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Maritime automatic target recognition for ground-based scanning radars by using sequential range profiles

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Abstract: Classification of marine targets using radar data products has become an important area for modern research society. However, due to several reasons such as the similarity between ship structures and spatial specifications, classification of marine targets constitutes a challenging problem. In almost all of the studies, this problem has been handled by focusing on a single instance of range profiles or synthetic aperture radar data. However, this approach is seen to achieve only a particular success. This study introduces a novel classification approach that is shown to provide additional classification enhancements by exploiting the extra information extracted from sequential range profiles generated by ground-based marine surveillance radars. With this purpose, both synthetic and measuremental range profiles are taken into consideration. Synthetic profile data are generated for seven marine targets by using an electromagnetic scattering simulation tool (RASES)[1]. On the other hand, a total of 2387 range profile data of 171 different target tracks are collected for five different marine target class types by using an X-band marine surveillance radar. Each target tracked for a long period of time to gather sequential HRRP data subsets. HRRP data subsets are used to generate HMM based transition matrix probabilities and sequential classification results by evaluating proposed method. Probabilistic neural network (PNN) and convolutional neural network (CNN) classification algorithms applied to gather classification results. The proposed method results are compared with both single value classification and majority voting rule (MVR) method results. According to the examination results, the proposed classification approach provides remarkable enhancements in the correct classification rates when compared to the case of single profile data approach.

Key words: Maritime automatic target recognition, sequential data classification, synthetic/measuremental range profiles

1. Introduction

Marine target classification is a widely used tool in various areas such as border surveillence, military target identification and homeland security. In order to accomplish classification process, high-resolution range profiles (HRRP) [1, 2], synthetic aperture radar (SAR) and inverse synthetic aperture radar (ISAR) [3, 4] images have been utilized. Among the data sources, HRRPs are easier to access compared to SAR and ISAR images. Whereas, it is extremely hard and costly to obtain ISAR images from ground-based radar systems in real-time operation of radar systems. Hence, HRRPs are appreciated to be more effective for the target classification purposes of sensor systems.

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[1]TÜBİTAK BİLGEM) (2020). RASES [online]. Website https://www.bilgem.tubitak.gov.tr/en/urunler/rases-radar-cross-section-computation [accessed 21 April 2020].

Variations in target types, and the quantity and distribution of HRRPs in database have been constituting great importance on the overall classification performance. For a superior target classifier performance, the HRRP database should be extended with the help of range profile instances of miscallaneous azimuth and elevation aspect angles. On the other hand, there might be insufficient measuremental range profiles especially for the marine targets rarely cruising. Therefore, for these types of targets, training libraries should be enriched with the help of synthetically-generated HRRPs. In order to generate synthetic range profile data, computer-aided design (CAD) models of ship target classes are utilized. Additionally, electromagnetic scattering simulation tools should be used to generate range profiles for each target.

Within the great majority of radar applications, the classifiers consider only a single HRRP for each classification request. This type of classifiers produces independent estimations on the class information corresponding to each HRRP with varying characteristics. On the other hand, there are few algorithms which use sequentially generated HRRP data. In [5], SAR images of ground targets which are generated by 1° intervals using hidden Markov model (HMM) have been automatically classified. Laterveer et al.[6] focused on low-frequency underwater active sonar images to classify foreign objects placed at sea bottom surface using Markov random field algorithm. Runkle et al. [7] have tried to classify targets using multiaspect profile data. Multiple radars have been used to generate range profiles from multiple viewpoints. Classification results from all viewpoints are combined to generate the ultimate classification decision using HMM. Vespe et al. [8] have used HRRP data of ground vehicles to classify targets. Targets have been represented by range profiles collected from different viewpoints. By relying on the extracted features that are evaluated via the Fourier transformation of each individual range profile of each viewpoint, corresponding classification decisions are separately made.

A great portion of the researches that have employed "multilook", "multiaspect" and "sequential" approaches have been considering multiple test data in order to produce the classification decision. The investigation in [9] has introduced a sequential HRRP classification process that consists of an HMM-based classification algorithm and a RELAX-based feature extractor by assuming that each HRRP is captured from the same elevation aspect angle. Few of the existing researches have addressed the problem of determining the optimal HRRP sequence with different aspect angles among a sequentially gathered target echoes, as provided in [10]. Here, Ji et al. [10] have focused on an underwater target database consisting of five different targets and have generated sequential scattering data by assuming equally-likely target occurance probabilities while employing an HMM-based classification algorithm. The investigation in [11] has focused on segmenting the simulation-based ISAR data of aerial targets into 2–5 pieces in order to enhance the combined classifier scheme of RELAX and HMM by the virtue of multilook approach. In [11], each echo corresponding to the segmented pieces are considered as individual and different targets, and the multilook approach results in the combined classification decision. Another multilook approach has been introduced in [12] that performs automatic target recognition (ATR) of 10 different ground vehicles. After evaluating the correlation between the test data and 5 different range profiles with the most similar aspect angle, the final classification decision is made by maximizing the correlation value. The study provided in [13]has synthetically calculated the radar cross section (RCS) of eight different aerial targets with the help of a dedicated software, and has realized maneuvering target recognition by using the synthetically generated sequential HRRP data and HMMs as the classifier. A multiaspect classification method is proposed using the SAR images of 10 different ground vehicles in [14]. Multiple images of each target in the same elevation angle but in different azimuth aspects are selected. Each sample of all targets is evaluated by using the ranking-based decision algorithm [15] and the Bayesian decision to obtain the combined multiaspect classication result. Another realization of multiscale classification approaches has been introduced in [16] that focuses on the classification of synthetically generated range profiles of three aerial targets by using the edge points of range profiles as features. With the purpose of extracting features, the differential images with the largest neighbouring entropy difference are considered as the edge points, and the classification success is seen to be enhanced by using a weighting algorithm to define the class membership degree. Jiang et al. [17] have proposed a decision fusion algorithm for a given HRRP sequence consisting of synthetically generated and measuremental SAR images of ground vehicles. Firstly, the HRRP sequence is decoupled into the angle and range spaces via singular value decomposition (SVD) to achieve the span of the left and the right singular vectors, respectively. Then the range space matching result and the angle space correlation are fused with the singular values as weights. In [18], recognition results for both the stationary and moving targets are compared by using the conventional dimension reduction method and a support vector machine (SVM)-based classifier, and have shown that considerable enhancements in the classification accuracy could be achieved by considering single elevation angle and multiple azimuth aspect angles. In [19], a dataset consisting of the HRRPs of three scaled aircraft model has been constructed via microwave anechoic chamber measurements. Each HRRP in test database is individually classified by using a learning vector quantization (LVQ) network, and finally all classication decisions of the sequential HRRP data subset are evaluated by the majority voting rule (MVR) to result in a combined decision.

Note that, it might be extremely difficult to obtain a HRRP data for predefined target orientations (i.e. azimuth and elevation viewpoints). Hence, in order to supply synthetically generated HRRPs for the lacking target aspects, a simulation software (namely RASES[1]) that focuses on numerical electromagnetic scattering evaluation has been utilized. By using this software, it would be possible to generate the HRRP data corresponding to the predefined specifications (i.e. target class, azimuth and elevation angles).

Within this study, we propose a novel data fusion method which aims to boost the classification success of conventional single-HRRP-based schemes by exploiting sequential range profiles. In order to evaluate and exhibit the enhancements in the correct classification rates, the features corresponding to synthetically generated HRRP database is fed to artificial neural network (PNN)-based training process. For classification purposes, six different features are extracted by inspecting the spatial characteristics of the HRRP data for each target. Sequentially, the classification outcomes are given as input to HMM-based postprocessing. Classification results related to the synthetic HRRP data and post process outputs have guided this study to focus on real radar data. This study provides robust classification performance under challanging circumstances:

- Synthetically generated range profile data calculated by using simulation software to achive whether the proposed method provides significant classification performance echancement.
- Measurementally gathered data of real targets are collected from 5 different ground-based scanning radar stations.
- All HRRPs gathered ground-based scanning radar stations have different elevation angle value which is assumed constant in most of other studies.
- Two different classification algorithms (CNN and PNN) developed to examine proposed method performance.
- The proposed method, which includes transition matrix probabilities and a novel algorithm (explained in Section 2), is developed.
- The proposed method is compared with both single value classification and MVR method results.

The remainder of this paper is organized as follows. In the second section, the proposed fusion method that relies on processing sequential HRRP data is introduced. The inventory of the radar HRRP data that form the basis of this study and the data classification infrastructure are described in Sections 3 and 4, respectively. Classification results with/without using the proposed fusion method and with using MVR method are exhibited in Section 5. A brief conclusion on classification scores are provided in Section 6.

2. Proposed fusion method for enhanced maritime target recognition

Profile data signature depends on the type, size, orientation and scattering characteristics of targets, and the environmental conditions. After the generation of classification results, a fusion approach that has been inspiring from HMM, is performed by focusing on sequential HRRP data subsets of each target class. The well-known HMM approach is based on the transition matrix that describes the Markov chain. The transition matrix that is denoted by $\mathbf{T}$ is a stochastic matrix whose entry for the index pair (i,j) defines the probability that an element moves from the ith state to the jth state during the following step of the process. Assuming that the states are labeled as $1,2,\ldots,N$, then the state transition matrix is given as

$$\mathbf{T} = \begin{bmatrix} T_{11} & T_{12} & \ldots & T_{1N} \\ T_{21} & T_{22} & \ldots & T_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ T_{N1} & T_{N2} & \ldots & T_{NN} \end{bmatrix}.$$

Note that T_{ij} stands for the state transition probabilities $\forall \{i,j\} \in \{1,2,\ldots,N\}$ which satisfy the identity $\sum_{k=1}^{N} T_{ik} = 1$. The characteristics of the HRRP data changes due to the relative target motion experienced at every radar pulse transmission instance.

As shown in Figure 1 HRRP data subsets are evaluated and recorded with a group of the classification results. Transition probabilities (given in $\mathbf{T}$) are used to estimate the final classification result of an input HRRP subset. Within this study we assume individual classification results as transition matrix states. After the generation of classification results of ith and jth HRRP in each data subset, the count of T_{ij} transitions is divided to count of transitions starts with i. After all T_{ij} transition probability values generated proposed fusion algorithm is performed. The fusion of individual classification results corresponding to an HRRP data subset performed by relying on the combined posterior probability:

$$P_k = F_k T_{kk} \prod_{i=1, i\neq k}^{N} (1 - T_{ki}) \,. \tag{1}$$

Here, the observation frequency of class label k among all classification decisions is defined with F_k. Sequential data which consist of N individual HRRP realizations would yield N classification predictions and $N-1$ transition states. Each transition state is used to estimate the ultimate posterior probabilities of all target classes. Hence, by determining the target class with the highest post-processed probability [i.e. evaluated via (1)], the marine target classification is performed. After determining the target class with the highest probability, a correction methodology takes place throughout the considered HRRP labels. The class label of each HRRP within the sequential data subset is replaced by the final target class label if it is different.

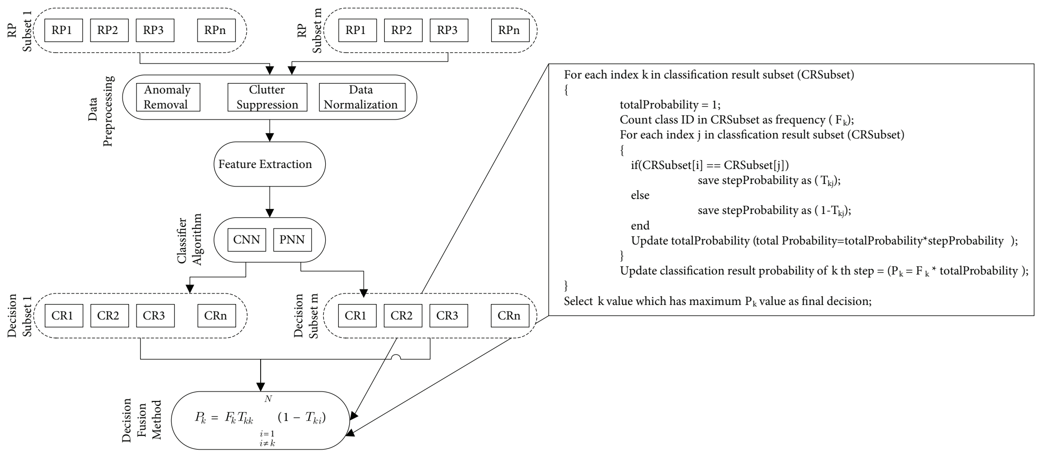


Figure 1. Graphical representation and pseudocode of classification process with proposed method.

3. Inventory of HRRP data

In this study two types of range profile data (i.e. synthetic and measuremental) are taken into consideration. Synthetically generated range profiles are examined priorly in order to test the performance of sequential data classification using the proposed fusion approach. In addition to the examinations on the synthetic profile data, further investigations are accomplished by using the measuremental range profiles of different maritime target classes.

3.1. Synthetically generated HRRP data

Range profiles present the scattered power levels of scatterer units in a medium with respect to range information. In order to evaluate range profile information, related electric field data is calculated initially. Accordingly, electric field related to a medium that is located in the far field, assumed to lie in x direction and have N scatterers can be defined in the frequency space as

$$E^s(f) = \sum_{n=1}^{N} A_n \exp\left\{-j2\pi\left(\frac{2f}{c}\right)x_n\right\}. \tag{2}$$

Here, A_n is the amplitude of the electric field strength returned from a scatterer and x_n gives the spatial position of the scatterer concerned. As it is clearly seen in the equation, there is a Fourier relationship between the $\frac{2f}{c}$ term and the spatial position. Therefore, by applying inverse Fourier transformation to (2), a range profile can be constructed:

$$E^s(x) = \int_{-\infty}^{\infty} \left[\sum_{n=1}^{N} A_n e^{-j2\pi\left(\frac{2f}{c}\right)x_n}\right] e^{j2\pi\left(\frac{2f}{c}\right)x} d\left(\frac{2f}{c}\right). \tag{3}$$

The solution of the integral given in (3) gives the scatterer power distribution with respect to range information as

$$E^s(x) = \sum_{n=1}^{N} A_n \delta\left(x - x_n\right). \tag{4}$$

In order to satisfy a predefined range resolution (Δx) constraint for the generated HRRPs, the numeric evaluation procedure is performed by relying on the identity $\Delta x = \frac{c}{2BW}$, where BW denotes the bandwidth of the electromagnetic waveform, and c is the speed of light.

For seven different maritime target classes that are bulk carrier (S1), cargo (S2), yacht (S3), fishing vessel (S4), military type-1 (S5), military type-2 (S6) and military type-3 (S7), the synthetic HRRPs are generated by utilizing their three dimensional computer aided design (3D-CAD) models as shown in Figure 2a. An electromagnetic signature computation and simulation software named RASES[1] is utilized to generate synthetic range profiles for the azimuthal aspect intervals of $[-45°, 45°]$ or $[135°, 225°]$ where radar to ship nose direction stands for zero degree of aspect. Out of the mentioned aspect intervals, the possibility of getting a beneficial range profile is substantially vanished due to the fact that the target scatterer surfaces are emerged within a fairly narrow range interval in the related profile. Sequential HRRP realizations corresponding to neighboring viewpoints separated $0.1°$ from each other among $[-45°, 45°]$ and $[135°, 225°]$ are obtained. The variation potential of even a slight angle offset of $0.1°$ might be easily seen by examining the scattering characteristics of HRRPs shown in Figure 2b. 1801 different HRRP realizations are obtained for each ship class which has resulted in a very extensive range profile database of totally 12607 HRRPs. 60% of the generated simulation-based data is employed to train the classification structures. Additionally, 20% of them is used for the evaluation of the transition matrix entries, and the remaining 20% is used for testing the classifier and the decision fusion method.

3.2. Ground-based scanning radar HRRP data

Within the scope of this study, measuremental range profile data are collected from five different ground-based scanning radar stations. Each radar station owns its operational area of responsibility (i.e. surveillance territory). Since radar stations are in different geographical locations, they track targets from different elevation angles ranging from $9.91°–27.42°$. For the sake of its considerable classification performance achieved for the synthetic data, the proposed fusion approach is applied to the measuremental HRRP data of different maritime target types. Sequential range profiles of 171 different maritime targets belonging to the ship classes military type-4 (M1), military type-5 (M2) and military type-6 (M3), cargo (M4) and fishing vessel (M5) have been collected. Among all the HRRPs, the number of different targets tracked during data collection process as the target types military type-4, military type-5 and military type-6 that belong to the superclass military are 22, 65 and 37, respectively. On the other hand, cargo and fishing vessel classes that belong to the superclass civilian have been represented by 29 and 18 different target tracks, respectively. Here, note that the variations in the number of measuremental HRRPs for the considered maritime target classes are caused by the conjunctural opportunities and limitations. Eventually, the entire measuremental HRRP database of 2377 total instances consists of 218 HRRPs for military type-4, 553 for military type-5, 758 for military type-6, 412 for cargo and 436 for fishing vessel. All of the HRRP data gathered manually at 30 second intervals by tracking targets in radar operational area. Additionally, each HRRP data has different aspect angle and also velocity changing between 3-35 nautical mile per hour. Here, the training database is constructed by reserving the HRRPs corresponding to the tracked targets with seven or less range profile instances. Accordingly, the training data pool consists of 44 HRRPs for military type-4, 310 for military type-5, 157 for military type-6, 82 for cargo and 81 for fishing vessel.

Following the training stage, range profiles of the tracked targets which has 8 or more range profiles are considered for the evaluation of the transition matrix defined in Section 2 and the testing purposes for the classifier and the proposed fusion method. In order to evaluate the transition probabilities between target class based decisions, a total of 843 HRRPs that might be disassambled to 91 HRRPs for military type-4, 105 HRRPs for military type-5, 317 HRRPs for military type-6, 164 HRRPs for cargo and 166 HRRPs for fishing vessel are utilized. Finally, the remaining HRRPs for each target classes with at least 8 HRRPs are considered for the test purposes. In this instance, 83 RP for military type-4, 138 RP for military type-5, 284 RP for military type-6, 166 RP for cargo and 189 RP for fishing vessel is used for testing. Number of HRRPs collected via the ground-based scanning radar stations are represented in Table 1.

Table 1. Inventory of the measuremental HRRPs.

Class ID	Track count	Training data	Test (transition)	Test (fusion)	Total RP count
M1	22	44	91	83	218
M2	65	310	105	138	553
M3	37	157	317	284	758
M4	29	82	164	166	412
M5	18	81	166	189	436
Total	171	674	843	860	2377

4. Classification infrastructure

In order to measure the performance of the fusion method proposed by this study, conventional and state of art classification algorithms are used. The entire measuremental HRRP database is applied to successive preprocessing blocks with the purposes of anomaly removal, normalization and clutter reduction. After obtaining the normalized and clutter-free HRRPs with nominal spatial specifications, feature extraction process is carried out. By focusing on both the synthetic and measuremental HRRPs, the spatial features those characterize the maritime targets such as platform length, the number of peaks, the normalized position of the peak, the distance between two highest peaks, the symmetry factor and the center of mass. Probabilistic neural network (PNN) and convolutional neural network (CNN) classifier algorithms are taken into consideration within this study.

4.1. Data preprocessing

In order to perform the training process as successful as possible and to represent the investigated target classes by the most revealing HRRPs (i.e. collected/generated), a number of preliminary processes should be applied to the HRRP pool. For this purpose, anomaly detection and exclusion (i.e. discarding the data with unusual specifications), normalization (mapping of the data values to a certain range), thresholding, noise/clutter reduction could be performed. Applying appropriate preprocessing procedures allows for accurate feature extraction and classification.

4.1.1. Anomaly removal

For a random variable or a random-like data element, the values out of the natural and/or expected variation interval (e.g., values that are extremely distant to the mean value) are considered as anomalies or outliers. If not prevented, anomalies lead to high-level errors in the training stage of classification applications and cause degradations in the design of decision surfaces. Hence, the removal of data anomalies are of significant importance especially in the presence of relatively higher noise and/or clutter effects. Although different approaches might be considered for the determination of data anomalies, a very often method is to determine and discard the values deviating from the mean value by 1 to 3 times the standard deviation for the variables or data sets following normal distribution. For this purpose, an anomaly detection has been carried out in order to remove the HRRPs which are not suitable for classification when evaluated in terms of the target length distribution. Accordingly, the length information of each HRRP has been estimated by inspecting the range profile data. Afterwards, the HRRPs from which the estimated target lengths are out of the predefined length interval are discarded from the classification stage. here, the predefined interval might be represented as $[\mu_L - \alpha_L\sigma_L, \mu_L + \alpha_L\sigma_L]$ where μ_L, σ_L are the average and the standard deviation of the target lengths belonging to the same target class, and α_L is a positive integer that controls the extent of the anomaly removal process. Figure 3 shows anomaly removal process of speed and aspect angle features. Range profiles, not in threshold boundary as indicated by red lines, are removed.

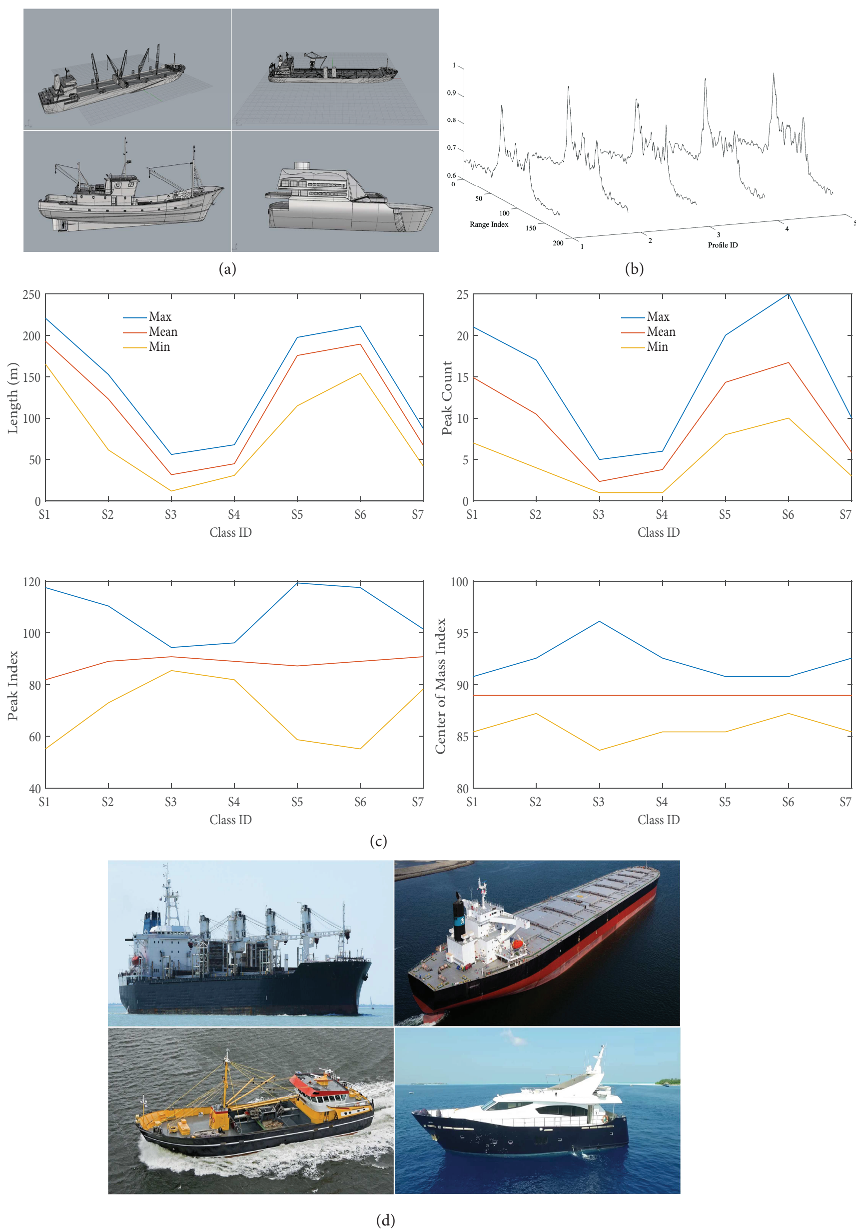


Figure 2. Synthetic HRRP data (a) 3D-CAD models of evaluated maritime target classes, (b) sequential HRRP realizations, (c) graphical representation of extracted features for each target class, (d) photos of real targets.

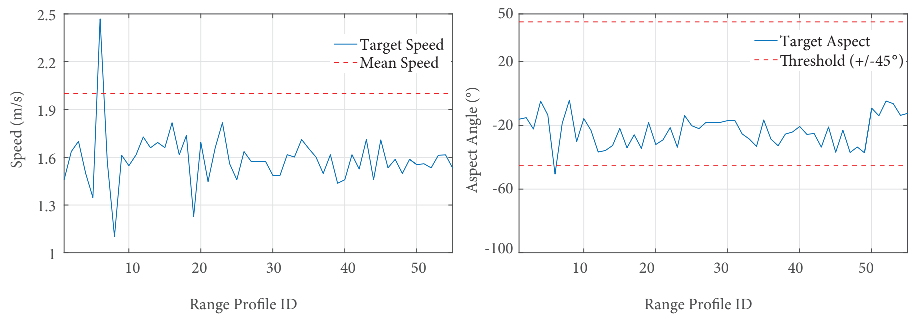


Figure 3. Anomaly removal process for speed and aspect angle.

4.1.2. Data normalization

In target classification applications, data normalization is a frequently used approach, especially when the feature values corresponding to different target classes are in different dynamic ranges. In cases where data normalization is not applied, the higher-valued features have the potential to dominate the cost function in the classifier design stage. The normalization process ensures that all attributes remain within a predefined interval. As applied in this paper, a commonly used methodology in the sense of normalization is to perform a linear transformation onto the attributes for them to satisfy the statistical specifications of zero mean and unit variance values.

4.1.3. Clutter suppression

For the purpose of eliminating the clutter effects within the data, several methods could be applied according to the temporal, spatial or spectral characteristics of the disturbance. Here, the spatial characteristics of the HRRP data were taken into consideration to eliminate the clutter and noise degradations by performing thresholding, nonlocal means (NLM) algorithm [20, 21], interpolation and spatial filtering methods, respectively. As seen from the example HRRP given in Figures 4a and 4b, the target-related information-bearing pixels lay at the center part of the two-dimensional image whereas the edge regions at the boundaries of the image mainly consist of clutter or noise.

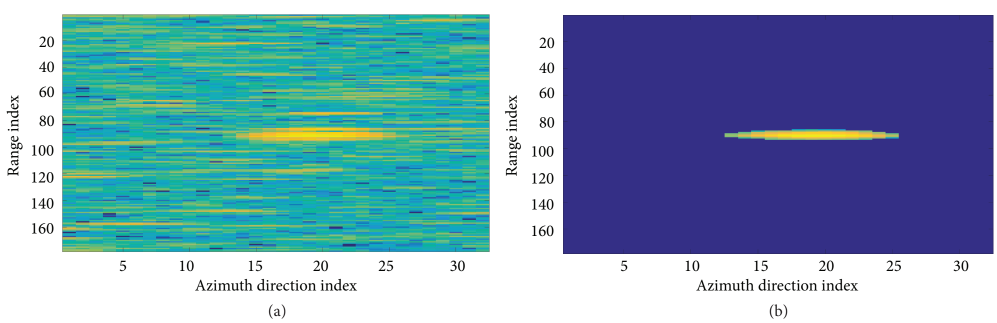


Figure 4. Clutter suppression for a sample profile data: (a) a typical HRRP from fishing vessel class, (b) the HRRP after clutter suppression.

In the profile data, it is seen that the marginal regions contain information of varying amplitude level and approximately the middle region contains target information. In the light of this information, one of the methods that can be applied in terms of eliminating the clutter is to limit the data according to the noise/clutter level obtained by averaging the values in the edge regions. Accordingly, after this thresholding process realized by decreasing the values below the calculated threshold value to zero value, the unwanted pixels within the data is reduced to a certain extent. Interpolation is applied in addition to thresholding to prevent momentary high-level transitions in the noise/clutter zone and to further clarify the target data zone. Two different methods are used to eliminate unwanted clutter. The first is to calculate the distance of the location from which the heaps occur to the profile data center, and to synchronize the data in the heap region to zero if the respective distance is above a certain value. An exemplifying scenario on the clutter suppresion process of HRRP data could be seen in Figures 4a and 4b.

4.2. Feature extraction

One of the most important stages in target classification applications is the extraction of features. The quality of the extracted features directly affects the classification performance. The main purpose of this process is to transfer the available raw data to a suitable space to ensure the generation of the best and sharpest decision surfaces. The respective feature spaces differ in some respects, such as the ability to distinguish classes, computation time, computer memory requirement, or applicability to the raw data available. Among the feature spaces considered in the literature, the one that offered high performance in maritime target classification has been utilized in the classification studies. Accordingly, inputs for classifier structures were obtained by using spatial feature information. In this work, general information about six spatial features are evaluated which are platform length, the number of peaks, the normalized position of the peak, the distance between two highest peaks, the symmetry factor and the center of mass.

4.3. Classifier structures

After the preprocessing, feature extraction and dimension reduction, the classification process is carried out by assigning the feature data to be classified according to the relevant decision surfaces to the appropriate class by utilizing the PNN and CNN structures.

4.3.1. Probabilistic neural networks (PNN)

Probabilistic neural networks are also known as Bayes–Parzen estimators [22]. Bayesian decision rule and Parzen density functions are used to construct the probabilistic network structure. A PNN network consists of several subnets, each of which serves as a Parzen probability density function (PDF) estimator for a different class. The first layer of PNN networks consists of feature vectors to be classified. In the second and third PNN layers, the value of the Parzen PDF is calculated using the data in the training data set. Based on the Parzen approach, the estimated PDF for an input feature vector $\mathbf{x}$ and the target class i has the form of

$$\hat{f}_i(\mathbf{x}) = \frac{\sigma^{-m}}{N(2\pi)^{m/2}} \sum_{n=1}^{N} \exp\left[\frac{(\mathbf{x}-\mathbf{x}_n)^T(\mathbf{x}-\mathbf{x}_n)}{2\sigma^2}\right]. \tag{5}$$

Here, m is the size of the input vector, σ is the softening parameter, N is the number of training data vectors, and $\mathbf{x}_n$ denotes the nth feature vector in the training data set. As seen in (5), in the second layer of the PNN network structure, all the training data of a target class are taken into consideration in the core function, the exponential base functions are mainly collected in the third layer, and thus the Parzen PDF function is constructed to calculate the similarity to the related class for any feature vector to be tested. In the fourth and last layer of the PNN network, the Parzen PDF value of each class for the test data is evaluated together with the preliminary probability value, if available, and assignment is made for the input test vector. Considering Bayesian decision rule, classification rule is defined as

$$\mathbf{x} \in C_i \Leftrightarrow P_i\hat{f}_i(\mathbf{x}) > P_j\hat{f}_j(\mathbf{x}), \forall i \neq j \tag{6}$$

where C_i represents ith target class, and P_i represents the a priori probability for the ith class.

4.3.2. Convolutional neural networks (CNN)

Deep learning is a set of artificial neural networks based on deep architecture, where the number of hidden layers is increased and a feature of each problem is learned. In this architecture, a feature belonging to the problem is learned in each layer and this feature creates an input to the upper layer. Thus, from the lowest layer to the top layer, a structure is established in which the most complex quality is learned from the simplest layer. In order to classify maritime targets from HRRPs, the CNN method that is one of the deep learning methods has been utilized. In the convolution layers, feature maps are created by filtering the input signals by the convolution filters of certain sizes. In the first convolution layer 20 filters of size 5×5 are generated. This kernel provides to bring out coarsest features on the data images. Similarly, deeper features are discovered via the following feature maps found in the CNN. As shown in the figure, second convolution layer has 50 filters of size 5×5, third convolution layer has 500 filters of size 4×4 and last convolution layer has 5 filters of size 2×58. Since these feature maps perform different levels of feature learning related to input signals, no additional feature extraction stage is applied before classification in CNN-based classifier structures. The number and diversity of the convolution filter to be used are directly related to the diversity of features to be learned in each layer. Within the pooling layers, data size of feature maps is reduced by applying `mean` or `max` operations. The nonlinear separation surfaces between the data related to the target classes could be more appropriately designed by processes. In the fully connected layer, a connection is established between all feature maps that might move through separate branches and the output layer. During the training of CNN networks, filters of the convolution layers and coefficients for the fully connected layer are initialized by relying a specific rule. In addition, the error cost function is calculated by applying all input data vectors reserved for training to the system and considering the class labels. Convolution filter coefficients and fully connected coefficients are updated after each input data usage by using back propagation method by considering the principle of error cost function minimization.

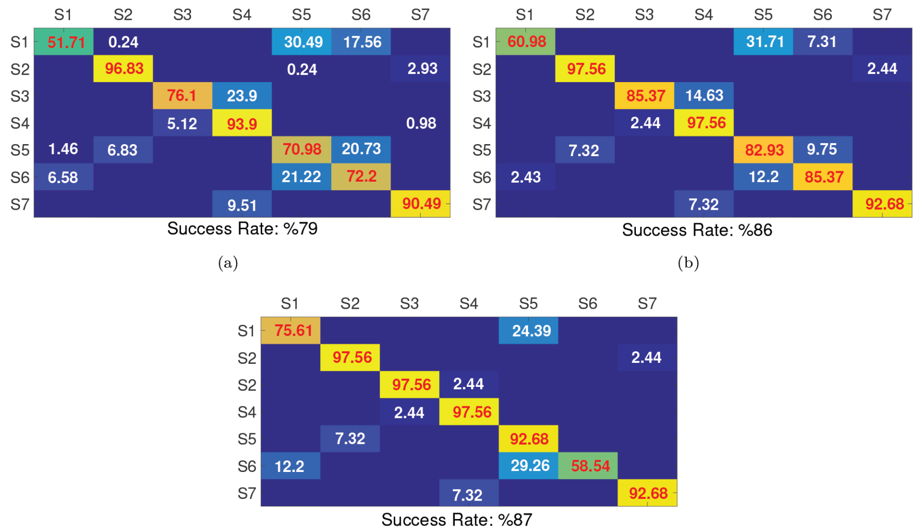
5. Results

Synthetically generated and measuremental HRRP data are used to examine the classification performance of the proposed fusion method that relies on the additional information mined from the sequential data. In terms of the synthetic profile data, seven different maritime target classes are taken into consideration. Moreover, PNN-based classifier infrastructure is utilized to evaluate the classification performance of the decision fusion method. On the other hand, five target classes are considered for the measuremental HRRPs, and, both PNN- and CNN-based classifier infrastructures are employed. Classification results that have been evaluated by the comparative investigation are discussed in the following subsections.

5.1. Classification results for synthetic HRRP data

For the case of the synthetic range profiles, a total of 12607 HRRPs are considered for seven different target classes. Initially, classification results are obtained for the case where fusion method is not applied. The classification results are visualized in terms of a confusion matrix in Figure 5.

As can be inferred from Figure 5a, 79% of the input test profiles are classified correctly after the initial classification process. HMM-based transition matrix is constructed by using the range profiles under consideration. The entries of the transition matrix for synthetic HRRPs are given in Table 2. As shown in the table, each target class is seen to be confused with one or more other target classes depending on the considered



(a) (b) (c)

Figure 5. Confusion matrix for the synthetic HRRP data set and the PNN classifier in the: (a) absence of the fusion method, (b) presence of the MVR method, (c) presence of the fusion method.

classification process.

Table 2. Transition probabilities evaluated for synthetic HRRP data.

	S1	S2	S3	S4	S5	S6	S7
S1	0.565	0.004	0	0	0.213	0.218	0
S2	0.002	0.98	0	0.002	0.006	0	0.01
S3	0	0	0.78	0.22	0	0	0
S4	0	0	0.14	0.826	0.001	0	0.033
S5	0.108	0.007	0	0	0.616	0.269	0
S6	0.13	0	0	0	0.291	0.576	0.003
S7	0	0.13	0	0.045	0	0	0.942

Classification results of all sequential HRRPs are generated by using MVR in order to compare with fusion algorithm results as shown in Figure 5b. By utilizing the transition matrix and the decision fusion method, classification results achieved by the usage of PNN classifier together with six predefined spatial features are demonstrated in Figure 5c. As shown in Figure 5c, average correct classification rate is seen to be increased from 79% to 87% by exploiting the additional information gathered from the transition probabilities. When the synthetically generated HRRPs classification results examined, it has been observed that the proposed fusion algorithm has better classification performance improvement.

5.2. Classification results for measuremental HRRP data

Similar to the case of synthetic HRRPs, classification performance of the proposed fusion method has been tested for both CNN- and PNN-based classifiers. For each classifier, confusion matrices have been evaluated for the absence/presence of the decision fusion method and presence of MVR method. Figure 6a depicts the evaluated confusion rates for CNN classifier where the proposed fusion method and MVR method has not been employed. In this case, correct target classification rate is calculated as 73%.

In order to utilize the decision fusion method as a postprocess tool for the CNN classifier results, the

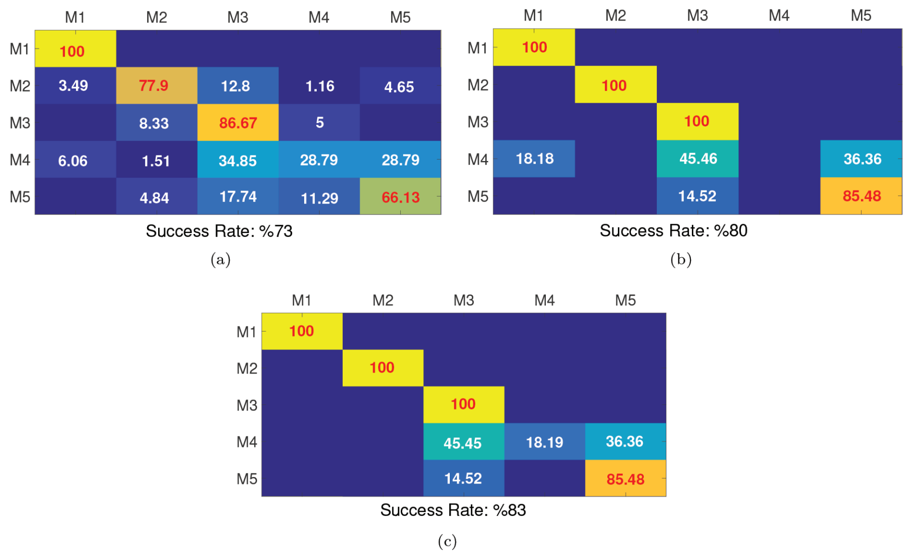


Figure 6. Confusion matrix for the measuremental HRRP data set and the CNN classifier in the: (a) absence of the fusion method, (b) presence of the MVR method, (c) presence of the fusion method.

entries of the transition matrix are evaluated that have been presented in Table 3. When the classification results obtained using the CNN classification algorithm, it is observed that fusion method has better classification performance improvement.

The average success rate is seen to increase from 73% to 80% by the virtue of MVR method where the proposed fusion method produces 83% classification success rate as shown in Figures 6b and 6c. On the other hand, by carrying out the evaluation steps for the PNN classifier, the transition matrix, the confusion matrices corresponding to the absence of the decision fusion method, presence of MVR method and presence of the decision fusion method results are evaluated and presented in Table 4, Figures 7–7c, respectively.

Table 3. Transition probabilities evaluated for measuremental HRRP data and the CNN classifier.

	M1	M2	M3	M4	M5
M1	0.976	0.024	0	0	0
M2	0	0.796	0.148	0.037	0.019
M3	0	0.098	0.746	0.091	0.065
M4	0	0.089	0.312	0.355	0.244
M5	0	0.029	0.131	0.159	0.681

Table 4. Transition probabilities evaluated for measuremental HRRP data and the PNN classifier.

	M1	M2	M3	M4	M5
M1	0.902	0.025	0	0	0.073
M2	0.	0.764	0.144	0.078	0.014
M3	0	0.097	0.619	0.186	0.098
M4	0	0.047	0.294	0.424	0.235
M5	0.032	0.01	0.118	0.215	0.625

According to the evaluated performance results, correct classification rate is seen to increase from 80% to 86% with the help of the proposed fusion method. When the classification results obtained by using PNN classification algorithm and fusion method with the measurementally gathered data are examined, it is observed that the classification performance of all classes is increased. Additionally, fusion method has better classification performance improvement comparing to MVR method.

6. Conclusion

Throughout the extensive investigation of this paper, the advantages of the proposed fusion method on the average classification accuracy of neural network-based classifiers focusing on the both the synthetic and

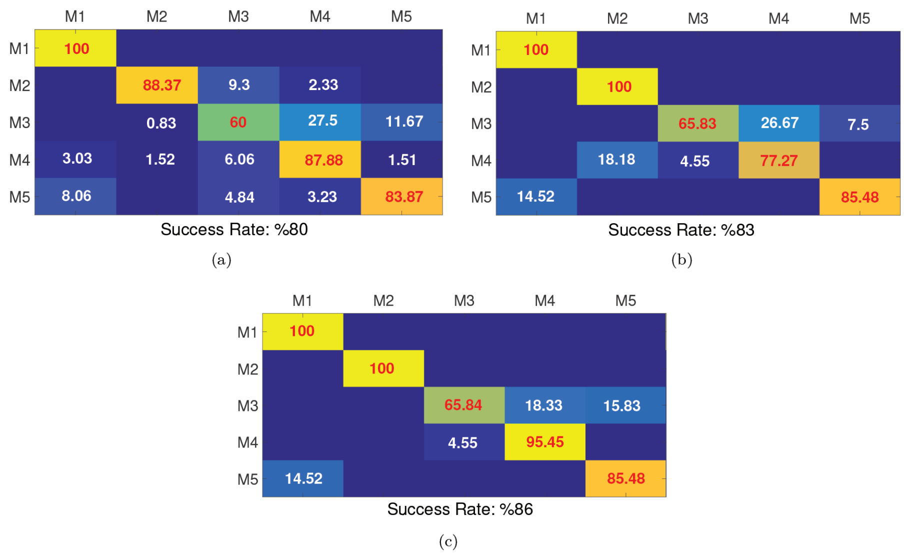


Figure 7. Confusion matrix for the measuremental HRRP data set and the PNN classifier in the: (a) absence of the fusion method, (b) presence of the MVR method, (c) presence of the fusion method.

measuremental HRRPs collected by or generated for ground-based scanning radars are investigated. Within this scope, synthetic range profiles related to seven maritime target classes are taken into consideration whereas for the measuremental scenario, number of different target classes could have been set as five. The results of the classification analyses have clearly shown that the proposed fusion method could be utilized to construct classifier infrastructures achieving enhanced classification success in maritime target recognition.

Due to the restrictions and costly nature of the range profile measurements, five maritime target classes could have been taken into account. On the other hand, HRRPs from different elevation angles considered within this study. Further researches on the inclusion of more target types and different sequential data lengths would be worth to be carried out in order to achieve additional enhancements and inspiring viewpoints.

Contribution of authors

The authors contributions are as follows: B.B. and N.D illustrated concept, B.B. and N.D. defined methodology, B.B. developed software, B.B. collected and integrated data, B.B. and N.D. did formal analysis, B.B. performed the experiments, B.B. wrote original draft, B.B. and N.D. reviewed and edited the paper.

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