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Review on Digital Signal Processing (DSP) Algorithm for Distributed Acoustic Sensing (DAS) for Ground Disturbance Detection

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Abstract

Fiber break because of third-party intrusion has become one of the challenges in maintaining the fiber-based communication link, especially those buried underground. Hence, we investigate the feasibility of using Distributed Acoustic Sensing (DAS) system to sense possible surrounding activities that might cause fiber break. This paper reviews the current digital signal processing (DSP) algorithm used in the DAS system designed to detect ground disturbance, highlighting the specific design parameters for each technique. These parameters include identification rate, classification accuracy, detection accuracy, training time, and signal-to-noise ratio (SNR). The algorithms used are near-field beamforming, phased-array beamforming, image edge detection, gaussian mixture model (GMM), gaussian mixture model - hidden Markov model (GMM-HMM), faster region-based convolutional neural networks (R-CNN), transfer learning, dual-stage recognition network, group convolutional neural network (100G-CNN), and support vector machine (SVM). By reviewing the existing techniques used in the DAS system for ground disturbance detection, we can determine the best DSP algorithm that should be implemented for fiber break prevention, enabling us to design a DAS system specifically for it in the near future.

1. Introduction

The digital transformation that is happening globally has utilized the use of optical fiber in telecommunication lines replacing Copper cable, which had much lower bandwidth [1]. However, optical fiber cable installation is significantly more expensive than copper cable [2], making its maintenance crucial. Fiber break due to third-party disturbance has become a challenge in maintaining the fiber-based communication link [3]. Hence, we explore the feasibility of using Distributed Acoustic Sensing (DAS) to sense the surrounding activities that might cause a break, such as digging, drilling, and shoveling.

Distributed Acoustic Sensing (DAS) technology uses fiber optic cables as distributed sensors to monitor and analyze acoustic signals. The concept of using fiber optics for sensing can be traced back to the late 1970s, one of which was studies on the application of optical time domain reflectometer (OTDR) techniques and it was employed to identify the loss of optical fiber links [4]. Back then, research in the field of DAS was more focused on utilizing Rayleigh scattering within the fiber to detect acoustic waves. Further advancements in DAS technology came with the introduction of coherent detection techniques [5]. These techniques enhanced the sensitivity, resolution, and spatial coverage of DAS systems. Over the years, the capabilities and performance of the DAS system have gone through many improvements through the usage of new fiber optic technology and signal processing techniques. For instance, researchers explored the use of phase-sensitive detection for signal processing and achieving higher sensitivity [6].

DAS systems can be optimized and designed to detect acoustic waves that propagate through multiple medium, typically ground [7], air [8], [9], and underwater [10]. In each medium, DAS utilizes the same working principle where it enables real-time strain and vibration measurements along the entire length of a fiber optic cable. However, each medium might need different DAS techniques based on the application it is used for. For example, DAS systems that sense acoustic waves through air medium usually need some extra configuration rather than using only the fiber cable as the sensor. One example is the research done by Tang et al., where they developed handmade microphones for their DAS systems to sense airborne sound [8].

As a result of the continuous development of fiber optic technology, DAS has found applications in numerous sectors, including oil and gas exploration [11]–[13], perimeter security [7], [14]–[17], earthquake monitoring [12], [18], [19], and railway monitoring [20]–[23]. DAS is a well-known method for subsurface imaging and monitoring in wells, especially for Vertical Seismic Profiling (VSP) surveys [24]. This method allows for an extensive investigation of reservoirs' subsurface structures and properties. In perimeter security, a DAS is used to continuously monitor and detect acoustic disturbances or vibrations along a fiber optic cable, signaling unauthorized access, infiltration attempts, or perimeter breaches. Due to the ability to detect and analyze earthquake seismic waves, disclosing their position, magnitude, and properties, there has been an increasing number of DAS implementations in seismology and earthquake monitoring applications [19], [25]. The implementation of DAS in railway monitoring applications has improved railway safety, maintenance, and productivity by providing continuous track monitoring, train identification and localization, wheel and bearing monitoring, and tunnel monitoring [23].

Research in DAS continues to advance, focusing on improving the systems' performance in terms of accuracy and reliability [26]. New fiber designs [10], [13], [27], [28], sensing mechanisms [9], [29]–[33], deep learning (DL) [17], [34]–[36], machine learning (ML) [37]–[41], support vector machine (SVM) [42], [43], and data processing algorithms [7], [15] are being explored to enhance the capabilities of DAS.

In this paper, a review of the existing DSP algorithm that was employed in DAS systems designed for ground disturbance detection was conducted to determine the possible algorithm to improve the detection performance of the DAS system and determine the best design of a DAS system with the most significant potential for preventing fiber break.

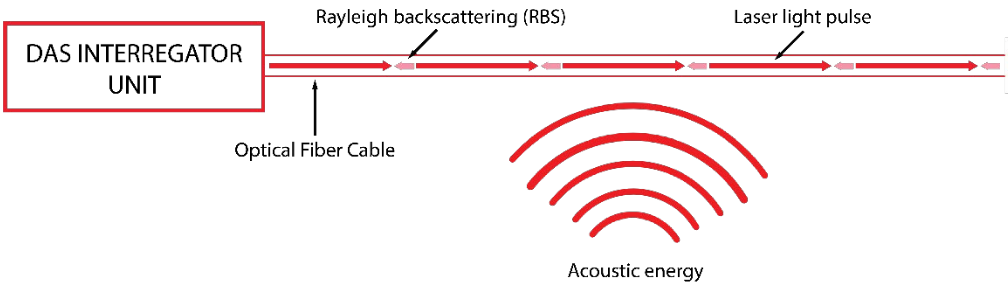

Fig. 1 *DAS basic working principle*

2. Basic Working Principle of DAS

Distributed Acoustic Sensing (DAS) is a relatively new fiber optic technology that has undergone rapid development in recent years. DAS detects acoustic waves by measuring variations in Rayleigh backscattering of a laser pulse resulting from the axial strain of a fiber that experiences elastic vibrations [44]. By exploiting the scattering properties of light in optical fibers, DAS enables the transformation of the entire fiber length into an endless array of acoustic sensors. The fundamental principle behind DAS is Rayleigh scattering which occurs when a light signal interacts with external perturbation caused by acoustic energy in the fiber material [45]. These interactions cause the light to scatter in all directions, including back along the fiber. **Fig. 1** shows the basic working principle of DAS.

To implement DAS, optical time-domain reflectometry (OTDR) is commonly employed. OTDR works based on the principle of time-domain reflectometry, where a short pulse of light is launched into the fiber, and the backscattered light is measured as a function of time. By analyzing the backscattered light intensity changes, DAS systems can identify the location and intensity of acoustic disturbances along the fiber [46]. **Fig. 2** shows a sample of the OTDR setup. However, traditional OTDR cannot respond to external interference [26], as it heavily relies only on backscattered light intensity measurement to analyze the external perturbation that happened along the optical fiber. Both external perturbation and interference affected the intensity of the backscattered light, making it almost impossible to differentiate between the two and accurately identify the cause of the measured variation. The phase-sensitive optical time-domain reflectometry (Φ-OTDR) technique was used instead to overcome this problem. Unlike the traditional OTDR, which usually uses a broad linewidth laser, Φ-OTDR utilizes a narrow linewidth laser, significantly improving SNR and spatial resolution performance. The analysis of backscattered light in Φ-OTDR encompasses not only intensity but also phase, enabling the extraction of more precise details associated with the external perturbation [47]. Through the analysis of both intensity and phase, the Φ-OTDR can distinguish between external perturbation and noise or interference. **Fig. 3** depicts the Φ-OTDR based DAS system. To analyze the backscattered light, digital signal processing (DSP) techniques will be utilized to process the acquired signal. DSPs extract essential information from the obtained signal and improve the accuracy and interpretability of the received results [48]. Some critical components of DSP in DAS are localization, event detection, and classification. Through DSP techniques such as beamforming, the location of the acoustic sources can be determined [49]. In addition, the DSP algorithm enables event detection and classification by detecting and classifying specific events or patterns in the acquired data, which can be achieved through deep learning [17].

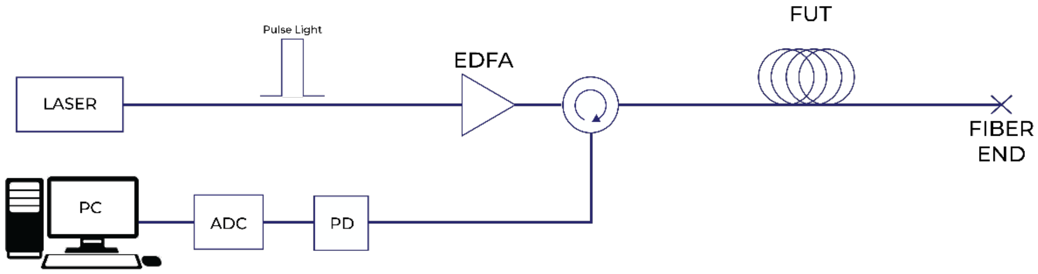

Fig. 2 *OTDR setup*

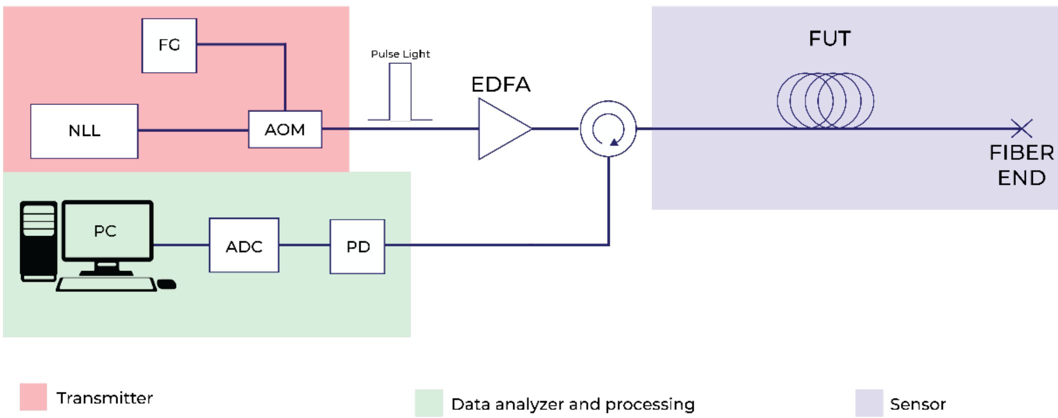

Fig. 3 *Φ-OTDR based DAS system*

3. DSP Algorithm Used in DAS System for Ground Disturbance Detection

Ground disturbance detection is usually used in perimeter security applications whereby some of the focus of the application is to detect intrusion that happened on the ground's surface. Examples of this intrusion are human activities such as walking or digging, heavy machinery such as excavating, and vehicles such as passing cars. The main things usually discussed in this application are the performance of localization, detection, and classification accuracy of the event, where state-of-the-art DSP algorithms have been used to improve it.

One of the pioneers of using DAS in perimeter security applications was OptaSense, which proposed using DAS for border monitoring by using the existing or new fiber optic communication cable [14]. In 2012, OptaSense employed its own DAS System unit with the most recent signal processing method at the time, which was phased-array beamforming. For detecting human foot traffic, vehicles, mechanical and manual excavating, and general human activity, OptaSense has demonstrated a high Probability-of-Detection and low false and nuisance alarm rates. It provides a cost-effective solution with better performance than the traditional monitoring system. Oak Ridge National Laboratory (ORNL) has independently evaluated OptaSense DAS for border smuggling and illicit trafficking prevention. Their findings conclude that the OptaSense DAS system achieved the 90% Probability of Sense, Ps for all activities and soil conditions tested.

In 2013, OptaSense later discussed more about their system by discussing their methods for detecting different intrusions [7]. To detect walking activity on compact sandy soil, they employ near-field beamforming to estimate the location of the footsteps on the ground surface. The location of footsteps can be determined by implementing near-field beamforming to approximate the distance and lateral offset of these sources of SH waves along the cable. This beamformer focuses on estimating the seismic propagation velocity of the dominant SH (horizontally polarised shear wave) mode generated by footsteps traction. In addition, they also tested their DAS system in a snowy environment where snow depth of 0.2 to 0.3 meter covered the ground that was frozen. Despite those conditions, the DAS system could still detect footsteps with an SNR of 30 dB.

Dejdar et al. proposed a post-processing algorithm for edge detection using the Sobel and Prewitt operators instead of the conventional differential method commonly used in DAS systems [15]. The DAS system was entirely regulated by the FPGA. It was tested on a prepared test path that included a specific location for optical security cables, such as buried in the ground or mounted on a secure fence. Sobel and Prewitt edge detection methods with three different kernel sizes and a simple conventional differential method were used to detect any intrusion, whereby the conventional method was used as a reference to analyze the performance improvement. The noise level of the derived Rayleigh traces was reduced using the moving average method. The detection effectiveness was determined using SNR, with the Sobel operator of size 5 x 5 producing the most excellent results with average SNR of higher than 21dB at a distance of 5 meters from the sensing fiber.

Table 1 *DSP algorithm used for DAS in the perimeter security application*

Published Year	Researcher	Method Used	Performance
2012	Owen, et al.	Phased-array beamforming	Probability of sense, Ps = 90%
2013	Duckworth, et al.	Near-field beamforming	Footstep localization in snowy terrain SNR = 30dB
2022	Dejdar, et al.	Image edge detection	Average SNR of > 21dB

3.1 Employing Deep Learning

In recent years, more research on the use of deep learning (DL) in DAS systems has emerged, including the use of Faster Region-based Convolutional Neural Networks (R-CNN) in high-speed railway perimeter monitoring. Xiao et al. introduced the use of Faster R-CNN to enable DAS systems to recognize a variety of irregular intrusion occurrences [35]. In their system, a DAS system that utilized Φ-OTDR technique was designed to collect acoustic signals. The data of the signal were then subsequently standardized in both temporal and spatial domains and transformed into Spatio-temporal pictures. The Spatio-temporal features were then extracted using the Faster R-CNN to classify and detect five irregular intrusion events: excavating, thorn cage pulling, climbing, wall chiseling, and train background noise interference. An experiment was initiated, and the results of the tests show that their system's average detection accuracy for all strange intrusion events is above 89%. Furthermore, improvement in term of the detection accuracy was achieved when compared to conventional methods which are ConvLSTM and anti-noise ConvLSTM. The system can also tell the difference between background noise that doesn't pose a danger and noise that does, which helps a lot to lower the number of false positives.

Yang et al. presented pipeline safety early warning (PSEW) systems based on DAS. The purpose of this system is to identify and pinpoint third-party events that have the potential to cause damage to long-distance energy transportation pipelines. These system play a crucial role in ensuring both pipeline safety and the continuous delivery of energy [36]. Nevertheless, the huge cost associated with collecting extensive real-site data sets for model building, coupled with the low proportion of labelled data, typically amounting to less than 0.5%, hinders the practical implementation of PSEW systems in natural environments. In their paper, they suggest a unique semi-supervised learning model for monitoring pipeline safety in real time. The semi-supervised learning model with the utilization of sparse stacked autoencoder (SSAE) is suggested for damage event recognition and spatiotemporal localization. The utilization of the SSAE is specifically employed to extract features that are more robust, particularly when trained on unlabelled data.

On the other hand, the fully linked network that has been trained using a limited amount of labelled data is employed for the purposes of localization and identification. An experiment using real-world long-distance energy pipelines of the PipeChina demonstrated an improvement in terms of identification and location performance with a significant amount of unlabelled data and a small amount of labeled data under low SNR conditions, potentially

Int. Journal of Integrated Engineering Vol. 16 No. 2 (2024) p. 102-113

lowering data collection and system deployment costs. The unlabelled data encoding has strong spatiotemporal transferability, which can increase the portability of the PSEW system. Furthermore, the decoded feature has good visualization, and the model is relatively small in size and latency. Based on the various unlabelled datasets and the collection frequency (100Hz and 500Hz), it can be observed that all classification performance evaluation values are above 90%.

In the same years, Shi et al. developed a method for event recognition with high precision based on transfer learning which was built for DAS systems based on Φ-OTDR [34]. The motivation behind this method is because, although deep-learning-based event identification systems achieve high levels of classification accuracy, they require substantial computational resources and extended training. The results of conducting experiments on a data set consisting of 4254 samples on a portable computer demonstrate the efficiency of employing a transfer-learning-based approach for event recognition in Φ-OTDR. This method exhibits enhanced classification accuracy and decreased training time. Moreover, through the process of freezing the head of a specific portion which is one-fifth of the pre-trained AlexNet, the neural network is able to achieve a higher level of accuracy, specifically an increase of 1.9% resulting in an overall accuracy of 96.16%. Additionally, this freezing technique also leads to a reduction in training time, with a decrease of 27.2% equating to a total training time of 275 seconds. According to supplementary testing, the network demonstrates a classification accuracy of 95.67% even when the training database's capacity is decreased to 1146.

Table 2 *Deep learning employed in DAS system*

Published Year	Researcher	Method Used	Performance
2021	Xiao, et al.	Faster Region-based Convolutional Neural Networks (R-CNN)	Detection accuracy of >89%
2021	Yang, et al.	Semi-supervised learning model based on sparse stacked autoencoder (SSAE)	Classification accuracy of > 90%
2021	Shi, et al.	Transfer Learning	Classification accuracy of 96.16% and reduced training time by 27.2% (275s)
2022	He, et al.	Dual-stage-recognition network	Classification accuracy of 97.6%
2022	Yan, et al.	Group Convolutional Neural Networks (100G-CNN)	Classification accuracy of 99.6%

Furthermore, He et al. proposed the use of a dual-stage-recognition network to reduce the number of false alarms, thereby increasing the accuracy of the DAS system in detecting actual intrusion in an environment with undetermined disturbances, such as animal activities [16]. This is possible because this method enables much more precise and effective recognition of intrusion patterns. The dual-stage recognition network is made up of two stages: the pre-recognition stage, which is responsible for shallow classification, and the sub-recognition stage, which is responsible for differentiating between events that are quite similar.

The decision tree classifier can classify three target events of non-intrusion, human-animal interactions, and mechanical movements in the pre-recognition stage based on temporal energy and frequency spectrum information. Following that, at the sub-recognition step, the target events of human and animal actions can be distinguished further by combining time-frequency analysis with the BP neural network. Furthermore, the characteristics information of the time-frequency energy distribution is efficiently compressed by the proportion statistics of four energy levels in order to improve the computing efficiency of the BP network model. This method was evaluated for a month and produced an average recognition accuracy rate of 97.6% for five normal occurrences with a rapid average response time of 0.253 s. This indicates that it is very promising in recognizing intrusion events in a practical context.

Unlike (He et al., 2022), Yan et al. focused on recognizing mixed intrusion events, which occurred when multiple intrusions occurred simultaneously and in close proximity [17]. Current identification schemes will prove challenging to recognize the numerous events; hence the use of group convolutional neural networks was proposed to solve this problem. A method based on a convolutional neural network with 100 groups (100G-CNN) was proposed, and this model was designed to get the most useful information from sample vibration information for feature extraction and classification. It can learn to extract features in the time dimension by analyzing how the vibration changes at different places. It makes getting valuable features from the raw data possible and reduces the time needed for training and recognition. An experiment was conducted to evaluate the performance of this method, and it was determined that the proposed 100G-CNN model is significantly more stable than a conventional CNN model. In addition, the proposed algorithm's average classification accuracy during training can reach 99.6%. Consequently, the proposed scheme has tremendous potential in the field of fiber perimeter security.

3.2 Employing Machine Learning

In DAS, machine learning (ML) facilitates more efficient and accurate acoustic signal analysis, improves data interpretation, and contributes to better decision-making in various applications, including perimeter security. Tejedor et al. implemented ML into their DAS system, which is developed to detect external threats in the vicinity of the gas pipeline. Various methods were implemented, resulting in mixed classification performance in determining threats happening along the gas pipeline under surveillance. Furthermore, the incorporation of pattern recognition strategies (PRS) has been implemented to enhance the classification of detected vibrations into a group of relevant activities. This integration has proven to be effective in significantly reducing the occurrence of false alarms, thereby improving the cost-effectiveness of the system. A Gaussian Mixture Model (GMM), a generative model-based method, was used in [37]–[41] for pattern classification. During the training phase, each class was initially represented by a Gaussian Mixture Model (GMM) consisting of a single component. During the testing step, the feature vector is assigned to the class that has the highest probability, which is determined based on the collection of Gaussian Mixture Models (GMMs).

The DAS+PRS surveillance system [37]–[41] encompasses two operational modes: machine and activity identification, which involves identifying both the machine and the performed activity, and threat detection, which aims to detect any suspicious threats to the integrity of the gas pipeline. In 2016, Tejedor et al. introduced the first pipeline integrity threat detection system that utilizes distributed acoustic sensing (DAS) for data collection [37]. As previously mentioned, the utilization of GMM for pattern classification is motivated by its low consumption of resources and excellent performance in pattern matching tasks. This study presents a comprehensive assessment and comparison of several position selection and normalization techniques. The evaluation was conducted utilizing a rigorous experimental methodology and real-world field data. The result on threat detection is considerably good, with the ability to correctly recognize 80% of the threat activities and average classification accuracy of 64.3%. Due to the rigorous experimental procedure and complexity of the task, the machine + activity identification achieved only 45.2% average classification accuracy.

The following year, Tejedor et al. (2017) improved their previous system by implementing contextual information at the feature level and applying a system combination strategy for pattern classification [38]. Tejedor et al. incorporated a post-processing technique for combining the results of the pattern classification system with the feature vectors that span various temporal contexts which consists of short, medium, and long. This combination was performed at the probability level, and it involves calculating a new probability for each original feature vector in order to recognize this as the class with the most significant probabilities. The probability of each combination was carried out by using three methods. First, the sum method was employed to add up the probabilities derived from the contextual feature vectors and the result was normalized by the number of temporal contexts. Next, the product method was employed to multiply the probabilities derived from the contextual feature vectors, followed by normalizing the result by the number of temporal contexts. Lastly, the maximum method assigns the class with the highest probability, based on the contextual feature vectors, to the original feature vector. The results reveal that the system combination using contextual feature information improves the results for each individual class in both operational modes and the overall classification accuracy, as compared to a previous system [37] based on the same rigorous experimental design. The average classification accuracy achieved 54.9% for machine + activity identification and 68.3% for average classification accuracy for threat detection.

In 2018, the DAS+PRS surveillance system was further improved by introducing the Gaussian Mixture Model-Hidden Markov Model (GMM-HMM) [39]. Instead of only using GMM for pattern classification, Tejedor et al. incorporate GMM-HMM into the system, which consists of two different processes: training and recognition. In the training process, it uses data from numerous field test recordings and only needs to be conducted once. In the machine + activity identification mode operation, a GMM-HMM with a single Gaussian component for each activity was built. In contrast, two different GMM-HMMs representing threat and non-threat classes, with single Gaussian components, were constructed in the detection mode operation. The GMM-HMM training involves estimating the Gaussian component's mean and entire covariance matrix and the transition matrix probabilities for each HMM state [50]. In the recognition process, the Viterbi algorithm [50] was used to classify each acoustic test frame as the class with the highest probability (machine+activity or threat/non-threat). The Viterbi algorithm identifies the most effective path between acoustic test frames and previously trained GMM-HMMs. For each acoustic test frame, three recognition processes were executed to compute three individual frame-level decisions. In the machine + activity identification mode, the average classification accuracy is 45.7%, which slightly improves over the GMM approach's accuracy of 45.2%. However, in term of threat detection, the average classification accuracy is much lower which is only 56.4% compared to the GMM approach which is 64.5%.

To improve the result of [39], the same method used in [38] was applied to their current DAS+PRS system [40]. Tejedor et al. (2019) proposed the implementation of contextual information at the feature level in a GMM-HMM-based pattern classification and employed a system combination strategy for acoustic trace determination [40]. The system combination is based on the majority vote of the decisions made by the individual contextual information sources and the number of states utilized for HMM modeling. Based on the same rigorous experimental setup, the system combination from the contextual feature information and the GMM-HMM methods experiment result was improved for both machine + activity and threat detection modes compared to the previous [39] systems. While the average classification accuracy for threat detection improved by 10.4%, reaching 67%, the average classification accuracy for machine + activity increased by 13.4%, reaching 59.1%.

The result presented by [37] was further enhanced in the year 2021 when Tejedor et al. (2021) suggested a multi-position technique in GMM-based pattern classification systems [41]. This approach functions in a real-field scenario by undergoing the same rigorous experimental procedure. Using multiple positions for model training improves system performance for activities with consistent behavior and high energy. Still, it decreases system performance for activities with multiple behavior and low energy, as determined by a rigorous experimental procedure. Concerning threat detection, they have demonstrated that the multi-position approach can improve overall accuracy. The average classification accuracy for the machine + activity mode was 48%, a 2.8% increase. In comparison, the threat detection mode's average classification accuracy is 69% which is a 4.5% increase compared to the GMM-based system approach.

Table 3 *Machine learning employed in DAS system*

Published Year	Researcher	Method Used	Performance (Classification Accuracy)
2016	Tejedor, et al.	Gaussian Mixture Model (GMM)	Machine + Activity Mode: 45.2% Threat Detection Mode: 64.5%
2017	Tejedor, et al.	Contextual Gaussian Mixture Model (GMM)	Machine + Activity Mode: 54.9% Threat Detection Mode: 68.3%
2018	Tejedor, et al.	Gaussian Mixture Model-Hidden Markov Model (GMM-HMM)	Machine + Activity Mode: 45.7% Threat Detection Mode: 56.4%
2019	Tejedor, et al.	Contextual Gaussian Mixture Model-Hidden Markov Model (GMM-HMM)	Machine + Activity Mode: 59.1% Threat Detection Mode: 67%
2021	Tejedor, et al.	Multi-Position Approach in Gaussian Mixture Model (GMM)	Machine + Activity Mode: 48% Threat Detection Mode: 69%

3.3 Employing Support Vector Machine

The DAS system developed by (Shi et al., 2021) was incorporated with support vector machine (SVM) methodology. Li et al. proposed a technique that leverages transfer learning and support vector machines (SVM) to efficiently construct a classifier of high precision using a limited number of training samples and a conventional device devoid of a graphics processing unit (GPU) [42]. To conduct pre-processing on the raw data, a simple bandpass filtering and scaling procedure was employed. Transfer learning is utilized in the extraction of class identification features by the pre-trained AlexNet model. These features are subsequently employed in the direct construction of SVM classifiers without undergoing any feature selection procedure. The study's findings, which utilized 4254 samples and encompassed eight distinct event categories, demonstrate that the support vector machine classifier can achieve a classification accuracy of 94.67%. This level of accuracy was attained by employing extracted features and conducting a training process that lasted for a duration of 13 seconds. Notably, the training was conducted on a portable computer with an Intel i5-7300HQ processor without a GPU. Furthermore, further research indicates that a classification accuracy of 90.82% can still be achieved when the training data size is decreased from 4254 to 1146.

Table 4 *Support vector machine employed in DAS system*

Published Year	Researcher	Method Used	Performance
2022	Li, et al.	Transfer learning and Support Vector Machine (SVM)	Classification accuracy of 94.67%
2023	Saleh, et al.	Pre-existing Support Vector Machine (SVM)	Classification accuracy of 95%

Another implementation of SVM into the DAS system was introduced by Saleh et al., who developed a DAS system to detect intrusion happening in the vicinity of critical energy infrastructure [43]. The researchers put forward a classification framework for human activities utilizing a Distributed Acoustic Sensing (DAS) system. This framework employs a Support Vector Machine (SVM) that operates alongside a coexisting SVM. The input features for this system are derived from the envelope of the gammatone filter cepstrum coefficient (GFCC). The detection and classification campaign consists of four independent phases which are evaluation, classification, detection, and feature extraction. In order to improve the ability to detect signals, a method that combines wavelet and normalized differential techniques is utilized with the aim of enhancing the SNR. A feature extraction technique utilizing a Gaussian filter (GF) is employed to implement an auditory filter. This process involves six sub-phase processing steps, which include envelope wrapping, identification of local maxima, averaging the dataset, truncation of the dataset, rearrangement of the dataset, and random permutation. These steps are integral to the management of the dataset during the feature extraction process. The primary goal of this methodology is to reduce the number of dimensions in problem spaces, hence addressing computational constraints. A pre-existing Support Vector Machine (SVM) classifier was utilized to perform the task of classification. Human activities such as jumping, tapping, and walking can be categorised into three distinct groups: jumping versus tapping, jumping versus walking, and tapping versus walking. In general, the classification performance was considered satisfactory as it exceeded the threshold of 95%.

4. Discussion and Conclusion

Ground disturbance detection systems based on DAS technology play a crucial role in perimeter security applications by detecting surface-level intrusion caused by various human activities and machinery. The previous section reviewed the DSP algorithm used in the DAS system for ground disturbance detectors, focusing on the performance of localization, detection, and classification accuracy of the event. OptaSense, one of the pioneering companies in this domain, introduced a cost-effective solution utilizing DAS technology in 2012 [14]. They demonstrated how DAS is perfect for ground disturbance detection. Their system demonstrated high detection rates and low false alarms, surpassing the traditional monitoring systems' performance which was a camera surveillance system. The following year, OptaSense introduced its method for detecting different types of intrusion, employing near-field beamforming to estimate the location of footsteps on the ground surface [7]. This improved the ability of the system to detect and locate the intrusion happening in places of interest. In the recent year, we were introduced to using post-processing algorithms for edge detection, specifically the Sobel and Prewitt operators, as an alternative to the conventional differential method commonly used in DAS systems [15]. Their algorithm, implemented on an FPGA, exhibited improved performance of the SNR of the system.

Subsequently, research on applying deep learning (DL) to DAS systems has gained momentum. One of them was the use of faster region-based convolutional neural networks (R-CNN) in detecting strange intrusion events in high-speed railway perimeter [35]. Other than having good recognition accuracy for all the peculiar intrusion events, faster R-CNN also have better performance compared to traditional methods in term of detection accuracy. In addition, Yang et al. introduced a pipeline safety early warning (PSEW) system based on DAS to detect and pinpoint third-party events that pose a risk to long-distance energy transportation pipelines [36]. The authors propose an innovative semi-supervised learning framework for real-time pipeline safety monitoring. A study conducted by PipeChina utilized existing long-distance energy pipelines to observe enhancements in identification and location accuracy. The experiment successfully demonstrated that incorporating a substantial quantity of unlabelled data and a limited amount of labeled data under low signal-to-noise ratio (SNR) conditions can potentially reduce costs associated with data collection and system deployment. The utilisation of transfer learning has been proposed as a viable approach to mitigate the computational and training requirements associated with deep-learning-based event identification techniques, regardless of its notable efficiency in classification accuracy [34]. Shi et al. proposed a transfer learning-based approach for event recognition that demonstrates enhanced precision in classification and reduced training time.

In the subsequent year, He et al. proposed the utilization of a dual-stage recognition network as a means to mitigate false alarms and improve the precision of detection in settings characterized by uncertain disturbances, such as animal behaviors [16]. By integrating temporal energy and frequency spectrum information, as well as utilizing a decision tree classifier and a BP neural network, this methodology facilitated the accurate and efficient identification of intrusion patterns. DL has also been employed as a solution for detecting multiple events occurring simultaneously in close proximity [17]. The utilization of 100G-CNN for feature extraction in the temporal domain, through the analysis of vibration variations at different locations, has facilitated the acquisition of advantageous features from the unprocessed data. Consequently, this approach has resulted in a reduction in the duration needed for training and recognition tasks.

In the meantime, Tejedor et al. conducted a study investigating the incorporation of machine learning (ML) techniques into distributed acoustic sensing (DAS) systems with the aim of identifying ground disturbances [37]–[41]. This research spanned from 2016 to 2021 and involved the implementation of various methods. Over the course of several years, a series of enhancements were implemented, resulting in notable improvements to the performance of the system. The authors employed Gaussian Mixture Models (GMM) as a method for pattern classification in their preliminary study [37]. Their findings demonstrated considerable potential in threat detection, accurately identifying 80% of threat activities. The average classification accuracy achieved was 64.3%. In contrast, the classification accuracy of the machine + activity identification mode was found to be significantly lower, with an average of 45.2%.

Further enhancements were implemented by integrating contextual information at the feature level and employing system combination strategies [38]. Incorporating contextual feature information in the system combination resulted in a notable enhancement in the overall classification accuracy. Specifically, the average accuracy for machine + activity identification increased to 54.9%, while the accuracy for threat detection improved to 68.3%. In a subsequent iteration of the system, the integration of GMM with Hidden Markov Models (HMM) was introduced, resulting in the development of GMM-HMM [39]. The incorporation of this integration yielded marginal enhancements compared to the GMM approach, exhibiting an average classification accuracy of 45.7% for machine + activity identification and 56.4% for threat detection.

To optimize the system's performance, contextual information and system combination strategies were implemented in the GMM-HMM-based pattern classification [40]. As a result, enhancements were observed in the identification of both machines and activities, with an average classification accuracy of 59.1%. Additionally, there was an improvement in threat detection, achieving an average classification accuracy of 67%. The authors of their latest publication have put forth a novel methodology that involves a multi-position approach within Gaussian Mixture Model (GMM)-based pattern classification systems [41]. The aforementioned methodology demonstrated enhanced efficacy in identifying potential threats, as evidenced by an average classification accuracy of 69%.

Additionally, there was a marginal improvement in accurately identifying both machine and activity, resulting in an accuracy rate of 48%. In summary, the author primarily employed Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM) for pattern classification and successfully obtained enhanced outcomes by incorporating contextual information and employing system combination strategies. The range of average classification accuracy for threat detection varied between 56.4% and 69%, whereas for machine + activity identification, it ranged from 45.2% to 59.1%.

In addition to ML and DL, support vector machines (SVM) have also been employed in ground disturbance detection using the DAS system. However, the utilization of SVM in this context remains comparatively limited compared to ML and DL. The classification accuracy results were relatively comparable to those obtained from implementing deep learning. In their study, Li et al. improved their DAS system by integrating SVM methodology, resulting in a classification accuracy of 94.67% across eight event categories [42]. The researchers employed transfer learning and SVM without conducting feature selection. The training process was performed on a portable computer that did not possess a Graphics Processing Unit (GPU). In a recent study by Saleh et al., a DAS system was developed with the aim of detecting intrusions in the vicinity of critical energy infrastructure [43]. The system employed SVM classification and inputted Gammatone filter cepstrum coefficient (GFCC) features. The researchers were able to attain a classification performance that met the criteria for satisfactory performance, exceeding a threshold of 95%, for various activities, including jumping, tapping, and walking.

Overall, the performance of ground disturbance detection based on DAS can be improved by introducing a new algorithm scheme and integrating DL, ML, and SVM into the system. However, there are still other ways to improve the system's performance, such as using a new fiber design. In recent years, the use of enhanced fiber in DAS has been on the rise. The enhanced fiber in DAS is a fiber with higher Rayleigh backscattering signal power than conventional fiber, which significantly increases the detection capabilities of the DAS system. However, this method will require a new fiber to be installed, increasing the cost of deployment. Hence, it may not be a good solution, especially for the application that uses existing installed fiber.

Furthermore, the integration of DAS with other sensor technologies that complement its capabilities has the potential to improve system performance. An instance of integrating DAS with video surveillance, infrared, or seismic sensors can result in the fusion of multi-modal data, thereby enhancing the accuracy of detection and mitigating the occurrence of false alarms. This approach exhibits potential efficacy and practicality in perimeter security implementations. This may be very effective and practical for perimeter security applications but may not be applicable for specific applications, including those for fiber break prevention.

In conclusion, this paper systematically reviews the DSP algorithm used by the DAS system for ground disturbance detection. The latest methods mainly use improved algorithms and ML, DL, and SVM integration into the system. Based on the algorithm reviewed, integrating DL into the DAS system was the most used method that produced high classification accuracy. All reviewed DL algorithms achieved at least 89% classification accuracy; some even almost reached 100% accuracy [17]. The DL algorithm that piqued our interest the most was the Dual-stage-recognition network [16] and Group Convolutional Neural Networks [17]. The difference between these two is the issue that they are trying to solve where He et al. was trying to solve the false alarm caused by unwanted disturbance such as animal activities, while Yan et al. aimed to classify two different activities that happened at the same time that was near to each other. Both have the potential to be used in the DAS system for fiber break prevention; however, the classification of two different activities that happened concurrently in close proximity prove to be more beneficial for this application as the same issue may be faced during the deployment.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Hafiz Zulhazmi Jabidin, Siti Azlida Ibrahim, Mohd Saiful Dzulkefly Zan, Siti Musliha Aishah Musa, Kan Yeep Choo, Ahmad Ashrif A.Bakar, Mohd Ridzuan Mokhtar, Tee Connie, Hairul A. Abdul-Rashid;* ***data collection:*** *Hafiz Zulhazmi Jabidin, Amilia Mansoor, Ngo Hong Yeap, Nurul Ain Abdul Aziz;* ***analysis and interpretation of results:*** *Hafiz Zulhazmi Jabidin, Siti Azlida Ibrahim, Siti Musliha Aishah Musa;* ***draft manuscript preparation:*** *Hafiz Zulhazmi Jabidin. All authors reviewed the results and approved the final version of the manuscript.*

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