Multi-Channel Synthetic Aperture Radar Based Classification of Maritime Scenes

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ABSTRACT We present novel experimental evidence that demonstrates the effectiveness of exploiting scene motion information for the analysis of scene structure in maritime imaging applications. We analyze data captured by our novel airborne Multi-channel SAR (MSAR) system that is particularly suited to sampling the velocity profile of scatterers in the maritime environment. While previous works have shown the utility MSAR systems for correcting scene motion induced blurring artifacts, our work shows, for the first time, how the information furnished by an MSAR system can systematically render accurate classification of maritime scenes into different perceptual categories. We offer a methodology that is superior to traditional classification techniques that are based purely on the spatial structure of an image. Furthermore, the simplicity of the feature space involved together with the demonstrated classification performance on imagery captured by our airborne MSAR system underscore the strength of the methodology.

INDEX TERMS Multi-channel synthetic aperture radar (SAR), ocean imaging, image classification.

I. INTRODUCTION
Two well-known issues in SAR imaging are the displacement and blurring effects caused by uncompensated motion of either the platform or the scene [1], [2]. While the effects of platform motion can be compensated using information gathered from inertial navigation units, scene motion is largely handled, in single phase center SAR systems, by employing blind deblurring algorithms that exploit statistical and physics-based models to capture spatially varying motion signatures, with varying degrees of success [3], [4]. The deleterious effects of scene motion (on the quality of SAR image formation) is particularly accented in maritime imaging applications where virtually every scatterer in the scene undergoes motion governed by complex physical processes that are difficult to characterize. In such cases, traditional approaches to scene induced motion compensation are known to be inadequate [5]. Recently, Multi-channel SAR (MSAR) imaging has been demonstrated as a powerful approach to systematically ameliorating the aforementioned scene induced motion error problem [5]–[10]. In particular, the additional along-track receivers provide new, independent information about the scene that can be used to correct automatically for the underlying scene motion.

Based on this foundation, we address a fundamental question as to whether the in-scene motion information derived from an MSAR with along-track phase centers can be effectively exploited to extract higher-level perceptual information in particular to perform scene classification. And, if so, can generic MSAR parameters be found that provide useful, interpretable characterization of the in-scene motions?

We answer these questions by demonstrating, for the first time, an efficient and flexible classification algorithm that utilizes the in-scene MSAR-derived motion information. This method complements existing approaches to classification [11]–[19] and image segmentation [20]–[27] that exploit the spatial structure of static amplitude images. Our experimental results, performed on imagery captured by the U.S. Naval Research Laboratory (NRL) airborne MSAR system [5], [8], [9], demonstrate how the motion information furnished by an MSAR system can be systematically used to enhance maritime scene classification in a manner that is superior to purely amplitude-based approaches.

The MSAR airborne system operates at X-band with a center frequency of 9.875 GHz and uses linear frequency
modulated chirped waveforms with a bandwidth of 220 MHz to achieve a range resolution of approximately 0.7 m. The peak radiated power is approximately 1.4 kW, while the aggregate pulse repetition frequency (PRF) of 25 kHz and pulse length of 6 μs produced an average power of 210 W. The system flies on a Saab 340 aircraft using a belly-mounted radome with a nominal incidence angle of 70°. Typical altitude and airspeeds are 914 m (3000 ft) and 70 m/s, respectively. The system use a linear array of 16 receive antennas with a transmit horn located at each end. During each pair of pulse intervals (one for each horn), four of the 16 receive antennas are connected to a four-channel receiver and sampled by a high-speed data recorder. After each pair of pulses, a bank of microwave switches is reconfigured to connect the next group of four receive antennas to the receiver and data recorder. In this manner, 32 phase centers are generated, one corresponding to each combination of transmit and receive antennas, and each are sampled at a rate of 3.125 kHz. This is sufficient to allow production of 32 SAR images, one corresponding to each phase center, that are free from azimuthal ambiguities. Further details of our MSAR system and its performance are given in [8].

Our new classification approach aims to identify targets and surface features through differences in the number and velocity of their scattering centers. Employing data from an MSAR system that supports $M$ along-track phase centers, we construct an $M \times M$ covariance matrix at each pixel to quantify the complex (i.e. magnitude and phase) correlations amongst the $M$ signals. These correlations promise to be very useful target/clutter discriminators. As with many classification schemes such as SAR polarimetry [28], eigenanalysis of this covariance matrix serves as the basis of our approach. We derive new classification parameters from the obtained eigenvalues and eigenvectors. Our empirical results indicate that the entropy of the covariance matrix, coefficients and phases of the eigenvector components, and eigenvalue spectrum provide a basis for maritime scene characterization.

The novelty of our approach stems from the inclusion of motion information, rather than purely amplitude and amplitude texture information, for scene classification. Our covariance matrix is unique in that it correlates the returns from multiple along-track channels. Additionally, apart from improving image quality, the MSAR processing corrects both motion distortions and motion-induced displacements, which improves the coherence of our covariance matrix [8].

We provide the first demonstration of this technique using our airborne NRL MSAR dataset that was captured with multiple along-track phase centers. The approach shown here can be easily extended to an MSAR system that supports both along-track and cross-track phase centers which would produce data with a covariance matrix rich with information on both motion and height. It is anticipated that this will allow even better classification of the dynamic sea surface in addition to the vessels that ride on it.

The rest of this paper is organized as follows. In Section II, we provide a detailed description of our classification methodology that forms the basis of our image classification algorithm. Sections III and IV develop the MSAR features used for classification and the classification algorithm employed. In Section V, we demonstrate the performance of our maritime scene analysis algorithm applied to the NRL MSAR datasets. Finally, we conclude in Section VI with a summary of our results together with directions for future research.

II. METHODOLOGY

Our scene classification methodology takes advantage of the motion characteristics of maritime scenes. The classes of interest (vessels, ambient water, etc.) all have time dependent characteristics that are exploitable by the unique motion-sensing properties of the MSAR system.

A. MOTION RELATED POSITION CORRECTION

The displacement effect in SAR imagery is described by the well-known Doppler shift $\delta^\prime_a$[

$$\delta_a = R \ast V_r/V_p$$

(1)

where $R$ is the range from platform to target, $V_r$ is the target range speed, and $V_p$ is the SAR platform speed. The motions associated with a scatterer results in a spatial spreading and shifting of the target signature within the image. Therefore a purely spatial analysis of the image will not allow an accurate inference of the time varying motions associated with each scatterer comprising the scene. The first step is to reposition target signatures back to their true location in the image. We utilize MSAR’s imagery from multiple along-track phase centers to correct motion-induced displacements. These position corrections can be achieved using methods such as Velocity SAR (VSAR) [5]–[10] or Along-Track Interferometry (ATI) [5], [29]. Here we use the VSAR algorithm which repositions all of the backscatter generated from a given target, regardless of its associated Doppler velocity and displacement, to a more compact, corrected position. The VSAR procedure has been extensively described elsewhere [5]–[10], although here we retain the complex pixels throughout. Specifically our VSAR processing steps are 1) Form image stack using each of the M phase center images. 2) Perform the FFT for each pixel along the time stack. 3) Shift each velocity component back to the origin in order to enforce stationarity. 4) Trim edges to remove non-overlapping portions. The VSAR-based repositioning of target backscatter returns to the appropriate complex image pixel positions allows coherent analysis of target motion via eigenanalysis of the $M \times M$ covariance matrix.

B. COVARIANCE MATRIX

To capture motion information at each pixel, $(i, j)$, we start by constructing the covariance array for all phase-center pairs $(m, n)$:

$$C_{ijmn} = < I_{ijm} I^*_{ijn} > .$$

(2)
The spatial averaging implied in (2) is over a window smaller than the smallest targets of interest. In practice, we use a $5 \times 5$ pixel window for spatial averaging in (2). For practical purposes, we subsequently subsample to half the smoothing window size to reduce final pixel dimensions. At each pixel, $(i, j)$ we generate the $M$ eigenvalues $\lambda_m$ and eigenvectors $\overline{v}_m (m = 1 \text{ to } M)$ of the covariance matrix $C$

$$C \overline{v}_m = \lambda_m \overline{v}_m$$ (3) for use in our classification procedure. We dropped the $(i, j)$ indices for brevity. The eigenvalues and eigenvectors characterize the in-scene motions at each pixel throughout the MSAR collection time.

**C. POINT TARGET VELOCITY ANALYSIS**

After VSAR processing, the set of MSAR images, each spatially co-located but offset in time, form an along-track interferometric image stack. The phase differences between pairs of images in the stack provide estimates of the average radial displacement of the dominant scatterers for a given pixel. The phase difference depends on the time difference between the pair of images, the average velocity of the dominant scatterers, and the imaging geometry, i.e. look direction and incidence angle. The imaging geometry and in-scene scatterer velocity determine the radial velocity, $v_{\text{radial}}$, of the scatterer toward, or away from, the radar. Therefore, the radial displacement of the scatterer, $\Delta d$, is $v_{\text{radial}} \cdot \Delta t$, where $\Delta t$ is the time difference between the interferometric pair. The absolute along-track interferometric phase difference is then

$$\Delta \phi_{\text{abs}} = 2 \cdot \Delta d / w = (2 \cdot \Delta t / w) \cdot v_{\text{radial}}$$ (4) where $w$ is the radar wavelength. The observed phase difference, $\Delta \phi_{\text{obs}}$, lies within the range $[0, 2\pi]$. Therefore,

$$\Delta \phi_{\text{obs}} = \Delta \phi_{\text{abs}} + (2\pi n)$$ (5) where $n$ is an integer. For a point scatterer moving at constant velocity, the observed phase difference, $\Delta \phi_{\text{obs}}$, (modulo $2\pi$), and time difference, $\Delta t$, will generate the same radial velocity, $v_{\text{radial}}$, independent of the pair of images chosen from the stack. Therefore, at each pixel, the phases of the interferometric image stack advance linearly in time. This, of course, assumes that the scattering does not significantly de-correlate during the imaging time and that the imaging geometry remains relatively fixed.

For the specific case of our MSAR images, the time difference between adjacent images is fixed, $\Delta t \sim 0.001$ seconds, as is the radar wavelength, $w \sim 3$ centimeters. For a pixel containing a coherent, dominant scatterer, the MSAR image stack will be proportional to

$$S \propto \begin{bmatrix} 1 & e^{i\Delta \phi} & e^{i2\Delta \phi} & \cdots & e^{i(M-1)\Delta \phi} \end{bmatrix}$$ (6) using $M$ images, and the resulting covariance matrix is then

$$C = S^\dagger \cdot S \propto \begin{bmatrix} 1 & e^{i\Delta \phi} & \cdots & e^{i(M-1)\Delta \phi} \\ e^{-i\Delta \phi} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ e^{-i(M-1)\Delta \phi} & \cdots & 0 & 1 \end{bmatrix}$$ (7)

where $S^\dagger$ is the Hermitian conjugate of $S$.

Eigen analysis of this covariance matrix identifies a single large eigenvalue and its associated eigenvector. By inspection, the associated eigenvector of the rank-1 matrix in (7) is proportional to $[1, e^{-i\Delta \phi}, \ldots, e^{-(M-1)\Delta \phi}]$. The phases of the eigenvector components are determined directly from the phases of MSAR images; they progress linearly from the first to the last component. This is the ideal case for a rank-1 covariance matrix with no spatial decorrelation. In practice, we find that the covariance matrices are often nearly rank-1. The secondary eigenvalues are much weaker than the primary eigenvalue and thus the secondary eigenvectors do not affect the analysis of the dominant eigenvector. However, if there is no dominant scatterer, or the scattering decorrelates, or the in-scene motion is not uniform, then the phases of the eigenvector components become random and the in-scene scatterer velocities are not retrieved by eigen analysis.

The sum of all eigenvalues, $\lambda_m$, at a given pixel is the total power backscattered by the full set of MSAR images averaged over the $5 \times 5$ window mentioned in Section II.B. For a rank-1 covariance matrix, only the first eigenvalue, $\lambda_1$, is non-zero. As the rank of the covariance matrix increases, additional eigenvalues become non-zero. However, in many cases we find that the eigenvalue spectrum rapidly decays, i.e. $\lambda_1 \gg \lambda_2 \gg \lambda_3 \gg \lambda_4 \cdots \lambda_M \sim 0$.

**III. FEATURE EXTRACTION: PRELIMINARY OBSERVATIONS**

Given the phase history data received at the various phase centers of the MSAR system, we form a complex image for each phase center using a chirp-scale algorithm (though in general, any SAR imaging algorithm, such as backprojection, can be used). The VSAR processing then corrects this image stack, repositioning the targets to their actual in-scene locations. The VSAR procedure has been presented previously [5]–[10], however in the method presented here we perform the VSAR correction retaining the coherent, complex data for each channel. This allows the $M \times M$ covariance matrix of the VSAR corrected image pairs to characterize the in-scene motions observed by the MSAR system. After the spatial averaging mentioned in Section II.B, eigen analysis of the covariance matrices generates the eigenvalues $\lambda_m$ and eigenvectors $\overline{v}_m (m = 1 \text{ to } M)$, as in (2)–(3).

To motivate our feature extraction approach, we consider the sample image in Fig. 1 where we examine a region, highlighted by the yellow box, of an MSAR dataset collected using the NRL airborne MSAR system that contains identifiable ambient water, surf, boats and their wakes, beach and land. The system collected 32 MSAR phase centers,
here we use $M = 8$ of the phase centers for our analysis. Preliminary testing showed that higher $M$ was not necessary for our purposes here (although our analysis is extensible to any arbitrary number of phase centers).

The key idea is to perform an eigenanalysis of the multichannel covariance matrix associated with each scatterer in the image. This is indeed a novel idea in the realm of multichannel processing which was inspired by earlier works in polarimetric analysis of SAR images [28]. The explicit form the box-car averaged covariance matrices that we employ is given by:

$$C_{mn}^{ij} = \sum_{i=-\Delta_x}^{\Delta_x} \sum_{j=-\Delta_y}^{\Delta_y} c_{i-k,j-l,m,n}$$

where $\Delta_x$, $\Delta_y$ are the local spatial windows along the respective image axes, and $c_{i-k,j-l,m,n}$ are the rank-1 covariance matrix from (2). The calculation in (8) serves the two-fold purpose of reducing image speckle and increasing the rank of the covariance matrix, $C_{mn}$, by aggregating motion information in a localized neighborhood of each pixel. The resulting eigenvalues and eigenvectors, as shown in Fig. 2 and Fig 3, reveal valuable information relating to the signature motion characteristics of the classes of interest.

**A. CLASS EIGENVALUES**

Fig. 2 shows plots of the normalized eigenvalue means and standard deviations for $5 \times 5$ pixel boxes in the image within six different classes - ambient water, surf, boat, wake, land and beach areas. (Specific class regions are identified on the image in Fig. 6.) Fig. 2 shows individual eigenvalues normalized by the sum all eight eigenvalues, i.e. $\lambda_i = \hat{\lambda}_i / \sum_j \hat{\lambda}_j$, where $\hat{\lambda}_i$ are the eigenvalues calculated from the averaged covariance matrix. Overall the eigenvalues beyond the 2nd or 3rd are greatly reduced in magnitude for most classes. The ambient water class is an exception; the eigenvalue spectrum falls off slowly and the normalized dominant eigenvalue is only about 0.4 owing to a more uniform distribution of velocities. On the opposite extreme we see that the stationary land region has almost all of its energy in a single dominant component with a small standard deviation. The other classes have eigenvalue distributions somewhere between these two extremes. Both the plot shapes and the standard deviations vary sufficiently to be useful as part of a classification feature.

**B. CLASS EIGENVECTORS**

In Fig. 3 we plot the phases associated with the dominant eigenvector components and their standard deviation for $5 \times 5$ pixel boxes in the image within six different classes - ambient water, surf, boat, wake, land and beach areas. Overall we see that the complex phases of the eigenvector components for most of the classes are centered about zero. For ambient water the complex phases vary widely (large error bars) owing to non-uniform motion from pixel to pixel and to the signal strength (RCS) approaching the noise floor. The tight error bars of the land and boat phases imply that both display well-defined, uniform motion throughout the MSAR collection interval. For the boat, we find that the phases of the eigenvector components are tightly centered along a slope consistent with the theoretical discussion in Section II.C. Only the boat shows a non-zero velocity; the land is not in motion. The remaining classes, i.e. surf, wake and beach, display phase results intermediate between ambient water and land/boat classes.

An important subtlety here is that amplitude and velocity information may be correlated. Consider the ambient water class, which has both low backscatter amplitudes and surface motions random in speed and direction. Eigen analysis separately addresses these effects. As the backscatter amplitude approaches the system noise floor the covariance matrix decorrelates generating random phases. If the backscatter is insignificant, i.e. above the noise floor, then the random motion of the water surface decorrelates the covariance matrix. In either case, the covariance matrix analysis retrieves uncorrelated motions, i.e. large phase error bars consistent with zero velocity. Indeed, spatial SAR amplitude information, e.g. low backscatter, has traditionally been exploited for SAR image classification of ambient water. However, boat wakes appear brighter than ambient water, but they still decorrelate due to random surface motion. Conversely, the backscatter from a small boat may blend into the returns from a rougher sea. In this case, the boat may be detected due to its coherent motion, rather than its backscattering amplitude. The point is that amplitude and velocity information may be correlated for a given class, but in different imaging scenarios and for different classes the correlations change.

Our MSAR based analysis enables motion-based discriminatory information to be elicited from the data, which provides target class separation measures complementary to the standard amplitude information. This motion information augments amplitude-based feature sets, providing new information with which to classify SAR imagery. MSAR based analysis, as will be demonstrated below, provides robust classification performance over a range of target classes, employing a richer set of features.

**IV. MSAR BASED CLASSIFICATION ALGORITHM**

Using the concepts and insights described in previous sections, in this section we describe our MSAR based classification algorithm that makes judicious use of the discriminatory information embedded in the MSAR covariance matrix.
FIGURE 2. Eigenvalue spectrums for the six classes in the MSAR image. Shown are the means and standard deviations of eigenvalues averaged over the highlighted areas in Fig. 6.

FIGURE 3. Means and standard deviations of the phases of the first (dominant) eigenvector components.

A. CLASSIFICATION ALGORITHM FLOW CHART
The overall flow chart of our algorithm is shown in Fig. 4. Steps 1 and 2 of the flowchart describe the MSAR image formation process that we described in Section II. Steps 3 and 4 of the flowchart describe the key steps of constructing the MSAR covariance matrix and eigenvalue/eigenvector extraction described in Section III. In this section we fully delve into step 5 of the flowchart that involves the critical steps of feature extraction, from the underlying eigen-structure of the MSAR covariance matrix, followed by classification of the scene pixels.

B. CLASSIFICATION FEATURE CONSTRUCTION
We employ a judicious use of eigenvectors and eigenvalues described in Section III to construct the feature maps that emphasize class characteristics. The simplest and most
straightforward idea is to directly input all eigenvalues and eigenvectors into a classification algorithm and thereby put the entire burden of finding useful class separations solely on the classifier model. A more directed method is to construct mappings derived from the eigen components that bring out certain desired class features. By iteratively reducing the number of features, we find that to build a robust classifier it suffices (and is desirable) to limit ourselves to the largest eigenvalues and associated eigenvectors. The other eigenparameters either add undesirable noise or have no useful effect on confidence measures computed by the classification model. We normalized the eigenvalues and concentrated on the phases of the eigenvector components, since the phases relate directly to in-scene motion typical of maritime scenes. Guided by analysis such as that in Section III, we construct eigen-feature maps to differentiate amongst the desired classes. These mappings were culled from over 30 initial features by removing features that did not significantly contribute to classification quality via a Sequential Backward Selection (SBS) procedure [30]. They can be categorized into eigen-derived features (shown in Fig. 5) that characterize different degrees of randomness in motion, spatial uniformity and speeds.

After the SBS we arrived at six features directly related to the largest eigenvalues and properties of their associated eigenvectors at each pixel. The eigenvalue parameters provide the spectral characterization of the covariance matrix. Since only the first few eigenvalues differ significantly from zero, they and their associated eigenvectors are all that is needed to describe the covariance matrix. The information culled from the eigenvectors relates directly to in-scene motion, i.e. the phases and phase coherence of the eigenvectors components. Finally, in order to capture local spatial variations another four features are derived from local spatial standard deviations. These spatial variations are reminiscent of the coefficient of variation often used in SAR amplitude-based classifications.

From our experimental design process we distilled the following set of ten features. Keeping more features does not produce better confidences or classifications, whilst removing additional ones shows rapid degradation of classification quality. However we point out that the selected features are not necessarily unique; alternative feature sets may produce similar results provided that the new feature set captures the same information. We relegate more detailed investigations along these lines to future work.

In this paper, our aim is to provide a demonstration of the classification potential of such MSAR-based velocity information, not necessarily an ultimate or unique set of features. We now outline each feature used in more detail. In particular, the following list presents the equations used for our MSAR eigenvalues and eigenvector based classification method:

1) **FEATURE 1-ENTROPY**
Characterization of the eigenvalue spectrum can be accomplished via the (von Neumann) entropy

\[ F_1 = - \sum_{m=1}^{M} \lambda_m \ln \lambda_m \]  

Entropy is related to the distribution of eigenvalues, \( \lambda_m \), and is a measure of the number and randomness of significant scatterers. For example in ambient regions, we expect distributed scatterers rather than a single dominant scatterer leading to high entropy. Uniform local motion (e.g. ship, land) will have a dominant eigen component and low entropy. The entropy provides an overall, average description of the eigenvalue spectrum.
2) FEATURE 2 TO 4-EIGENVALUE DIFFERENCES
The shape of the eigenvalue spectrum is also a useful characteristic of the motion. This measure is somewhat related to the entropy but more focused on the number of significant scatterers, i.e. the strengths of the dominant and secondary components, and the thus the rapidity of the spectral decay. We found that the largest three eigenvalues \( (m = 1, 2, 3) \) characterize the eigenvalue spectrum; the remaining are mostly noise, i.e. close to zero. We normalize as follows to remove some scene amplitude dependencies included in the first eigenvalue (see the discussion in Section II.C):

\[
F_{2,3,4} = (\lambda_m - \lambda_{m+1})/\lambda_1, \quad m = 1 \rightarrow 3
\]  

(10)

3) FEATURES 5 TO 6-EIGENVECTOR COHERENCE
If the speed of the target is uniform over the collection time then the images collected by the along-track apertures will differ only by a phase; for evenly spaced apertures the phase difference between adjacent apertures will be a single constant. The coherence across elements of an eigenvector is related to the uniformity of the speed over the entire collection interval. Again, we consider the vector elements, labeled by \( k \), only for the first two eigenvectors \( (m = 1, 2) \) since these relate most directly to target motion. Eigenvector coherences will be high for classes such as land, boats, and regions of uniform surf. Ambient water and wakes do not display strong phase coherence across the components of the eigenvectors.

\[
F_{5,6} = \left| \frac{\sum_{k=1}^{M-1} v_{k,m} v_{k+1,m}^*}{\sum_{k=1}^{M-1} |v_{k,m}|^2} \right|, \quad m = 1 \rightarrow 2
\]  

(11)

4) FEATURES 7 TO 8-LOCAL EIGENVALUE VARIATION
Local (spatial) standard deviations of the eigenvalues for the first two eigen components highlight information similar to the coefficient of variation for amplitude-based classification. As explained above, this captures information about the surrounding region uniformity or texture.

\[
F_{7,8} = \sqrt{\frac{1}{n} \sum_{ij} (\lambda_{ij,m} - \xi_m)^2}, \quad m = 1 \rightarrow 2
\]  

(12)

where the summation over \( ij \) is over the \( n \) pixels of a small window centered at the pixel of interest, and \( \xi_m \) is the mean of \( \lambda_m \) using the same averaging window.

5) FEATURES 9 TO 10-EIGENVECTOR PHASE SLOPE
As described in Section II.C and shown in Fig. 3, the eigenvector phase slope (related to velocity) discriminates between some classes. To capture this information we derive features using the local average phase slope divided by the local average standard deviation of the phase slope. This feature will be higher for moving targets such as boats where the dominant and secondary scatterers are coupled by the boat’s motion.

\[
F_{9,10} = \left| \frac{S_m}{D_m} \right|, \quad m = 1, 2
\]  

(13)

Here \( S_m \) and \( D_m \) are the local (spatial) mean and standard deviation of the phase differences between adjacent eigenvector components, \( \Delta_k = \phi_k - \phi_{k+1} \).

\[
S_m = \frac{1}{n(M-1)} \sum_{ij} \sum_{k=1}^{M-1} \Delta_{ij,k,m},
\]

\[
D_m = \frac{1}{n(M-1)} \sqrt{\sum_{ij} \sum_{k=1}^{M-1} (\Delta_{ij,k,m} - S_m)^2},
\]

calculated over a small window centered at the pixel of interest.

C. CLASSIFICATION PROCESSING DESCRIPTION
In this paper, we use supervised classification with 6 classes (ambient, surf, boat, wake, beach, and land). Training data is derived from small sections of the scene appropriate for each class. This training data is fed into Support Vector Machine (SVM) classifiers [17] to derive classification models. Among the several possible non-linear SVM models [17], in our experiments we found the simple linear SVM model to be sufficient for furnishing robust and consistent results. The model is then applied to the entire scene to arrive at the class map. It is important to note that our methodology works equally well with other classification schemes and is not limited to the use of SVMs.

Our experimental results below show that our algorithm delivers much improved classification performance on data captured by the NRL MSAR system. We expect better results could be possible with the inclusion of height information provided by adding a cross-track component to the MSAR system (as proposed in future collections).

V. EXPERIMENTAL RESULTS
In this section we demonstrate the performance of our proposed MSAR-based classification method for the MSAR data region shown in Fig. 1. The overall procedure follows the flow chart in Fig. 4. The classification procedure employs a straightforward supervised classification scheme with a linear SVM model. Ground truth is derived from both in situ observations [8] and precise geo-registration of the MSAR imagery to optical Google Earth images.

A. GENERATE FEATURES
The feature maps used in the classification procedure were generated from the eigenvalues and eigenvectors at each pixel using the equations given in Section IV.B. The 10 feature maps are shown in Fig. 5.

We see the entropy map (Fig. 5, Feature 1) is bright in ambient regions where there are a large number of weak scatterers and motion is random. Features 2-4 shown in Fig. 5 are eigenvalue differences which are bright in higher motion regions (boat, wake, surf), but already much reduced by the third eigenvalue difference. Features 5 and 6 from Fig. 5 show the eigenvector coherence for the first two eigenvectors, which are bright on land and boat regions. Again, these fall off rapidly as we move away from the dominant eigenvector. Features 7 and 8 in Fig. 5 represent variations of the
eigenvalues in a small window about each pixel giving some
 textual information that is complementary to the correspond-
ing pixel-based information. Eigenvector phase information
is introduced by Features 9 and 10 for the two eigenvec-
tors. The dominant eigenvector phase slope (Feature 9) is
noisy except for the boats and land areas. The value on the
boats is significantly higher than anywhere else. On land
the eigenvector phase slope is very low, but very accurately
determined as shown by Feature 5 (consistent with what is
shown in Fig. 5 and the equations in Section II.C). Feature
9 benefits the class map generation by distinguishing boats
from land and is not present for an amplitude-only situation.
The second eigenvalue phase slope (Feature 10) highlights
the surf region, where the secondary scattering mechanism
displays velocity dependence.

B. SELECTING TRAINING DATA
Training data was generated using small regions of the image
for each class as shown in Fig. 6. The size of class windows
were chosen to be as small as possible while still capturing
the essential variations in motion. The windows for boats are by
necessity slightly smaller however boats have more compact
motion variations. The total area of the training windows is
kept small compared to the whole scene used for classifica-
tion testing. These training regions are extracted from each of
the 10 features and fed into the SVM classification learner.

C. CLASS MAP
We applied our image classification algorithm on the region
of interest shown in Fig. 1, using the features shown in Fig. 5.
For comparison we also produced classifications using the
amplitude image and local standard deviation about each
pixel (for some texture information). The resulting classifi-
cation maps are shown in Fig. 7.

We observe that our algorithm does remarkably well at
finding ambient, boat and land regions. It also does remark-
ably well in distinguishing beach region from land and water.
Though the algorithm has some difficulty distinguishing dif-
ferent water disturbances (e.g. surf vs. wake), overall it ren-
ders an acceptable qualitative partitioning of these classes.
Furthermore, repeating this process on a different set of eight
phase centers using the first sets’ training model gave virtu-
ally identical results (not shown), which further indicates the
robustness of the approach.

Fig. 7 shows a comparison between the amplitude derived
classification map and the corresponding classification map
derived from our MSAR based approach. We clearly see that
the amplitude based approach does not distinguish land from
boat since it has no direct access to velocity information
(derived from the phases of the eigenvector components) as
discussed in Section II. Furthermore the traditional amplitude
based approach fails to detect the wake outside of the training
box, and finally it fails to distinguish clearly the surf and
beach classes in comparison to our MSAR based approach.
The percentage of correctly identify targets is plotted
in Fig. 8. The MSAR-based approach (blue) provides a more
accurate classification of the targets than the amplitude only
classifier. The main differences between the two methods
involve moving targets, i.e. ambient water, surf and boat, and
to a lesser extent wakes and beaches. Only the land class
is similarly identified by both methods. In fact, if the eigen
features and amplitudes are combined to provide a super-set
of classification features, the classification improvement over
the MSAR feature classification is minimal, at best.

Our MSAR based classification algorithm is superior to
the traditional approach to SAR based image classification
in several respects. First, the selected features are well suited
to physical interpretation of in-scene scattering mechanisms.
The dominant eigenvector phases and their standard devia-
tions contain information that characterizes scatterer motion.
The ability to employ in-scene motion information is a unique
aspect of our MSAR classification technique. The dominant
eigenvalue contains image amplitude information, similar to
that typically used in amplitude-only classifiers. As shown
is Figs. 7 & 8, the results employing our classification fea-
tures either with, or without, image amplitudes and standard
deviations are equivalent. Second, overall the size of the training boxes is relatively small compared to the size of the scene i.e. we demonstrate excellent classification performance with limited training size. This feature renders our algorithm especially suitable for large-scale image classification problems. And, as pointed out earlier, classifiers trained on one set of MSAR channels and applied to an MSAR scene formed from a different, disjoint, set of channels produces very good classification results. Finally, the basic approach, eigen analysis of multi-channel covariance matrices, is easily extensible. Incorporating additional along-track channels merely increases the dimension of the covariance matrix; the analysis remains the same. Including cross-track channels changes the interpretation of the phases of the eigenvector components, but not the underlying methodology. Our techniques can therefore render high quality image classification when implemented in practical MSAR systems.

VI. CONCLUSION

In this paper, we describe a novel and robust classification procedure for maritime scenes using an MSAR system, which provides a powerful means of detecting motion in the scene. While previous research on MSAR data analysis has focused mainly on the imaging aspects, in this paper we demonstrate the power of MSAR based analysis for classification in maritime environments. Indeed our classification scheme is ideal for the maritime environment where every location is undergoing some form of motion.

We experimentally demonstrated, for the first time, the utility of our motion-based image classification algorithm using NRL MSAR imagery for a scene containing boats, wakes, surf, land, beach and ambient water classes. Our unique MSAR-based classification technique demonstrates great promise in separating these different motion classes.

We emphasize that our technique compliments previous approaches to image classification by exploiting motion information provided by the MSAR’s unique along-track, multi-aperture configuration that is highly sensitive to in-scene velocities. In future work, our technique will be extended to include height information via cross-track phase centers and sparsity approaches to improve practicality.

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