Application of point enhancement technique for ship target recognition by HRR

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ABSTRACT

We present an evaluation of the impact of a recently developed point-enhanced high range-resolution (HRR) radar profile reconstruction method on automatic target recognition (ATR) performance. We use several pattern recognition techniques to compare the performance of point-enhanced HRR profiles with conventional Fourier transform-based profiles. We use measured radar data of civilian ships and produce range profiles from such data. We use two types of classifiers to quantify recognition performance. The first type of classifier is based on the nearest neighbor technique. We demonstrate the performance of this classifier using a variety of extracted features, and a number of different distance metrics. The second classifier we use for target recognition involves position specific matrices, which have previously been used in gene sequencing. We compare the classification performance of point-enhanced HRR profiles with conventional profiles, and observe that point enhancement results in higher recognition rates in general.

Keywords : High range-resolution radar, automatic target recognition, nearest neighbor, position specific matrices, Euclidean metric, Manhattan metric, Minkowski metric, ship target recognition, range profile, point enhancement, signal reconstruction.

1. INTRODUCTION

The problem of ship classification by high-range resolution (HRR) radar has recently attracted much interest.[1-7] For most of these recognition tasks, finding the locations and the magnitudes of the dominant target scatterers is of key importance. Superresolution processing techniques for HRR profiles can help in the accurate extraction of such features, and there have been some recent efforts in this direction.[8-11] There has also been some limited work evaluating such superresolution methods in terms of the recognition of ground targets, based on HRR data.[12]

Recently a new method for superresolution, point-enhanced reconstruction of high range-resolution (HRR) radar profiles has been proposed.[13] This approach poses the problem of the formation of the HRR profiles from phase history data as an optimization problem. Resolution and feature enhancements are achieved by imposing non-quadratic regularizing constraints on the solution of the optimization problem. This method was emprically shown to preserve and enhance target features such as scatterer locations, better than conventional HRR profiles. In this work, we conduct an evaluation of the impact of this point-enhanced reconstruction method on automatic target recognition (ATR) performance. We use radar observations of three classes of civilian ships, and form HRR profiles using the conventional fast Fourier transform (FFT) technique, as well as the point enhancement technique. We then use these two types of profiles as inputs to a number of pattern recognition systems, and for each classification system we compare the recognition performance of point-enhanced and conventional profiles.

We consider two fairly simple types of classifiers. The first type of classifier uses the well-known nearest neighbor rule. We form different versions of this classifier using three types of features, and three distance metrics. The three types of

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features we use are based on: the amplitudes of the HRR profiles themselves; the lengths of the ships; and the estimated radar cross section (RCS). The three distance metrics we use are the so-called Euclidean, Manhattan, and Minkowski metrics, which essentially correspond to different types of vector norms. The second type of classifier we consider is inspired by ideas from gene sequencing, and is based on the so-called position specific matrices. The main idea is to quantize the amplitudes of the HRR profiles, and seek a good match to the hypothesized classes in terms of the quantization level at each spatial location in the profile.

As a result of our recognition experiments, we observe that point-enhanced profiles have higher classification accuracy than conventional profiles in all the cases where classification decisions are made implicitly or explicitly based on point-based features, such as scatterer locations.

2. POINT ENHANCEMENT TECHNIQUE

In this section, we provide a brief overview of point-enhanced HRR profile formation. The details of the technique can be found in Ref. 13. The problem addressed by this method is the inverse problem of obtaining a complex HRR profile from the received, pre-processed HRR phase history signal. To this end, let $\mathbf{q}$ be a vector representing the sampled HRR profile, and $\mathbf{h}$ be the noisy sampled phase history data vector at a particular observation angle. Then, we have the following observation model:

$$\mathbf{h} = \mathbf{F}\mathbf{q} + \mathbf{w} \tag{1}$$

where $\mathbf{w}$ is measurement noise, and $\mathbf{F}$ is a high resolution to low resolution discrete Fourier transform (DFT) matrix. This definition of $\mathbf{F}$ reflects the belief that the underlying object (hence its profile) possesses high-frequency features that are not captured by the resolution supported by the data. The conventional way to reconstruct the HRR profile is through an inverse DFT, which, in this framework can be represented by $\hat{\mathbf{q}}_{\text{CONV}} = \mathbf{F}^H \mathbf{h}$, with appropriate normalization. In contrast, the point-enhancement approach formulates the HRR profile reconstruction problem as the following optimization problem:

$$\hat{\mathbf{q}} = \arg\min_{\mathbf{q}} \quad J(\mathbf{q}) \tag{3}$$

where $J(\mathbf{q})$ is chosen to be an objective function of the following form:

$$J(\mathbf{q}) = \|\mathbf{h} - \mathbf{F}\mathbf{q}\|_2^2 + \lambda \|\mathbf{q}\|_p^p \tag{4}$$

where $p<2$ and λ are scalar parameters, and $\|\cdot\|_p$ denotes the ℓ_p-norm. The first term in the above objective function is a data fidelity term. The second term is a regularizing constraint whose role is to suppress artifacts and increase the resolvability of the scatterers in the HRR profile. The optimization problem in Eq. (4) can be solved by using an efficient iterative algorithm proposed in Ref. 13.

This profile formation approach has relations to the field of adaptive signal representation. Adaptive signal representation addresses the problem of finding optimal representations of signals as combination of elements from an overcomplete dictionary. Such techniques have previously been used for feature extraction from HRR profiles. One adaptive signal representation technique, called basis pursuit denoising finds an optimal representation by minimizing an objective function of the same mathematical form as Eq. (4), with p=1. Hence, we can interpret the point-enhanced signal reconstruction method as one of finding the optimal basis pursuit-type denoised representation of the observed HRR data, in terms of the complex exponential dictionary elements.

3. CLASSIFICATION

In this section, we describe the two types of classifiers we use for evaluating the impact of the point enhancement technique on ship target recognition performance using HRR data. The first group of classifiers is based on the nearest neighbor rule, where each individual classifier uses a different distance metric, or a different feature. The second type of classifier is based on position specific matrices, an idea previously used in gene sequencing.

3.1. Nearest Neighbor Algorithm

The nearest neighbor technique is a well-known approach in statistical pattern recognition[14]. We choose to use this technique in classifying range profiles due mainly to its simplicity. The technique requires no explicit knowledge about the class probability density functions describing the variability of the range profiles. Its classification power is limited, however our goal in this study is not to use an advanced classifier, but rather to compare the recognition results of conventional versus point-enhanced HRR profiles, given a particular classifier.

The nearest neighbor algorithm is a non-parametric technique, which uses minimum distance classification. Let X denote the set of labeled training feature vectors:

$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_\mathrm{n}\}. \tag{5}$$

Given an observation feature vector **y** to be classified, we compute the distance (using an appropriate metric to be discussed below) between **y** and all the vectors in **X**. The observed vector **y** is assigned to the class of the vector $\mathbf{x}_i \quad (i \in \{1, \cdots, \mathrm{n}\})$, which yields the smallest distance. One might also use a generalization of this basic approach, known as the *k*-nearest neighbor technique, where the classification decision is made based on *k* vectors from **X,** which are closest to **y**, rather than just the single closest one.

In determining the closeness between two vectors, one can use a variety of distance metrics that are appropriate for the problem at hand. In this work, we construct classifiers using Euclidean, Manhattan, and Minkowski distance metrics. The distances between two arbitrary column vectors **x** and **y,** based on each of these metrics are defined as follows:

- Euclidean metric :

$$d_{\mathrm{EUC}} = \|\mathbf{x} - \mathbf{y}\|_2 = \sqrt{(\mathbf{x} - \mathbf{y})'(\mathbf{x} - \mathbf{y})} \tag{6}$$

- Manhattan metric :

$$d_{\mathrm{MAN}} = \|\mathbf{x} - \mathbf{y}\|_1 = \sum_{i=1}^{m} \left|\mathbf{x}_{(i)} - \mathbf{y}_{(i)}\right| \tag{7}$$

- Minkowski metric :

$$d_{\mathrm{MIN}} = \|\mathbf{x} - \mathbf{y}\|_p = \left(\sum_{i=1}^{m} \left|\mathbf{x}_{(i)} - \mathbf{y}_{(i)}\right|^p\right)^{1/p} \tag{8}$$

where $\mathbf{x}_{(i)}$ and $\mathbf{y}_{(i)}$ denote the *i*-th elements of **x** and **y** respectively, and m denotes the total number of elements in these vectors.

Now let us specify the features we use in the nearest neighbor classifier for the HRR recognition task. The first type of feature we consider is the reconstructed range profile amplitudes themselves. The second type of feature we use is RCS. In our study, the experimental radar used to collect the range profiles is calibrated before taking the actual measurements, by means of a spherical reflector with known RCS, which lets us obtain the RCS of ships from the range profiles. The third type of feature we use is the length of the ships. In order to obtain a length estimate, we assume that a target is fully contained within the range profile, and that there is a target free region near both range profile boundaries. This target free region is used to generate a noise estimate, which is used in conjunction with a threshold to detect the

Position														
Symbol	**a**	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**
A	6	8	7	14	0	0	0	14	2	11	0	11	0	1
B	2	1	6	0	14	14	14	0	1	2	14	3	5	7
C	2	4	1	0	0	0	0	0	2	1	0	0	2	2
D	4	1	0	0	0	0	0	0	9	0	0	0	7	4

Table 1: A sample position specific matrix.

start and end point locations of the target. We use these three types of features in separate classifiers, although one might combine them in a single classifier.

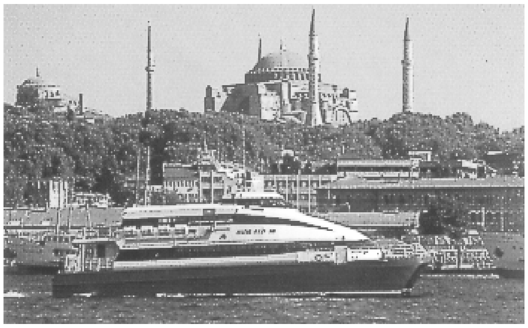
3.2. Position Specific Matrices

The second type of classifier we consider is similar to a technique used in gene sequencing[15]. A DNA molecule can be represented by a sequence of letters, where each position in the sequence is equal to one of four possible letters. Position specific matrices (or substitution matrices) are a way of characterizing the structures of the DNA molecules in a database, which could then be used to determine how much a given sequence query is related to the known sequences in the database. Scoring the similarity of two sequences using substitution matrices is equivalent to measuring the probability of a random occurrence for such an alignment, and high scores indicate a small probability that such an alignment happened by chance.

Without going further into the details of gene sequencing, we will now describe how we adapt these ideas and use them in HRR target recognition. Given a set of training profiles for a particular target class, which were aligned using a correlation-based algorithm, we first quantize the amplitudes of each profile into α levels. For illustration, let us say we choose α=4, then we can represent each spatial location in a profile by one of four letters (symbols) A, B, C, D. To characterize a particular class, we can then count the total number of occurrences (in our training set of profiles) of these four letters in each spatial location. We can represent this information as matrix with α rows and β columns, where each row corresponds to a particular quantization level, and each column corresponds to a particular spatial location. The number β is chosen in relation to the range resolution. The (i,j)-th entry of the matrix shows the total number of occurrences of the i-th quantized amplitude level, at the j-th spatial location index. Such a sample position specific matrix is shown in Table 1, where a set of 14 profiles was involved. We notice that for some positions all the sequences agree (e.g., columns d,e,f,g,h,k), but for others a high variability is observed (e.g., columns a,c,n). One can form such a matrix for each target class.

Now, an observed, and quantized profile can be classified by evaluating its "likelihood" under each of the target hypotheses. The entries in a position specific matrix are proportional to the estimated probability of observing a particular symbol at that position. Therefore a "likelihood" score of an observed profile for a hypothesized class can be computed as follows. First we identify a single row for each column of the position specific matrix for the hypothesized class that corresponds to the quantized amplitude level in the observed profile at that spatial location. We then take the product of these matrix entries. For example, the observed, quantized range profile ACCABBBAACBBBA will have a likelihood score of 6*4*1*14*14*14*14*14*2*1*14*3*5*1, under the hypothesis represented by the matrix in Table 1.

The observed profile is assigned to the class giving the highest score. If the training sets for each class contain different numbers of profiles, the position specific matrices could be normalized by the total number of profiles for that class.



(a) Sea Bus

(b) Ferry

(c) Tanker

Figure 1. Pictures of the types of ships used in the experiments: (a) Sea Bus, (b) Ferry, and (c) Tanker.

Target	No. of profiles in the training set	No. of profiles in the test set
Tanker	246	285
Sea Bus	92	81
Ferry	149	139

Table 2: Composition of the data set used in the recognition experiments.

4. REAL DATA EXPERIMENTS

We now evaluate the performance of the classifiers described in the previous section, given HRR profiles produced by point-enhanced versus conventional reconstruction. In our recognition experiments, we use three different civilian ship classes: oil tanker, sea bus and ferry. Pictures of these three types of ships are shown in Figure 1. Our training and test sets are composed of HRR data collected in distinct time periods during the same day. The numbers of each type of target profiles in each of these sets are shown in Table 2.

We present the results of our evaluations in the form of classifier confusion matrices, which show the percentage of correct and incorrect classifications achieved on test inputs of each type. In particular, the entry in row i, column j in a confusion matrix shows the percentage of profiles from target type i classified as target j. A single number characterizing the classifier's ability to recognize test inputs can be obtained through the total correct classification, which is defined as the percentage of all target test inputs that were correctly classified.

Table 3 to 5 show the confusion matrices for the classification experiments where the amplitudes of the HRR profiles themselves are used as the features. In the experiments with the Minkowski metric, p is chosen to be 3 in all cases.

	Tanker	Sea Bus	Ferry
Tanker	64	36	0
Sea Bus	0	100	0
Ferry	14	32	54
Total Correct Classification : 66 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	66	34	0
Sea Bus	0	100	0
Ferry	0	0	100
Total Correct Classification : 81 %			

(b) Point-enhanced HRR profiles.

Table 3: Confusion matrices summarizing the classification results using the nearest neighbor technique with the Euclidean distance metric, where profile amplitudes are used as the features.

	Tanker	Sea Bus	Ferry
Tanker	62	28	10
Sea Bus	0	100	0
Ferry	14	34	52
Total Correct Classification : 64 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	62	33	5
Sea Bus	0	100	0
Ferry	0	0	100
Total Correct Classification : 79 %			

(b) Point-enhanced HRR profiles.

Table 4: Confusion matrices summarizing the classification results using the nearest neighbor technique with the Manhattan distance metric, where profile amplitudes are used as the features.

	Tanker	Sea Bus	Ferry
Tanker	57	38	5
Sea Bus	0	100	0
Ferry	15	33	52
Total Correct Classification : 62 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	61	35	4
Sea Bus	61	39	0
Ferry	0	0	100
Total Correct Classification : 68 %			

(b) Point-enhanced HRR profiles.

Table 5: Confusion matrices summarizing the classification results using the nearest neighbor technique with the Minkowski distance metric, where profile amplitudes are used as the features.

	Tanker	Sea Bus	Ferry
Tanker	56	40	4
Sea Bus	18	82	0
Ferry	5	7	88
Total Correct Classification : 68 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	73	17	10
Sea Bus	5	91	4
Ferry	10	22	68
Total Correct Classification : 75 %			

(b) Point-enhanced HRR profiles.

Table 6: Confusion matrices summarizing the classification results using the nearest neighbor technique with the Euclidean distance metric, where the RCS feature is used.

	Tanker	Sea Bus	Ferry
Tanker	61	8	31
Sea Bus	0	100	0
Ferry	6	3	91
Total Correct Classification : 75 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	59	39	2
Sea Bus	0	100	0
Ferry	5	5	90
Total Correct Classification : 74 %			

(b) Point-enhanced HRR profiles.

Table 7: Confusion matrices summarizing the classification results using the nearest neighbor technique, where the ship length feature is used.

	Tanker	Sea Bus	Ferry
Tanker	51	0	49
Sea Bus	57	42	1
Ferry	9	1	90
Total Correct Classification : 60 %			

(a) Conventional HRR profiles.

	Tanker	Sea Bus	Ferry
Tanker	100	0	0
Sea Bus	0	75	25
Ferry	39	0	61
Total Correct Classification : 85 %			

(b) Point-enhanced HRR profiles.

Table 8: Confusion matrices summarizing the classification results using position specific matrices.

Each of these tables contains results for a different distance metric. We observe that point-enhanced profiles result in significantly higher correct classification percentages than the conventional FFT-based profiles with all three distance metrics. We also observe that the Euclidean metric performs better than the other metrics in this experiment.

Next, in Table 6, we present the results of nearest neighbor classification experiments where the feature used is RCS, together with a Euclidean distance metric. Again, point-enhanced profiles yield better recognition performance than conventional profiles.

Table 7 shows the results for the case where the ship length is used as a feature. We extract the length feature as described in Section 3.1. In these experiments, the total length of the range profiles were chosen to be 200 meters (longer than the length of any of the targets), so we always have a target-free region at the ends of the range profiles. We observe that point-enhanced profiles do not provide any improvement over conventional profiles when the ship length feature is used. This result is not surprising. While point-enhanced reconstruction aims to preserve localized, point features such as scatterer locations, it does not attempt to preserve spatially distributed features, such as length. Therefore point enhancement is not a good match for classification tasks where distributed features are to be used. In that case, a feature-enhancement technique that preserves region-based, distributed features would be of interest. One such region-enhanced reconstruction method has previously been applied in synthetic aperture radar imaging[16], and could potentially be useful for the HRR problem as well. We should also note that the data we used were limited in aspect angles, and the ship length feature may not be very reliable by itself when more diverse aspect angles are involved.

Finally, we present the classification results based on position specific matrices. In these experiments, we choose β based on the largest range resolution in the database, which is three meters, and we set the number of quantization levels α to 30. The results in Table 8 suggest that point-enhanced reconstruction provides a very significant improvement over conventional profiles in this case. In fact, point-enhanced profiles together with position specific matrices result in the best performance over all other combinations considered in this study. In forming the position specific matrices, we have not optimized the parameters α and β. We believe that a careful choice of these parameters might improve the recognition performance further.

5. CONCLUSION

We have presented a preliminary analysis of the impact of point-enhanced HRR profile reconstruction on ship target recognition performance. We have considered a three-class target recognition problem to compare the recognition performance of point-enhanced profiles and conventional profiles. We have constructed a classifier based on the nearest neighbor rule, and a classifier based on position specific matrices. In nearest neighbor classification, we have considered a number of different features, as well as various distance metrics. We have observed that point enhancement results in significant improvements in recognition performance in all cases, except when ship length (a distributed feature not preserved by point enhancement) is the feature used in classification. We believe that HRR profile reconstruction methods that preserve and enhance features which are implicitly or explicitly used by the recognition system, have a potential of improving target recognition performance. In the case of point enhancement, which we have analyzed here, the peak locations and relative amplitudes of these peaks are better predicted than in conventional profiles. This results in better recognition performance, especially with the classifier based on position specific matrices, which strongly relies on these features. Therefore we could say that the point enhancement technique with the position specific matrices is a good choice for ship classification by HRR.

The preliminary analysis we have presented here could be extended in a variety of ways. We intend to run extensive experiments using a larger number of target classes, under various sensing conditions. Furthermore, an evaluation based on more advanced classifiers is also a topic of interest for future work.

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