic time series data, entropy-based detection has been applied. Using seismic sensors and infrared imageries, a further pseudo-Wigner Ville distribution supplemented by Rényi entropy (PWVD-RE) has been employed with the CFAR detector to detect civilian vehicles. A signal's time-frequency distribution is a representation of the signal in three dimensions, including the time dimension, the frequency dimension, and the amplitude dimension [23]. Its primary use is to identify transitory occurrences within a signal.

III. The Proposed Work

This manuscript provides a comprehensive study of the many time-frequency methods currently in use for finding targets. In addition, an unique method for detecting targets utilising an improved time-frequency representation of the seismic signal is described in the research. When compared to solely time-domain or frequency-domain methods, time-frequency domain analyses emerge victorious. Because time domain and frequency domain analysis techniques supply only time and frequency information, whereas time-frequency approaches bring out both time and frequency information of the signal simultaneously. Thus, this chapter describes the various time-frequency approaches for target detection utilising seismic signal processing that have been presented in the literature.

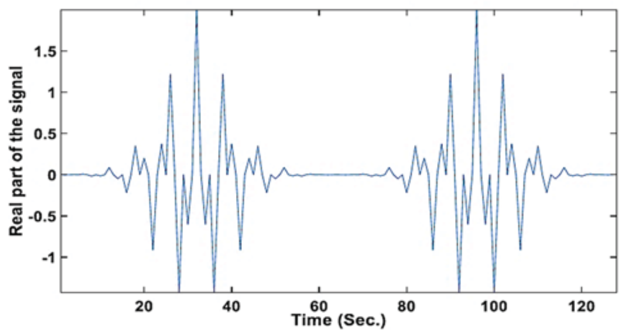

Fig. 1. Time domain non-stationary signal combination of four Gaussian wave packets.

With the SPWVD, you can independently tweak the time and frequency resolutions for enhanced cross term suppression. There are many possible window functions; we have used the Hamming window in this investigation because of its ability to operate in both the temporal and frequency domains. Absolute values of the time-frequency coefficients of the signal calculated using the Smooth Pseudo Wigner-Ville Distribution (SPWVD) are displayed in Fig. 2 below.

By recasting the non-stationary signals in a time-frequency domain using the SPWVD, we can do away with any cross terms or interference that may otherwise be there. Getting rid of these cross terms is a great help when trying to decode a seismic signal. Scientists have investigated SPWVD for a wide range of mechanical and biomedical applications, including: the mitigation of motion artefact in pulse oximetry, the differentiation between heart sounds with and without aortic stenosis, and the identification of rotor faults in brushless DC motors. Consequently, time-frequency coefficients based on SPWVD are investigated for extracting data about a ground target in motion. Positive and negative coefficients are used in SPWVD, making the coefficients complex numbers. Due to this, these coefficients can't be utilised as a P.D.F. (probability density function) in isolation (PDF). Therefore, the SPWVD coefficients need to be transformed into PDF format in order to be used in any subsequent study.

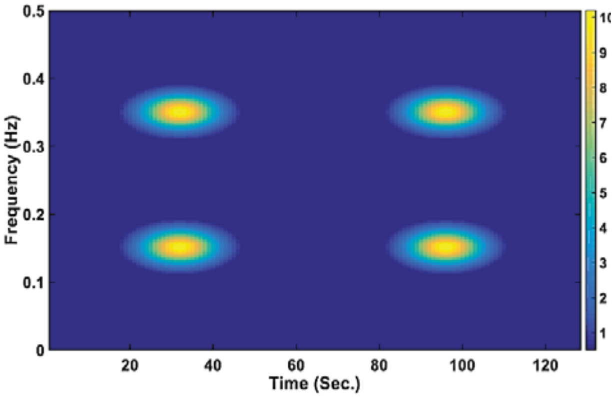

Fig. 2. Absolute value of Smooth Pseudo Wigner-Ville distribution (SPWVD) based time frequency coefficients of the signal.

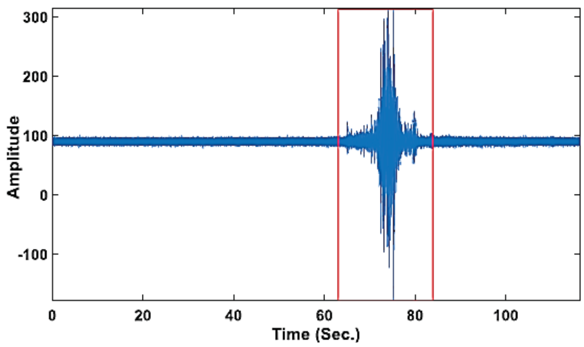

Fig. 3. Assault Amphibian Vehicle raw Seismic Signal.

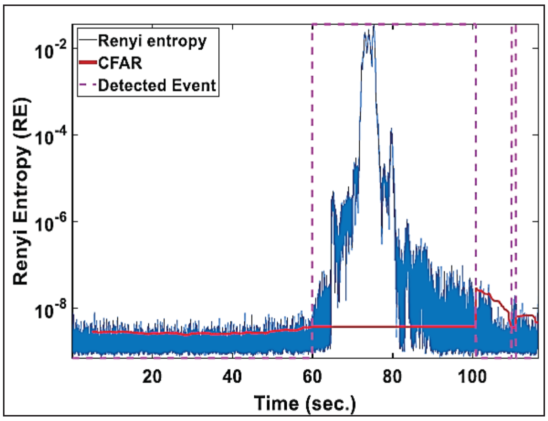

Fig. 4. SPWVD based Event detection results for AAV vehicle.

Event detection, represented by the pink dashed line, is depicted as having a binary state based on the result of a comparison between the CFAR threshold and the Renyi entropy.

The criterion of voting percentage with respect to CFAR threshold is met if and only if the presence or arrival of the moving ground vehicle is identified at roughly the time instant of 60s. This is because the threshold condition is met as the seismic signal strength grows relative to the noise strength, leading to an increase in the localised entropy value. The pink dashed line indicates the time period during which the ground target can be detected while still in motion. Results from a detection study using STFT-based time-frequency analysis are compared with those obtained using the same seismic data.

TABLE I. EVALUATION PARAMETERS-BASED COMPARISON OF SPWVD WITH STFT ALGORITHM.

Detection Time	True Positive Rate		False Positive Rate		F-Score	
	SPWVD	***STFT***	***SPWVD***	***STFT***	***SPWVD***	***STFT***
0.1	0.42	0.45	0.037	0.039	0.5	0.53
0.2	0.62	0.57	0.051	0.042	0.68	0.62
0.3	0.75	0.62	0.061	0.043	0.74	0.68
0.4	0.83	0.65	0.083	0.063	0.78	0.8
0.5	0.89	0.72	0.11	0.05	0.78	0.82
0.6	0.91	0.73	0.12	0.064	0.8	0.85

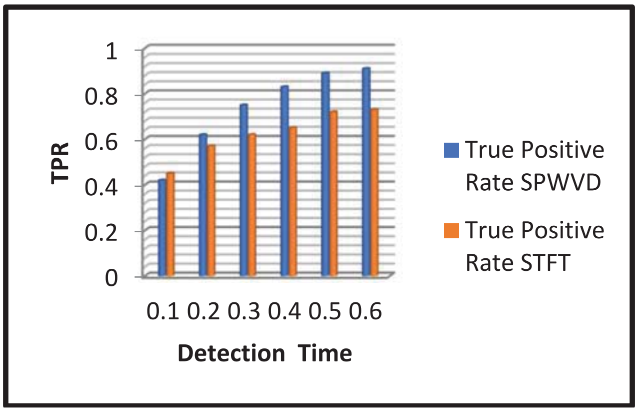

Fig. 5. TPR evaluation comparison for SPWVD with STFT.

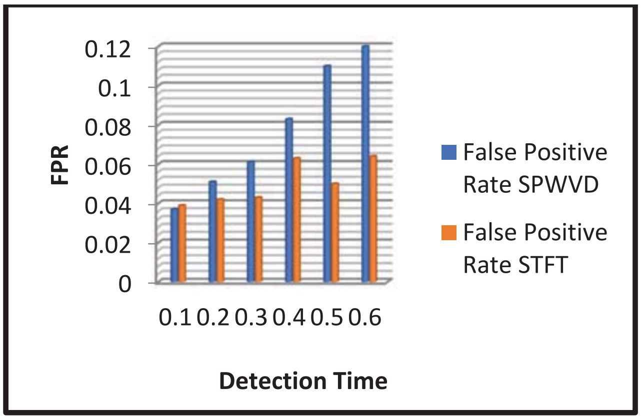

Fig. 6. FPR evaluation comparison for SPWVD with STFT.

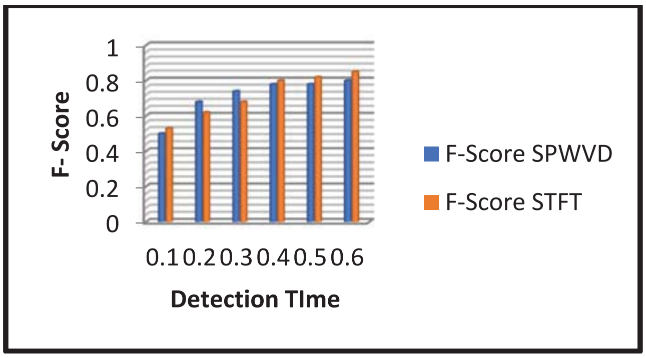

Fig. 7. F-Score evaluation comparison for SPWVD with STFT.

SPWVD's TPr is only a little lower than STFT's for small data packet sizes, but it's over 19% higher for larger packets, such as 0.6s. When the size of a data packet is increased, the corresponding Detection Time remains constant at about 0.6, and the corresponding STFT remains about 0.74. As higher TPr is usually desirable for any detection algorithm, it is inferred that larger Detection Time window size is better for the proposed detection technique. Similarly, FPR roughly 8% higher in comparison with STFT for Detection Time window size of 0.6s. A higher sensitivity correlates with a higher detection rate, but it does not explain the correspondingly greater false positive rates. F-score findings for time-frequency analysis approaches are displayed in Fig. 7; they demonstrate an improvement of roughly 8% above STFT for a 0.5s Detection Time window size.

IV. CONCLUSION

Seismic time-series signal analysis for the identification of moving ground targets has been a topic of intense study for a long time, owing to the wide range of potential military and civilian applications of this technique. Whether it's tracked or on wheels, the passage of a vehicle along a path causes seismic activity. Therefore, provide information that can be used in the identification of a possible target. While there are many feature extraction methods available, time-frequency analysis has shown the most promise for accurately pinpointing the location of seismic events with very little chance of a false positive. In this section, we provide a smooth-pseudo-Wigner-Ville distribution (SPWVD)-implemented time frequency analysis for seismic event identification. SPWVD provides a more accurate depiction of the time-frequency coefficients by using two window functions to cancel out cross-term interference along both the time and frequency axis. Based on this transformed probability distribution function, Renyi entropy is calculated as a regional index of seismic activity. The CFAR threshold on Renyi entropy, which automatically modifies the detection threshold, guarantees the arrival of a potential seismic event. The suggested technique was tested using a dataset that included the seismic footprints of both tracked and wheeled vehicles. Improved detection algorithm performance, as measured by F-score and lead time (Tlead), has been attributed to the use of SPWVD due to its superior noise suppression capabilities.

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