Implementation of feature extraction and deep learning-based ensemble classifier for interference mitigation in radar signals

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ABSTRACT

In automotive vehicles, radar is the one of the component for autonomous driving, used for target detection and long-range sensing. Whereas interference exists in signals, noise increases and it effects severely while detecting target objects. For these reasons, various interference mitigation techniques are implemented in this paper. By using these mitigation techniques interference and noise are reduced and original signals are reconstructed. In this paper, we proposed a method to mitigate interference in signal using deep learning. The proposed method provides the best and accurate performance in relate to the various interference conditions and gives better accuracy compared with other existing methods.

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1. INTRODUCTION

Now days the vehicles are equipped with special instruments such are called as autonomous vehicles where radars are mounted, it requires various functions including target detection and capable of long-range sensing. These operations can be performed automatically for the sake of user safety and to solve collision in between vehicles. Most popularly the radars with the functionality of frequency modulated continuous wave (FMCW) or the chirp sequence (CS) functionality is to be included but it is very challenging to accomplish the above specified functionalities with mitigating interference technique [1]-[4]. There are several methods used to solve/remove the problems in time amplitude and frequency domains related to interference. This paper proposed an algorithm for radar signal which includes complexity with a small computation and it identifies the targets with a range of smaller distances. The effect of interference is still remains; however the target is not detected when the interference signal is closer to the radar than the target [5], [6]. In our work we included the deep learning techniques in radars to mitigate interference in signalling systems. Deep learning has been developed recently in image, language and speech processing [7]-[10]. In this paper recurrent neural network (RNN) model is used for processing data (noise reduction), eliminating interference and to recover the original transmitted signal even in the existence of interference at the receiver [11]-[13].

2. AIM AND OBJECTIVE

The aim of this work is to design and implementation of feature extraction and better classifier for Interference Mitigation in radar signals. To obtain this goal, the primary objective is,

– To extract and classify the feature matrix by dimensionality reduction algorithm. This will enhance the performance for large dimension feature vector.
– To investigate the training and testing data toward recognizing their overlapped forms in both frequency and time domain hence can attain better prediction result.
– To analyse the signal recognition performance of compound signals by effective learning architecture and optimization method.

3. METHODOLOGY

The present research focuses on the design and implementation of feature extraction and deep learning-based ensemble classifier for interference mitigation in radar signals. Initially, the input signal is converted into binary form then extracts the feature for enhancing the recognition performance of the compound signal. The contribution of this research has four-fold: First, will pre-process, extract, and classify the feature matrix by dimensionality reduction algorithm (independent component analysis and fourier transform). This will enhance the performance for large dimension feature vector. The pre-processing stage includes time-frequency representation; multi-label classification and multi-decision thresholds optimization are used for output label decision. Second, will meta-heuristic based firefly algorithm is used to select optimal parameters and mitigate the interference in both time and frequency domain [14]-[19]. Third, will use effective deep learning approach (deep belief network) with various multi-label strategies toward enhancing the recognition performance. The combination of optimization and learning technique will be used for signal analysis and multi-decision thresholds optimization are used for output for output label decision. Finally, will test the performance using MATLAB simulation software and compare the results with the traditional method in terms of accuracy and signal to noise ratio.

4. MUTUAL INTERFERENCE IN AUTOMOTIVE RADARS

When multiple vehicles are connected to the radar then there exists interference. The use of FMCW waveforms increases the probability of this interference because of the high duty cycle. It is possible to observe radar-to-radar interference when vehicles are moving in their own path [20]-[26]. Interference in FMCW depends on the radar parameters like centre frequency, bandwidth, chirp duration and chirp repetition time. Because of the interference there is degradation is due to interference induced noise in the radar images [27]-[29]. The probability of encountering time-limited interference that leads to SINR degradation is much higher than the ghost target scenario. Therefore, throughout the transmission and reception interfering radar signals have non-identical transmit parameters.

5. DIMENSIONALITY REDUCTION- FEATURE EXTRACTION AND SELECTION

Dimensionality reduction is the process of reducing the number of variables/feature in review. Dimensionality reduction is categorized into feature selection and feature extraction. In feature extraction, the principal component analysis (PCA) is the algorithm which focuses on reducing the high dimensional space into lower space and independent component analysis (ICA) seperates independent space from mixed set of signals is used. In this paper we proposed ICA method for feature extraction [30]-[34]. Dimensionality reduction benefits are: by reducing the dimensions of the features, the space required to store the dataset also gets reduced, less computation training time is required for reduced dimensions of features, reduced dimensions of features of the dataset help in visualizing the data quickly and it removes the redundant features if present by taking care of multi-collinearity [35]-[37].

6. INDEPENDENT COMPONENT ANALYSIS (ICA)

ICA is a machine learning technique used to separate independent sources form a mixed signal. ICA focuses on independent i.e. independent components. ICA is based on information-theory and is also one of the most widely used dimensionality reduction techniques. The major difference between PCA and ICA is that PCA looks for uncorrelated factors while ICA looks for Independent factors [38]-[40]. If two variables are uncorrelated, it means there is no linear relation between them. If they are independent, it means they are not dependent on other variables.

7. META-HEURISTIC BASED FIREFLY ALGORITHM

The firefly algorithm (FFA) is a metaheuristic algorithm, the flashing behaviour of fireflies are implemented. The firefly's flash is act as a signal system to attract other fireflies. There are three rules used. On the first rule, each firefly attracts all the other fireflies with weaker flashes. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex. Secondly, attractiveness is proportional to their brightness which is reverse proportional to their distances. For any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly. Finally, no firefly can attract the brightest firefly and it moves randomly. Firefly algorithm used to solve different optimization problems. It is a meta-heuristic algorithm inspired by flashing behaviour of five flies.

Assumptions: fireflies are attracted to each other. Less bright firefly is attracted to the brighter firefly. Attractiveness decrease as distance between two fireflies increases [41]. If brightness for both is same, fireflies move randomly. New solutions are generated by random walk and attraction of fireflies and random walk is equal to the step size.

a) Firefly optimization algorithm
   1) Initialize parameters like population size, maximum iterations, dimensions, upper bound and lower bound.
   2) Generate population of n fireflies.
   3) Calculate fitness value for each firefly.
   4) Check if (t:= 1 to Max t)
   5) Update position and light intensity of each firefly.
   6) Report the best solution.
b) Advantages of firefly algorithm
   1) Firefly can compact the distinct minima with highly non-linear, multi-modal optimization problems very easily and efficiently.
   2) The speed of convergence of firefly algorithm is very high in probability of finding the global minima.
   3) It has the flexibility of integration with other optimization techniques to form hybrid tools.
   4) The best, average and worst case time complexities doesn’t require a good initial solution to start during its iteration process.
c) Application areas
   1) For solving travelling salesman problem to find out the shortest possible routes
   2) Digital image compression and image processing leads to the enhancements of identifying specific objects
   3) Feature selection and fault detection used to identify the patterns in an input signal, image or video
   4) Antenna design

8. DEEP BELIEF NETWORK (DBN)

One problem with the artificial neural networks is the back propagation can often lead to local minima. This occurs when ‘error surface’ contains multiple grooves. During back propagation may fall into a groove that is the lowest locally but not overall. Deep belief networks are a generative graphical model and it is represented to the solution of vanishing gradient problem will solve this problem by using an extra step called pre-training. Pre-training is performed before back propagation can lead an error that’s in the vicinity of the final solution [42], [43]. We can use back propagation to slowly reduce the error rate. Deep belief networks can be divided into two major parts. The first part contains multiple layers of restricted Boltzmann machines in order to pre train the network [44]. The second part is the feed forward back propagation network, which will further refine the results from restricted Boltzmann machines (RBM) stack [45], [46].

The neural networks are of different types and based on the application type, the neural network will be chosen. By adding extra layers will get accuracy of the performance of the model. If the layers are too less, then the training will generate the underfit model. If the layers are more in number, the generated model will go overfit. From the Figure 1 the input layer deals with the input and converts the input image in terms of RGB, the set of pixel intensities values are placed in an array thus called convolution. Each convolution has a set of input values to be taken and identify the maximum value from all the values called MAX POOLING layer. The new values will be generated and then apply a filter which is called a kernel and default weights are applied on the nodes (neurons) to get the hidden layer and this process will continue to the hidden layers in the network. The output layer is used to detect or identify the input from the set of generated patterns under training and the model will easily recognise the patterns effectively.

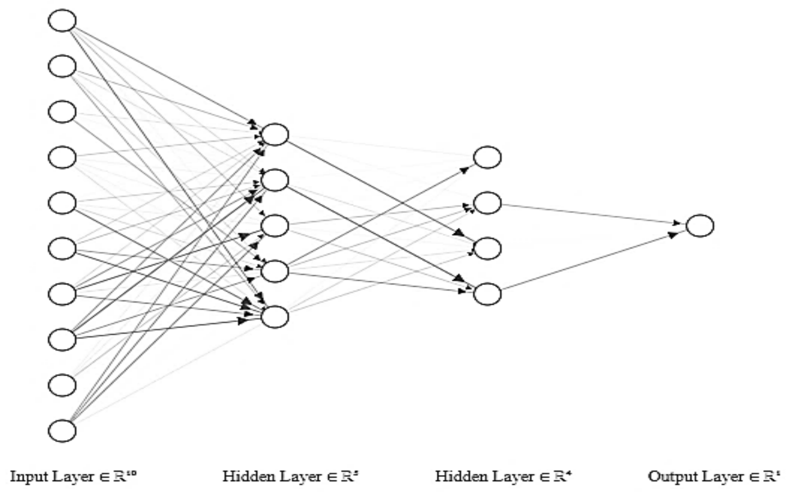

Figure 1. Deep belief network architecture

9. RESULTS

Figure 2 and Figure 3 shows signal interference mitigation after and before. From Figure 2 we can analyse that before transmission the signal added with interference (noise). From Figure 3 it is clearly observed that interference is eliminated from the signal. Figure 4 shows radar signal before feature extraction and Figure 5 represents radar signal after feature extraction. In this paper we proposed ICA for feature extraction**.**

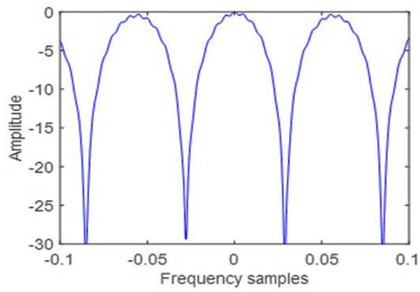

Figure 2. Signal before interference mitigation

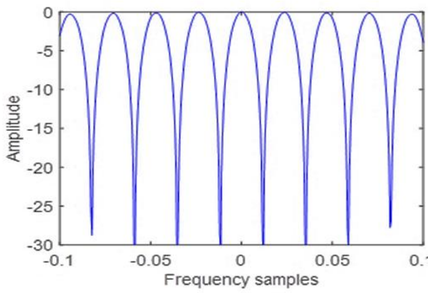

Figure 3. Signal after interference mitigation

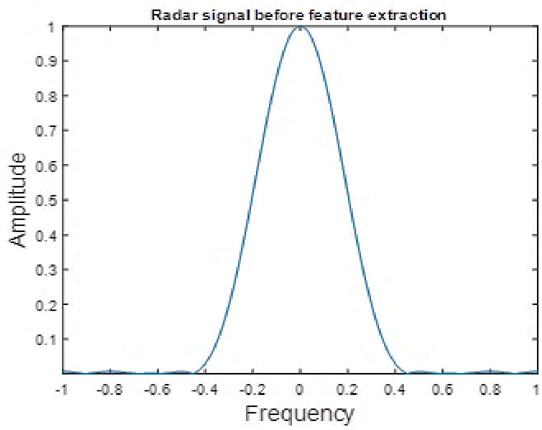

Figure 4. Radar signal before feature extraction

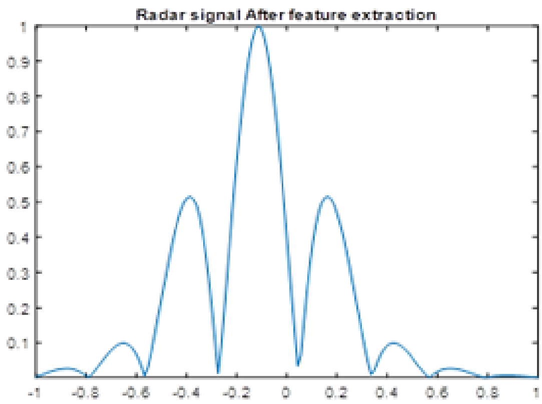

Figure 5. Radar signal after feature extraction

To improve the feature extraction process of deep belief network model for the transmitter data, comparison of output features of the primary data, the first hidden layer and the second hidden layer will takes place. The features from different layers can be compared through each and every node of the data which are processed by feature visualization through dropping high-dimensional data is scaled into 3-dimensional images by using ICA algorithm. Figure 6 depicts the plot axis for time sample, frequency sample and the amplitude of dimensionality reduction of the initial time-domain sampled data of 3D-image reconstructed signal using deep belief network (DBN). Figure 7 indicates that the model acquired nearly 96.4% accuracy when the signal-to-noise ratio (SNR) was 3dB and displays the deep learning methods which are used for the prediction of radar signals efficiently.

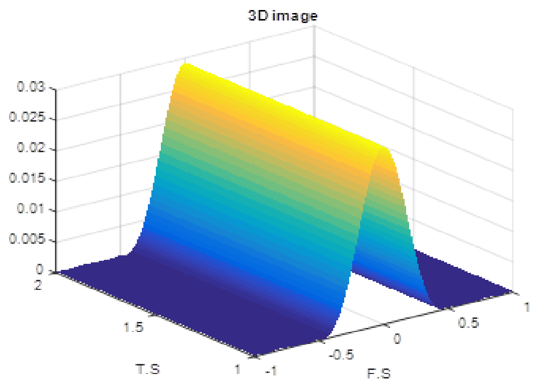

Figure 6. 3D image- reconstructed signal using deep belief network (DBN)

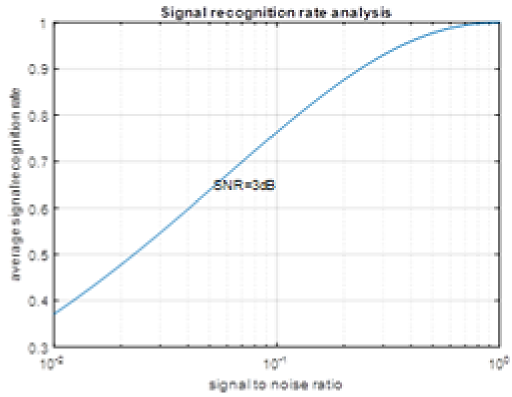

Figure 7. Signal recognition rate analysis

10. CONCLUSION

The design and implementation can be done for feature extraction and deep learning-based ensemble classifier for interference mitigation in radar signals. Initially, the input signal is converted into binary form then extracts the feature for enhancing the recognition performance of the compound signal. In this work pre-process, extract, and classify the feature matrix by dimensionality reduction algorithm (independent component analysis and fourier transform) implemented. This will enhance the performance for large dimension feature vector. The pre-processing stage includes time-frequency representation, training the model with multi-label classification and the decision tree with multi-decision thresholds optimization for output label decision. In this work meta-heuristic based firefly algorithm is used to select optimal parameters and mitigate the interference in both time and frequency domain and effective deep learning approach (deep belief network) with various multi-label strategies toward enhancing the recognition performance. The combination of optimization and learning technique will be used for signal analysis and multi-decision thresholds optimization for output label decision. Finally, the performance using MATLAB simulation software and compare the results with the traditional method in terms of accuracy and signal to noise ratio. The model acquired better accuracy when the signal-to-noise ratio is about 3dB and the deep learning methods can be used to predict the radar signals.

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