Open Water Detection From Baltic Sea Ice Radarsat-1 SAR Imagery
Juha Karvonen, Markku Similä, and Marko Mäkynen

Abstract—An algorithm for open water and sea ice discrimination for Radarsat-1 ScanSAR images is presented. The algorithm is based on segmentation and local synthetic aperture radar signal intensity autocorrelation. The algorithm performance is evaluated by comparing the results to operational digitized ice charts, in which the sea ice information is based on human interpretation of multiple data sources, including remote sensing data. The algorithm locates the open water of the digitized ice charts with about 90% accuracy.

Index Terms—Autocorrelation, Baltic sea ice, open water, Radarsat-1, synthetic aperture radar (SAR).

I. INTRODUCTION

RADARSAT-1 ScanSAR wide-mode images are used at the Finnish Institute of Marine Research (FIMR) for operational monitoring of the Baltic Sea ice conditions. Various kinds of algorithms for automated classification of these synthetic aperture radar (SAR) images have been developed and tested at FIMR. One important feature of these algorithms is to distinguish between open water and sea ice. For this purpose, the two-dimensional (2-D) signal autocorrelation is a useful measure [1]. Usually, the autocorrelation for sea ice is larger than for open water, i.e., the neighboring SAR pixels of sea ice are more correlated than those of open sea.

The small autocorrelation typical for open water is due to many factors. Scattering from open sea is mostly modeled by the composite surface model, where Bragg-resonant capillary—gravity waves ride on slowly undulating long waves [3]. There often exist several wave systems traveling different directions in open sea. In the Baltic Sea, the dominant wavelengths of these wave systems are typically from 25–40 m, rarely exceeding 100 m, i.e., usually the wavelengths remain well below the radar resolution [4]. Hence, the slope of ocean surface fluctuates randomly when averaged over a 100-m resolution cell. The capillary waves follow wind direction and their directional spectrum may be assumed to spread into relatively large range. In the presence of speckle the resulting backscattering amplitudes rarely form detectable spatial small scale structures. On the other hand, radar backscattering from ice fields varies more smoothly in the case of level ice, or forms detectable structures in the case of deformed ice.

Here we present an algorithm to extract Baltic Sea ice and open water areas from our operational SAR data. The algorithm is based on segmentwise autocorrelation with some simple additional rules to improve the classification.

For SAR data, either backscattering intensity, or backscattering intensity with various first-order and higher order texture measures have been applied to discriminate open water (and for sea ice classification) in literature. Typically, multiple features, including local incidence angle and some weather-related information, give the best classification results. However, our open water classifier only uses one texture feature, it is not heavily dependent on local incidence angle, and the classification results are adequate for our operational use.

II. OVERVIEW OF OPEN WATER DETECTION FROM SEA ICE SAR DATA

SAR-based sea ice classification is a very difficult task. The classification is dependent on many factors, e.g., on instrument properties and data processing, current weather and weather history. Backscattering from open water can cover the whole range of sea ice backscatter, depending on the energy density of resonant short ripple waves (determined by wind speed), the azimuthal angle relative to the wind direction as well as on the local incidence angle. In most cases, there are no simultaneous ground-truth data available, and visual classification based on either the SAR data or some additional remote sensing data is used instead of ground truth. Backscattering from sea ice and open sea at different incidence angles can vary significantly. Direct intercomparison of classification methods is thus impossible, unless exactly the same datasets are used.

Baltic Sea is a brackish water basin with low salinity. At C-band, which is the Radarsat-1 operating band, the dominating scattering mechanism in the Baltic Sea is surface scattering mainly due to surface roughness, and in most cases volume scattering in Baltic Sea can be omitted [4].

Many SAR-based sea ice classification schemes, including open water discrimination, have been developed for different SAR instruments.

Usually the amount of the SAR data has been rather small, and data have covered only limited areas. Different kinds of statistics have been applied for classification; some have used backscattering intensity and first-order statistics (local mean and variance) [5]–[9]. Higher order statistics (i.e., texture features) have also been studied, e.g., statistics based on the gray-level cooccurrence matrix (GLCM) in [10]–[13]. The classification results of using texture features are somewhat contradictory; some papers report improvements in classification using them [11], [13], and some do not see any significant improvement [8], [12]. This disagreement can, at least partly, be explained by different data, SAR sensors, data processing, and ice and weather conditions in various studies. In particular,
distinguishing between open water and first-year ice or new ice, based on SAR data statistics, can be problematic [5], [8].

Estimation of sea ice concentration and locating polynyas in the arctic areas have been studied in [14]. Local thresholding, which solves the backscatter incidence angle dependence problem by using different thresholds at different incidence angles, and wavelet coefficients (as a SAR texture measure) were used in the classification. The method gave reasonable results, compared to visual interpretation, for the sea ice concentration using European Remote Sensing satellite (ERS) and Radarsat-1 SAR data.

In [15], the derivation of the Baltic Sea ice concentration from Radarsat-1 SAR data was studied, based on local mean backscatter thresholds [14]. However, using only a method based on thresholding of backscattering coefficients very good classification results cannot be achieved due to the backscatter dependence on sea waves.

In [16], over 100 ERS SAR images from arctic areas were used for studying the separability of sea ice and open water. Additionally, air temperature and wind speed were utilized in the classification. Ground truth was replaced by visual classification of 5 km × 5 km data windows; then backscattering mean and standard deviation in these windows were computed. A multivariate regression analysis was applied to this SAR statistics complemented with meteorological and locational information. In separation of sea ice from water, correlation coefficients up to 0.90 between predictions (classifications) and manually classified data were achieved. These results were reported to be comparable to earlier studies in open water classification.

In [17], a semiautomated sea ice classification method for Radarsat-1 data over Arctic sea ice was presented. It is based on three features computed from the SAR data: power-to-mean ratio, estimation of the parameter of the Gamma density distribution, and entropy (derived from GLCM), in addition to the SAR pixel amplitude. The classification is based on fuzzy rules, which classify the data into eight categories. Actually four classes, i.e., calm water, turbulent water, and low and high concentration sea ice, are used, and these four classes are classified differently in radar near range and far range, thus yielding the total of eight categories.

Local autocorrelation, which is also the main SAR (texture) feature in this article, has been used for pixelwise open water detection in [1].

There exist multiple sea ice SAR classification schemes which utilize additional remote sensing data, e.g., Landsat and the Special Sensor Microwave/Imager, yielding improved results compared to classifiers based on SAR data only [18]–[20].

The methods using SAR backscattering directly do not perform very well, because in order to be reliable they should take into account the local incidence angle as well as an estimate of wind speed and direction. Some of texture measures are not so contingent on the local conditions. We have found that autocorrelation as a texture measure is not very sensitive to wave conditions and incidence angle. Additional data from other sources (remote sensing and other measured or forecast data) would further improve the classification.

III. ALGORITHM

In the development of our algorithm we used a set of 52 ScanSAR wide-mode images processed by KSAT in Tromsø, Norway. The images were mainly acquired during the winter 2003/2004, while some images were from the winter 2002/2003. Our training dataset consisted of 20 images from the winter 2003/2004, which mostly represented dry snow condition, but also some wet snow condition images were included. A test dataset of 20 images over the winter 2003/2004 was then used to evaluate the performance of the algorithm. These images also mostly represented dry snow conditions. A test set for wet snow conditions consisting of 12 images from the winters 2002/2003 and 2003/2004 was tested separately.

We have compared our algorithm results to the open water and sea ice separation available in daily digitized ice charts. The daily ice charts are produced by the Finnish Ice Service sea ice experts, and they are based on data from several remote sensing instruments and in situ sea ice measurements from coastal stations and ships. We also compare our algorithm performance to open water detection by direct pixelwise autocorrelation thresholding.

The image to be classified is first segmented, and the autocorrelation is computed for the segments rather than for single pixels. The autocorrelation of a segment is the mean of the local autocorrelation over the segment. The segmentation is based on the SAR intensity after an incidence angle correction [21], [22] has been applied. A contextual segmentation based on pulse-coupled neural networks (PCNNs) is used to reduce the effect of speckle on the segmentation [23]. This segmentation is further refined by a segmentation based on local autocorrelation. The size distribution of the resulting segments varies highly depending on the ice conditions, the range being from 1 km² to several thousand square kilometers. The largest segments occur in the open water areas.

The computation of an estimate for the pixelwise 2-D local autocorrelation, here denoted by \( C \), is carried out by using only the neighboring pixels. In the 2-D case, we utilize four directions: \((k_s, l) = (0, 1)\) corresponding to vertical direction, \((k_s, l) = (1, 0)\) corresponding to horizontal direction, \((k_s, l) = (1, 1)\) and \((k_s, l) = (1, -1)\) corresponding to the diagonal directions. The diagonal direction values at distance of \(\sqrt{2}\) pixels are linearly interpolated to the distance of one pixel. The local autocorrelation values computed only from the neighboring pixels exhibit high random fluctuation. To obtain a more robust estimate for \( C \), we first compute the autocorrelation in a \(11 \times 11\) pixel block, here denoted by \( B \), around the center pixel, in the four directions listed above separately. Then these directional autocorrelations are averaged to estimate \( C \). The pixelwise directional autocorrelation estimate for the direction \((k_s, l)\) is computed as

\[
C(k_s, l) = \frac{1}{|B|} \sum_{i,j \in B} (x(i,j) - \bar{x}_B) (x(i,j) - \bar{x}_B)
\]

where \( x(i,j) \) is the SAR pixel value at location \((i, j)\) \( [B] \) denotes the size of the pixel block \( B \), \( \bar{x}_B \) and \( \bar{x}_B \) are the sample mean and standard deviation in the pixel block \( B \). To compute the segmentwise autocorrelation for the segment, in which the center pixel lies, only the pixels inside the segment (and the block \( B \) are used in the computation of the \( C(k_s, l) \) values, and the autocorrelation \( C \) at the center pixel is computed as the weighted (by the relative amounts of samples in each direction) mean of the four \( C(k_s, l) \) values in the block. The autocorrelation of a segment is then the mean of the values \( C \) over the segment.
The threshold applied in the classification for the segmentwise autocorrelation is defined on the basis of training data consisting of Radarsat-1 data and the digitized ice charts. By using digitized ice charts, it is decided if a pixel in question represents open water or ice. Then a value of $C_k$ extracted from a pixel block $B_k$ is assigned to this pixel. This procedure yields the frequency distributions of the SAR autocorrelations for the open sea and sea ice areas. These distributions are modeled with a Gaussian mixture model. The number of components in this model is selected such that the coefficient of determination exceeds a threshold (here 0.95). The expectation-maximization algorithm [24] is used to estimate the parameters of the components.

The approach suggests two components for the open water, and three components for the sea ice distributions. However, based on the small mixing proportion of the other open water component, one may assume that the occurrence of this component is mainly due to the different resolutions of the SAR data (100 m) and the ice chart (nominally 1 km), i.e., the area boundaries and small details in the ice chart are not of the same precision as in the SAR image. This leads to some misclassification in the finer resolution near the boundaries as well as in the case of isolated ice floes appearing in the middle of open sea. The automated algorithm correctly identifies them as ice but in the ice charts they are not always indicated. The threshold is chosen to optimize the Bayesian decision rule between two densities, whose prior probabilities sum to one, i.e., the threshold is the point where the two posterior densities are equal.

The appropriate densities in this problem are selected with the following procedure. The open water density in the threshold determination is the mixture component with the large mixing proportion. The selected component from the sea ice mixture density is the component with lowest mean. These densities for the training data are shown in Fig. 1, gray corresponds to open water and black to ice.

Determining the Bayesian threshold in this case leads to a second-order polynomial equation for solving the threshold. We calculated the threshold using two types of prior probabilities for the two distributions: 1) the mixing proportions estimated from the training dataset and 2) the assumption of equiprobability of the distributions. The first assumption gave the value $T_{bi} = 0.258$ and the second $T_{bo} = 0.225$.

The algorithm first uses the lower threshold ($T_{bo}$) to define whether a segment certainly contains open water or not, and then tests the adjacent (in the sense of eight-neighborhood) segments to the open water segment for the upper threshold, and if the values are less than the upper threshold the open water area is expanded by these segments. Only one such expansion pass is performed. The threshold values are compared to the segment autocorrelation mean values instead of comparing the values of each pixel separately.

Finally, a filtering step is performed, and open water segments with size (in pixels) less than a given size threshold are set to ice. Different threshold is used for long and narrow segments, corresponding to typical shape of leads. The current thresholds values are 2000 pixels (corresponding to 20 km) for narrow segments, and 10 000 pixels (100 km) for other segments. A flowchart describing the main steps and data flow of the algorithm is presented in Fig. 2.

### IV. EXPERIMENTAL RESULTS

The classification performance of the algorithm for the training set, the test set, and the wet snow condition test set are shown in Table I. For comparison, also the results of pixelwise
thresholding classification using $T_{lo}$ and $T_{hi}$ are shown. The results are given as percentages of correctly classified pixels compared to digitized ice charts.

Using the proposed algorithm about 90% of the open water is correctly classified in all conditions, and over 80% of the ice is correctly classified.

However, when we compare what kind of ice is misclassified in wet and dry snow conditions, there are clear differences. In the dry snow condition most of the ice classified to open water is thin ice, but in wet snow condition most of the misclassified ice is rather thick; see Fig. 3. According to our visual interpretation, the misclassified open water areas are typically areas with some floating ice which produce higher local autocorrelation. The higher thick ice misclassification in wet snow condition is related to the wet snow attenuation of the backscattering. Thickest snow layers usually occur in ice areas with thick level ice, e.g., fast ice areas.

Two examples of the classification are shown in Figs. 4–6. The original Radarsat-1 image in Fig. 4 a is from the ice melting period representing wet snow conditions, the average snow cover thickness at that time was around 5–10 cm in the Finnish coastal ice monitoring stations of the Bay of Bothnia. The digitized ice chart of the same day and the classification result are shown in Fig. 5. In the other example, see Fig. 6, a digitized ice chart and the classification result for a Radarsat-1 image over the Gulf of Finland are shown. These figures are from a colder weather period and the snow cover thickness then was 30–45 cm. It can be seen that the shape of sea ice edge in the classification is more accurate, causing some difference to
the ice charts. There are also some areas of thin ice, according to ice chart, which are classified to open sea. Also, the edges of the SAR beam sometimes cause misclassification of open water to sea ice [e.g., the straight line seen in the open water in Fig. 4 and in the classification result in Fig. 5(b)].

V. DISCUSSION AND CONCLUSION

We have developed an algorithm to distinguish Baltic Sea ice and open sea in SAR images. The algorithm is based on thresholding of segmentwise local autocorrelation, and some simple rules developed to avoid obvious misclassification. The segmentwise mean values are estimates for the expectations, and the expectations associated to the ice and open water autocorrelation distributions are rather far apart from each other; see Fig. 1. On the other hand, the same figure shows that the pixelwise frequency distributions overlap each other significantly. Table I confirms that the segmentwise autocorrelation mean should be preferred instead of the pixelwise thresholding.

The proposed algorithm can distinguish between open sea and sea ice relatively well. Especially large open water areas are very well distinguished. Some very small open water areas may be misclassified to ice, this is due to the compromise we have made to avoid misclassifying some level and fast ice areas to open water. These ice areas may locally have relative small autocorrelation value but, typically for a larger area, the value exceeds the threshold value, and by classifying such small isolated segments into ice, most of these misclassifications can be avoided. Also, open water leads are classified correctly rather well, because the classification of these segments is not changed based on the segment size. The method also performs well over the whole SAR incidence angle range, unlike, for example, methods directly based on backscattering coefficient values.

The algorithm performs the classification in 100-m resolution, which is much higher than the resolution of digitized ice charts. The comparisons to digitized ice charts naturally contain some errors due to this resolution difference, because all the details visible in the classification result are not present in the digitized ice chart. This also reduces the classification rates of the comparison made to the digitized ice charts.

The algorithm performance was tested on two Linux computers. The executions times of the algorithm on a 900-MHz AMD Athlon computer with 256 MB RAM were about 1 h for one image in full 100-m resolution, and on a 3-GHz Pentium IV computer with 1 GB of RAM around 18 min, which is reasonable for our operational use.

The classification scheme could further be developed by using ice history information from the ice charts before the image acquisition, and also by utilizing weather history to approximate the current ice and snow conditions.

This open water algorithm will be integrated to be a part of the SAR-based operational Baltic Sea ice classification in use at the Finnish Ice Service.

REFERENCES


Ice Thickness Estimation Using SAR Data and Ice Thickness History

Juha Karvonen
Finnish Institute of Marine Research, email: Juha.Karvonen@fimr.fi

Markku Similä
PB 33, FIN-00931, Helsinki, Finland, email: Markku.Simila@fimr.fi

Istvan Heiler
Ph. +358 9 613941, Fax. +358 9 3231025
email: Istvan.Heiler@fimr.fi

Abstract—We introduce an algorithm for sea ice thickness estimation by augmenting the sea ice thickness history derived from the daily digitized ice charts for the Baltic Sea ice. This algorithm is designed for operational use and utilizes the C-band Radarsat-1 data.

I. INTRODUCTION

FIMR has been utilizing the Radarsat-1 ScanSAR data in operational sea ice monitoring for several years. Because the surface scattering dominates the backscattering at C-band [1], estimating sea ice thickness from RADARSAT SAR images is practically impossible. To overcome this fundamental deficiency we have adopted an approach in which, based on the evidence of the SAR data, we modify the ice thickness information present in the traditional ice chart. The ice experts at the Finnish Ice Service (FIS) daily produce an ice chart over the whole Baltic Sea after analyzing several different data sources including RADARSAT images and field observations.

From the digital ice chart one can generate an ice thickness map, where estimated minimum, mean and maximum ice thickness values are assigned to each segment. The objective of our algorithm is to refine and more accurately localize the relatively coarse ice thickness information present in the ice chart. The SAR data used are processed to a logarithmic intensity scale at Tromsø satellite sation in Norway, and then transmitted to FIMR, where the data are rectified to Mercator projection and land areas are masked off. In this research we have used Radarsat-1 ScanSAR Wide data in 100 m resolution.

II. PREPROCESSING

First, an incidence angle normalization algorithm developed for Baltic Sea ice [2] is applied to the SAR data. Then the incidence angle corrected images are segmented using a slightly modified isodata clustering algorithm [3]. The isodata algorithm is a variant of the k-means algorithm [4]. Instead of a predefined number of cluster of the k-means algorithm, isodata algorithm produces a data-dependent number of clusters adjusted by some input parameters (minimum distance between cluster, maximum variance inside a cluster, minimum number of samples in a cluster). In the isodata algorithm the clusters are merged and split according to these criteria during the iteration. In our isodata algorithm the split and merge procedures slightly differ from those of the standard isodata algorithm. Our variant does the splitting by applying 2-means (k-means with k=2) inside the cluster to be split, and merging is done by merging each sample separately to the cluster corresponding to the closest cluster center.

The values used in the isodata segmentation are not the pixel values, but are means computed in a round-shaped window with a diameter D around each pixel. For each such window the gradient inside the window is computed and thresholded with a threshold relative to the maximum and minimum gradients inside the window, T = α(g_{max} - g_{min}), where α is a coefficient. The locations of the gradient values exceeding T are considered as (linear) edge pixel locations. The connected edge contour is formed as follows. The direction of the edge is defined to be the first principal component of the edge pixel locations. The location of the edge is determined by assigning the principal component vector to the center of mass of the gradient pixel locations, see Fig. 1. Finally, the mean in the window is computed only including those pixel values which are on the same side of the edge as the mid-pixel of the window, and if the mid-pixel happens to be at the edge, the mean is computed for the edge pixels only.

Fig. 1. An example of a round-shaped image window with an edge (left), finding the gradient (middle) and showing the detected gradient direction (right). For visual purposes this window size is larger than the size used in the actual algorithm. Only the pixels lying on the same side of the detected gradient line as the mid-pixel (shown bright) are used in computing the mean value used in the segmentation.

III. COMBINING THE ICE THICKNESS HISTORY AND SAR DATA

After segmentation each SAR segment is compared to the segments in the ice thickness map. If over 50 % of a SAR segment is covered by one thickness segment, this thickness segment is extended to cover the whole SAR segment, otherwise the thickness segment remains unchanged. This step defines anew the boundaries of a thickness segment. Naturally, one can also apply some other threshold than 50 % coverage currently in use. Then the thickness values are
linearly mapped such that the minimum thickness is mapped to correspond to the minimum SAR segment intensity mean and the maximum thickness to correspond to the maximum SAR segment intensity mean inside the same thickness map segment. This procedure is applied to a thickness map and a SAR image of the same day, producing a map which we call an augmented ice thickness map. If we have at our disposal a new SAR image and the ice thickness map of the previous day, this procedure can be utilized to give an estimate for the current ice thickness distribution. The estimation works well if only minor changes in the ice conditions between the SAR acquisition and the ice thickness history have occurred.

However, due to the dynamic nature of drift ice fields, the changes in ice conditions can be radical. Especially this is true if the time gap between SAR data and ice history is larger than one day. For this purpose we have developed an algorithm which tries to correct the ice thickness map generated from the ice history with the aid of SAR data. The empirical observations guiding the correction procedure are that the areas with low spatial autocorrelation are often open water areas and the areas with high intensity and higher autocorrelation have often higher mean thickness. By utilizing these observations, certain changes (e.g. identification of open water areas) to the existing segmentation can be made. To ensure that these changes mostly lead to corrections instead of misinterpretations, certain thresholds for autocorrelation and intensity statistics need to be defined. These thresholds were estimated from a training data set containing simultaneous SAR and ice thickness data. In the training phase 10 different classes were determined. In the updating algorithm the image is then classified by utilizing these fixed class centers.

The features used in the classification are the local autocorrelation computed in a 11x11 pixel window around each pixel and the SAR segment intensity mean. The segments are further divided if the autocorrelation segments do not match with the intensity segmentation with a required accuracy, producing a segmentation with two values, intensity mean and autocorrelation, for each segment. These segment classes are then classified to probable open sea (four classes) and ice classes. The thickness is changed to zero (open sea) if the class of the segment is one of the open sea classes and the thickness in the previous ice thickness map is less than a threshold. The remaining six ice classes have values for minimum thickness associated to each of them, and if the ice thickness map thickness value is less than this minimum thickness, the ice thickness is set to a mode value in a neighborhood of the segment. This mode value is computed only for values greater or equal than the given classwise minimum thickness. The mode computing neighborhood is defined as the area of the bounding box of the segment enlarged by a constant factor into directions of its four sides.

IV. SOME EXPERIMENTAL RESULTS

Here we show as a case example the result of applying the algorithm to the Radarsat-1 SAR image of January 2nd 2003, shown in Fig. 2. The ice thickness maps directly derived from the digitized ice charts for the previous day and for the SAR acquisition day are shown in Figs. 4 and 5. The augmented ice charts are shown in Figs. 6 and 7, respectively.

V. DISCUSSION AND CONCLUSION

The algorithm was developed based on the Radarsat-1 ScanSAR Wide mode data acquired during the winter 2001-2002. The algorithm has been in operational test use during the winter 2002-2003. The images are available for the ice breakers of the Finnish Maritime Administration, and we have received some positive feedback from the end-users on the ships. The augmented thickness map is produced automatically...
after a Radarsat-1 image has been received at FIS, using the most recent digitized ice chart available. If the digitized ice chart is from the previous day, the correction is applied, else not. And the augmented thickness map is also produced every afternoon after the daily digitized ice chart has been completed, for all the Radarsat-1 images received earlier during the same day.

Evaluation of the thickness results is very difficult, and it is also dependent on the accuracy of the digitized ice chart which can contain some human-made errors, reflecting to the estimation result. Also the resolution in the digitized ice map is very low, and it is based on a very sparse set of field observations. In general the thickness results provided by our algorithms do not differ largely from those what an ice analyst would have assessed if he/she would have had the time to draw a more detailed ice thickness chart.

REFERENCES
Comparison of SAR Data and Operational Sea Ice Products to EM Ice Thickness Measurements in the Baltic Sea

Juha Karvonen¹, Markku Similä¹, Jari Haapala¹
Christian Haas², Marko Mäkynen³

¹ Finnish Institute of Marine Research (FIMR), PB 33, FIN-00931, Helsinki, Finland
Ph. +358 9 61394 424, Fax +358 9 3231025, Email: Juha.Karvonen@fimr.fi
² Alfred Wegener Institute (AWI), Bremerhaven, Germany
³ Helsinki Univ. of Technology, Laboratory of Space Technology (HUT/LST), Finland

I. INTRODUCTION

In February 2003, sea ice thickness measurements using an electromagnetic induction (EM) instrument were made in the Gulf of Bothnia and Gulf of Finland. We have made comparisons between the EM measurements and Radarsat-1 ScanSAR Wide mode SAR data, and also between our operational sea ice products (digitized ice thickness charts, and ice thickness charts refined by the latest Radarsat-1 image). The SAR images are in 100 m resolution, and the other products are in 500 m resolution.

The maximum daily temperatures during the EM measurement campaign were typically above zero degrees, probably making the ice surface and snow on the ice wet in the daytime, and thus attenuating the SAR backscattering from the sea ice. This data set mainly describes the statistics of wet snow or frozen snow-surface conditions, and a similar study for dry snow conditions would also be useful. The time gap between SAR image and the EM measurement varied from about 2 hours to about 9.5 hours, and the wind speeds between the SAR acquisition and EM measurement were relatively low (in maximum about 4 m/s in the coastal stations).

II. MEASURING THE ICE THICKNESS BY ELECTROMAGNETIC INDUCTION

Alfred Wegener Institute (AWI) has performed EM measurements in Gulf of Bothnia and Gulf of Finland in 2003 and 2004. The helicopter-borne EM instrument measures the distance to the water below sea ice based on low-frequency electromagnetic induction from the sea water. Sea ice is typically resistive and water is conductive and electromagnetic induction from the water occurs. The ratio between secondary and primary fields, transmitted and received/measured by the EM instrument, depends on the distance between the EM system and the conductive media, and on the electrical conductivity of the media. Main part of the secondary magnetic field comes from the sea water, and the instrument distance to the sea water can be derived from the measured secondary field strength. Then the ice (plus snow) thickness is the distance to the sea water, measured by the EM instrument, subtracted by the distance to the surface measured by a laser altimeter included in the instrument. The EM measurement principle is shown in Fig. 1.

It has been assessed that for level ice the accuracy of EM measurements is about 10 cm [1] [2] [3]. For ridged ice the accuracy is weaker due to water appearing between ice blocks. However, almost always the occurrence of an ice ridge can be detected.

III. SAR DATA PREPROCESSING

We have compared Radarsat-1 ScanSAR Wide mode SAR image data pixel values values and our operational sea ice products of the corresponding days with the EM measurements. The operational products are the ice thickness chart, derived from the digitized ice chart and the ice thickness chart refined by the information of the most recent SAR data [4].

The SAR data is received in a logarithmic scale from Kongsberg Satellite Services (KSS) in Tromsø, Norway. The relation between the measured SAR intensity $I$ and the pixel value $P$ in our images is

$$I = \left( \frac{B^P}{G} \right)^2,$$

Fig. 1. The EM measurement principle.
where \( P \) is the 8-bit image pixel value, logarithmic scale \( B = 1.024 \), and gain factor \( G = 0.16 \). The data has this far not been absolutely calibrated.

The data are in different resolutions, the sampling rate of the EM measurement is 3-4 m and the Radarsat-1 images are in 100 m resolution. The nominal resolution of digitized ice thickness charts is about 1 km, and the resolution of our operative SAR-refined ice thickness chart is 500 m. In 100 m resolution the flight line in maximum covers about 20 \% of the pixel area (assuming straight flight line over the pixel center), and in 500 m resolution this area is only 4 \%. The only reasonable way to compare these kind of data is to make statistical comparisons. The material covers five SAR images from 4 days, and about 1000 km of EM flight lines in total. The measurements were conducted in highly ridged drift ice area between February 17th and February 23rd 2003 in Gulf of Finland and Gulf of Bothnia.

![Image](image_url)

**Fig. 2.** Flight lines on Feb 17th 2003 drawn (dark lines) on a SAR-refined ice thickness map, Gulf of Finland. The scale in the figure is in cm.

Before the comparisons an incidence angle correction designed for Baltic Sea ice [5] [6] was applied to the SAR data, normalizing the SAR pixel values to correspond to an incidence angle of 35 degrees (in the middle of the Radarsat-1 ScanSAR Wide mode incidence angle range).

For each SAR and product pixel in the EM profiles a distribution of the EM values was computed, and the values derived from these distributions were used in the comparisons.

### IV. EXPERIMENTAL RESULTS

To analyze our data, we coarsely divided the sea ice, based on the EM ice thickness measurements, into three categories, one representing level ice corresponding to thermal growth, the other rafted ice, and the third representing ridged ice. Additionally there also exists open water. Level formed by thermal growth in our scheme, is defined as ice with EM thickness less than 50 cm (representing the estimated maximal thermal growth until late February, being about 50-60 cm), rafted ice is defined as ice with EM thickness range from 50 to 100 cm (corresponding to doubles of the level ice thicknesses), and ridged ice is defined as ice with EM thickness over 100 cm (including higher multiples of the level ice).

In our statistical analysis, the most significant statistical relationship between the incidence angle corrected SAR pixel values and the EM thickness distribution was established as follows. The range of the corrected SAR pixel values over their dynamic value range was first divided into 15 equal-sized bins. Then, given a fixed bin, we computed the conditional distribution of the three ice thickness categories based on the EM thickness values. It was observed that the fraction of small ridges (rafted ice) remained relatively constant independent of the SAR pixel value. In this data set with these thickness limits, this fraction remained at about 30 \%. On the other hand, the area covered by large ridges grows almost linearly from 0-10 \% at very low amplitude values to 90-100 \% at the highest amplitude values. The fraction of level ice decreased from 70 \% at low amplitudes to less than 10 \% at high amplitude values, see Fig. 3. If the limits in the three ice thickness categories are changed the figures of relative fraction change also but qualitatively they exhibit the same kind of behavior.

![Image](image_url)

**Fig. 3.** The relative amounts of the three different ice types as a function of incidence angle corrected SAR intensity.

We also examined the (cross-)correlations between the incidence angle corrected SAR pixel values, ice thickness of the ice charts, the SAR enhanced ice thickness charts and values computed from the EM measurements. For each SAR or product pixel, we first determined a distribution of the measured EM thicknesses. From this histogram we computed the relative amounts of the three ice classes, the mean thickness and the thickness mode over each 500 m pixel. In a 500 m pixel the number of EM measurements in one pixel was in maximum about 130 measurements, but this naturally for the case in which the flight line goes through the midpoint of the pixel. Actually, only the distributions where the number of EM measurements exceeded a threshold value (20) were used in the computations. The correlations are shown in Table I.

The trends seen in these correlations are consistent with the results presented in Fig. 3. The correlation between the SAR...
TABLE I
CORRELATION COEFFICIENTS BETWEEN THE PRODUCTS AND PIXEL-WISE VALUES DERIVED FROM THE EM MEASUREMENTS. THE PIXEL RESOLUTION IS 500M.

<table>
<thead>
<tr>
<th>Variable</th>
<th>SAR Thickn.</th>
<th>Refined thickn.</th>
</tr>
</thead>
<tbody>
<tr>
<td>level</td>
<td>-0.32</td>
<td>-0.41</td>
</tr>
<tr>
<td>rafted</td>
<td>0.02</td>
<td>0.16</td>
</tr>
<tr>
<td>ridged</td>
<td>0.30</td>
<td>0.07</td>
</tr>
<tr>
<td>mean</td>
<td>0.25</td>
<td>0.11</td>
</tr>
<tr>
<td>mode</td>
<td>0.16</td>
<td>0.14</td>
</tr>
</tbody>
</table>

pixel value and the relative amount of level ice is negative, the correlation between the SAR pixel value and the relative amount of rafted ice is practically zero, and the correlation between the SAR pixel value and the relative amount of ridged ice is positive. Also it can be seen that the correlations between the EM measurement values describing the thickness (mean, mode) and the refined thickness chart are slightly higher than the corresponding values for the ice chart.

The digitized ice thickness chart has three thickness values for each segment, i.e. the level ice minimum, mean and maximum thicknesses. In our data along the flight lines, we could find the following different classes described by the triplet thickness minimum-mean-maximum: 5-5-5, 5-5-10, 5-15-30, 10-15-30, 10-20-30, 20-25-40, 20-30-50, 20-35-50, 10-40-50, 30-40-60, 30-45-60 and 40-50-70.

The accuracy of the estimates given by different ice thickness charts is assessed as follows. First, the digitized ice charts are divided into bins with a varying bin width in the order described above. The SAR refined ice charts are divided into 30 bins with a fixed bin width of 2 cm. Secondly, the class-wise ice chart distributions for open water and the three ice types are calculated for each bin. In the ideal case, the amount of deformed ice types increases with the estimated level ice thickness (it is probable that older ice has gone through more deformations than younger ice). For the digitized ice charts this seems not to be the case. There occurs random-like fluctuation in the fraction of highly ridged ice areas up to the estimated mean level of about 35 cm. After that the amount of highly deformed ice area remains high and, approximately, at the same level, i.e., the higher bins are not significantly different from each other. For details see fig. 4 upper panel.

For the SAR refined thickness chart, the results are more satisfactory. Excluding the thin ice case (estimated thickness less than 4 cm), the amount of deformed ice types increases as a function of the level ice thickness estimate until about 35 cm. Then a state is reached where the fraction of deformed ice type remains approximately at the same level independent of the thickness estimate. This is explicable, because the initial data (ice chart thickness) has this same deficiency and in the forming of SAR refined thickness chart some very restrictive rules are applied [4]. These restrictive rules are necessary, because on the basis of single (speckled) pixel value one can not make any confident statement about the degree of ice deformation, see Table I. For details see fig. 4 lower panel.

In the areas identified to represent very thin ice, 1 to 4 cm, by the SAR refined ice chart, there occurred also relatively high fractions of deformed ice type (fig. 4). To explain this peculiar behavior, we checked the location of measurements where the SAR-refined ice chart thickness is less than 10 cm. More than half of the EM thickness measurements inside the pixel have thicknesses of more than 50 cm. We found that these measurements typically were made at the edges of thin ice or leads (open water areas), according to the SAR-refined ice chart. These erroneous pixels also typically appear in relatively short segments. Such errors are probably due to the time differences between the SAR images and EM measurements, it is probable that sea ice movement and reformation have taken place between the SAR and EM measurements. Probably a larger amount of EM measurements over areas with thin ice and even larger open water areas, not just narrow leads, would have yielded more accurate results for the thin ice areas (according to the SAR-refined ice charts).

V. CONCLUSION AND DISCUSSION

Only weak correspondence was observed when comparing the data sets pixel by pixel, i.e., the correlations between the SAR data or the operational products and the EM measurements are relatively low. This ambiguity is partly due to the ice movement between the SAR data acquisition and EM measurements, and possible inaccuracies in registration between the two data sets. One has, however, to keep in mind that quite different ice conditions can give a similar backscattering signature [7]. However, by examining a large data set, clear statistical relationships between ice types and the strength of backscattering could be detected.

On the basis of our data sets, it seems that at 100 m resolution the SAR data does not improve our a priori knowledge about the area covered by small ridges in the Baltic Sea. However, even at this coarse resolution the backscattering level corresponds quite well with the amount of deformed ice consisting of large ridges. We recall that the measurements were mostly made in highly ridged drift ice. Hence, the last conclusion is valid only for this kind of ice conditions.
The earlier comparisons, e.g. in [8], show that the ice thickness typically changes as the SAR mean intensity or texture changes, and EM measurements can be used as a method to include more precise thickness information into the SAR segments. Our experiments agree with this conclusion, and it seems that, based on a sample of SAR backscattering intensity values, it is possible to assign a crude estimate to the ice type distribution for the ice field from which this scattering originates. This assignment requires, however, a priori knowledge about the order of ice thickness. This information is provided by the initial datum of the algorithm.

EM profiling is a good tool for verifying our operational sea ice products. The SAR-refined ice chart seems to indicate better the local mean ice thickness than the ice chart, based on comparison to the EM measurements. The EM measurement statistics can also be used to make some algorithm improvements.

There are some restrictions in the EM measurements: the size of the instrument footprint is about 20-30 meters, i.e. measurements average over an area of this diameter. Also signals from fresh water, e.g., near river outlets, shallow water, no water at all, can cause misinterpretations. The calibration was performed for each flight line separately, assuming open water at the minimum, and in some cases this leads to underestimation (bias) by the minimum level ice thickness in the line (no open water).

In February-March 2004 several EM measurement flights were made in the Gulf of Bothnia. The data will be utilized in future comparisons. We also have high-resolution Envisat ASAR IMP and APP mode data acquired during this period, making statistical comparisons in more detail possible.

REFERENCES

Polarview@FIMR: WWW-based Delivery of Baltic Sea Ice Products to End-Users
Juha Karvonen, Jari Haapala, Jonni Lehtiranta, Ari Seinä
Finnish Institute of Marine Research (FIMR) PB 33, FIN-00931, Helsinki, Finland, Email: Juha.Karvonen@fimr.fi

I. INTRODUCTION
The Baltic Sea annual marine transportation is about 800 million tonnes, and expected to reach 1.2 billion tonnes by 2020. About 40% of this is transported during the winter months. It is the largest marine transportation in the World's ice covered seas. At any given time there are more than 2000 large vessels sailing in the Baltic Sea. During last ten years the marine traffic has increased by 34%, and this trend is expected to continue.

Sea ice information for navigational purposes is essential in the Baltic Sea. Winter navigation is made possible by the use of icebreakers, ice-strengthened vessels and by restricting navigation. The national maritime authorities restrict navigation by requiring a certain minimum ice class and size of the vessel for it to be assisted. These restrictions are determined per harbor based on the current and forecasted ice conditions. Also up to half of the smaller harbors may be closed for the winter. While the traffic has increased, the number of icebreakers has not increased. Thus the icebreakers need detailed information for route planning. The smoothness of traffic has been possible due to better ice monitoring, where use of EO data has become more and more important [19]. Considerable savings in ice navigation could be achieved by optimizing the use of satellite based operational ice monitoring. This has been the motivation for FIMR to participate in the PolarView project where preparation of suitable operational sea ice products and their efficient delivery to end-users have been addressed.

II. OPERATIONAL POLARVIEW SEA ICE PRODUCTS
FIMR has built a WWW-based service which makes our operational sea ice products publicly available. The service is available through the FIMR PolarView web pages, polarview.fimr.fi. This has been implemented as part of the PolarView project. PolarView offers integrated monitoring and forecasting services related to sea ice and snow in the polar regions using satellite earth observation data to support improved decision-making, planning and adaptation to climate change. PolarView is a GMES (Global Monitoring for Environment and Security) project, and GMES is a joint program of the European Union and European Space Agency (ESA).

A. Ice Thickness Charts
FIMR produces operational SAR-based ice thickness charts over the Baltic Sea. During the ice season 2005–06 totally 245 such charts were produced. These charts are automatically derived from digitized ice charts, which are drawn at the Finnish Ice Service (FIS) daily, using novel SAR information to update the charts.

Routine ice charts are drawn by ice service personnel and published by national ice services. World Meteorological Organization (WMO) ice symbols are used for showing ice conditions in 1–25 km scale. This resolution is too rough for ice navigation. On the other hand ice analysis also takes time, and ice charts are published hours after satellite data has been received. In order to provide information in the scale of ships and with shorter time-gap to the SAR acquisition, FIMR is publishing automated ice thickness charts. The algorithm [7], which combines SAR data and ground truth, provides ice thickness information in 500 m spatial resolution. The products are provided operationally and available for users typically about 30 minutes after SAR data is available.

The mean level ice thickness estimates given in the traditional ice chart by the Finnish Ice Service are compiled by an ice analyst from multiple sources including drilling measurements near coastline, systematic field observations, provided by the staff of icebreakers and other ships on sea, and ice growth estimates yielded by ice models. SAR images with a wide coverage are used to produce spatially more accurate ice thickness charts and also more rapidly than the routine ice charts.

In the first phase, an incidence angle correction designed for the Baltic Sea ice [6], [12] is applied to the SAR data. The SAR-based ice thickness charts are generated by refining the ice chart segments to better correspond to the segments of the incidence angle-corrected SAR images. The segments in the SAR images are based on a SAR segmentation algorithm [8]. Also the thickness values in the SAR segments are varied between the ice chart segment-wise minimum and maximum ice thickness values, based on the mean SAR backscattering values over the SAR segments. The open water areas in the SAR images are located based on an algorithm developed at FIMR [10] and the open water segments are also updated accordingly. An ice thickness chart is operationally produced after a SAR image has been received, using the latest available ice chart as an input. The resulting ice thickness chart (a thematic map) is color coded according to ice thickness based navigation restrictions.

The spatial accuracy of the resulting ice thickness charts as well as that of the routine ice charts have been analyzed using ice thickness measurements based on electromagnetic induction. The performed analysis has shown that the SAR-based ice thickness charts yield more accurate ice thickness values. Currently, the ice thickness chart can use RADARSAT-
1 ScanSAR Wide Mode images and Envisat ASAR Wide Swath images as its input data.

One improvement for the season 2006/2007 was that now the information of the digitized ice chart is changed less during a warm period, i.e. when the air temperature has been above zero for some time before the acquisition, according to the closest coastal temperature measurements. The temperature measurements are currently received on a daily basis.

Both RADARSAT-1 and Envisat ASAR-based ice thickness charts are published on the polarview@fimr web pages a few hours after the image acquisition. Also animations showing the ice development can be viewed on the polarview@fimr web pages. These animations are run separately for the RADARSAT-1 and ASAR data.

B. About Validation of the Ice thickness Charts

The spatial accuracy of the resulting ice thickness charts as well as that of the routine ice charts have been analyzed using ice thickness measurements based on a helicopter-borne electromagnetic induction instrument (HEM) [9]. The performed analysis has shown more accurate results for the SAR-based ice thickness charts. We have also made comparisons to ice thickness values measured by ice breakers in the winter 2005/2006, see Fig. 2. The mean error for the ice chart ice thickness was 10.84 cm and for the SAR-based ice thickness chart it was 8.55 cm. The results for the ice observations made by the coastal observers during the winter 2005/2006 gave the mean errors 12.00 cm for the ice chart thickness and 11.44 cm for the SAR-based ice thickness charts. It seems that in some cases the ice thickness charts overestimate the ice thickness, thus increasing the error. These ice observer observations were mostly made in the land fast ice areas near the coast, and the results seem to be better near the ship routes. The validation of the products will be performed every year using all the possible ice thickness measurements available, e.g. in winter 2006/2007 we had a field campaign in the Bay of Bothnia and also HEM measurements were made there, but the data has not been processed yet. Also ice breaker staff will provide us ice thickness measurements every winter. The product will be further developed and adjusted based on these comparisons.

C. Ice-Model Based Ice Forecasts

Also ice forecasts are published on the FIMR PolarView web pages. They are published daily around 7:00 UTC. The forecasts cover the area of the northern Baltic Sea with a spatial resolution of one nautical mile, and range over two days in three-hour steps. The model used is the HELMI model (HELsinki Multicategory Ice model). The model is forced with atmospheric model data from HIRLAM (HIgh Resolution Limited Area Model) weather forecast model.

The HELMI ice model is a multicategory sea-ice model. It has been used in climate research [1], [2] and operational applications. The model physics and numerics are the same both in operational and climate simulations. The only differences are in the horizontal resolution and the atmospheric forcing used. The model resolves ice thickness distribution, i.e. ice concentrations of variable thickness categories, redistribution of ice categories due to deformations, thermodynamics of the sea ice, horizontal components of the ice velocity and the internal stress of the ice pack. Variables of the HELMI model are:

- ice motion (vector fields, unit m/s)
- total ice concentration (scalar variable, unit %)

Fig. 1. An example of the ice thickness chart, Bay of Bothnia, March 26th 2007 at 16:04 UTC.

Fig. 2. Measured ice thickness (blue), ice thickness value of the ice chart (green) and estimated ice thickness value (red).
• mean ice thickness (scalar variable, unit m)
• ridged ice concentration (scalar variable, unit %)
• ridged ice thickness (scalar variable, unit m)
• regions of deformation (scalar variable, unit %)
• ice stress (tensor variable, unit Nm⁻²)

The model parameters, based on HELMI model runs, available on the polarview@fimr web-pages are ice motion, ice concentration, mean ice thickness, ridged ice thickness, ridged ice concentration, compressive region, and deformed ice fraction.

The redistribution function is dependent on ice thickness, concentration and the strain rates [17], [4]. Continuum scale sea ice models resolve an average behavior of the pack ice and the subgrid processes are neglected or taken into account in a simplified manner. The following assumptions of the deformation processes in the present model have been made: (1) deformed ice is generated only from undeformed ice categories i.e. rafted ice is not deformed further in the model, (2) cross-over thickness determines whether the undeformed ice is rafted or ridged. This assumption is based on the Parmeter law [13] and field observations [15]. It is also assumed that the thinnest 15 % of the ice categories experience deformations [17]. Further assumptions are that the shear deformations are not taken into account and the shape and porosity of the ridges is constant. These assumptions are based on the field observations [16], [5].

Ice motion is determined by the time dependent momentum balance equation, which takes into account the Coriolis force, wind and water stresses, the sea surface tilt term and the internal stress. The internal stress of pack ice is calculated according to the viscous-plastic rheology [3] but also relates consumption of the kinetic energy to the ice pack deformations [14].

The sea-ice model employs curvi-linear co-ordinates. Variables are spatially discretized in a c-grid. The advective part of the ice thickness and concentration evolution equation is solved by an upwind method. Momentum balance is solved by the line successive relaxation procedure proposed by Zhang and Hibler [18].

Present set-up of the model predicts evolution of five undeformed and two deformed ice categories. Ice categories are “advected” in the thickness space without any limits, except that the thinnest category is not allowed to exceed 10 cm. Deformed ice is divided into separate categories of rafted and ridged ice types.

The forecasts have been evaluated by comparisons to in-situ measurements and comparison to remote sensing data. The evaluation will be performed continuously (after each winter) and the model will be adjusted and developed based on these evaluations.

III. CONCLUSION

The FIMR PolarView web pages have been set up and they contain information to aid navigation in the area of the Baltic Sea, and this information is publicly available. The FIMR PolarView services have been used operationally by the Finnish and Swedish icebreakers and maritime administrations. According to them usability of services has been very good. According to the web server statistics, during January–March 2006 49,516 successful requests for Polarview@fimr pages (on average 550 per day) were made, and during the whole year 2006 over 130,000 request were made. In the first quarter of the year 2007 183,959 (2044 per day) request were made, showing that the use of the Polarview@fimr web pages has significantly been increased from the previous year.

The services are under continuous development, and also new products are under development. One such future SAR-based product could be the ice motion estimated from successive SAR images. For this purpose an algorithm for the ice motion detection has been developed at FIMR. Also the presentation of the existing products will be developed, for an example also the animations of the SAR-based ice thickness charts and ice predictions will probably be available in near-real-time next winter. Also some further developments in estimating ice thickness distributions based on SAR backscattering distributions have been made [20], [21].

REFERENCES

Fig. 3. SAR-based ice thickness chart over the northern Baltic Sea April 12th 2007 and the corresponding model output (at 7 a.m. UTC) showing the ice concentration, drift speed and drift direction indicated by the arrows. The ice thickness chart may show ice in some areas where there is no more ice, because the SAR data of that area is old.

BALTIC SEA ICE THICKNESS CHARTS BASED ON THERMODYNAMIC SNOW/ICE MODEL, C-BAND SAR CLASSIFICATION AND ICE MOTION DETECTION

Juha Karvonen, Bin Cheng, Markku Similä, Martti Hallikainen

1Finnish Institute of Marine Research (FIMR)
PB 2, FIN-00561, Helsinki, Finland, Email: Juha.Karvonen@fimr.fi
2Helsinki University of Technology (HUT), Department of Radio Science and Engineering

ABSTRACT

We have studied the estimation of the Baltic Sea ice thickness based on a thermodynamic ice model and SAR data to produce ice thickness charts (ITC’s) for navigation. Our new algorithm, also taking into account the ice motion between successive SAR images, has shown promising results.

Index Terms— SAR, Sea Ice, C-band, Ice Thickness Estimation, Thermodynamic Snow/Ice Model

1. INTRODUCTION

Currently, winter navigation in the Baltic Sea relies on the routine sea ice Charts (IC’s), visual interpretation of SAR data and SAR-based level Ice Thickness Charts (ITC’s) [1] provided by the Finnish Ice Service (FIS). Radarsat-1 ScanSAR Wide mode and Envisat ASAR Wide Swath mode images are used to produce spatially more accurate ITC’s than given by the traditional IC’s. A SAR based ITC is operationally produced after a radar image has been received, using the latest available digitized routine IC as an input (either from the previous day or the same day, depending on the receiving time of the SAR image). The ice area boundaries in the digitized IC are then relocated to correspond the area boundaries of the SAR image segments. And inside the generated segments, the thickness values are mapped to be between the segment minimum and maximum thickness values (given by the digitized IC) based on SAR image segment backscattering means (i.e. filtered SAR backscattering) values. The resulting ITC’s are delivered to the end-users in 500 × 500 m resolution. In the approach proposed here we have replaced the ice thickness information given by the digitized IC with the numerically modeled ice thicknesses computed in a grid covering the whole Baltic Sea together with SAR-based ice motion information.

We shortly describe the logic how the ice thickness values provided by an ITC are obtained. In the traditional IC’s a single segment (here called an IC segment) covers a large area where one level ice thickness class can be regarded to be dominant. The diversity in the ice characteristics inside an IC segment is represented by assigning a range of ice thickness values to each segment. As described above, the ITC algorithm assigns the largest thickness value, to correspond to the SAR segment with the strongest backscattering. The justification of this assignment is the following. If only level ice appear inside the IC segment, the small scale surface roughness on average increases with age, i.e. thickest level ice usually produces the strongest SAR response. If also deformed ice areas appear inside the IC segment, we assume that on average the amount of deformation events increases with the age of the ice field. According to this reasoning, the locally oldest and thickest level ice (with respect to its neighboring areas) is usually situated in the most deformed ice zones yielding on average the strongest SAR response. On the other hand, the ITC algorithm assigns the smallest ice thickness value in the given range to the smoothest area (the area with the weakest radar response) inside the IC segment. Crucial for this approach is that the given level ice thickness ranges for IC segments are realistic. During several winters in-situ measurements have been made throughout the whole ice season by the Finnish icebreaker staff. These data sets have shown that the values provided by the ITC’s are close to the measured level ice values. Hence, the input information received from the IC’s is of high quality.

The current operational ITC’s always require a digitized IC as its input, and this requires human interference in the processing chain. Our goal in this work is to be able to produce ice thickness charts also for sea areas where only coarse resolution IC’s, or no IC’s at all are available. A novel product based on a thermodynamic snow and sea ice model, named HIGHTSI (HIGH-resolution Thermodynamic Snow/Ice model) [2, 3], and SAR data has been developed. This fully automated algorithm can then be run without IC data as its input. We selected the Baltic Sea as our test area because the ice conditions in this area are rather well-known due to comprehensive monitoring and the operational ITC’s offer a natural reference for the development work. Also very representative SAR data sets are available because of the operational use of SAR data to aid navigation in the Baltic Sea.

2. ICE THICKNESS ESTIMATION ALGORITHM

This study is continuation to our earlier work [4]. We utilize an improved HIGHTSI snow/ice model to estimate the ice growth, SAR data to describe the spatial distribution of different ice thickness classes, and particularly, pairs of successive SAR images over their common areas are applied to detect the ice motion, a feature which was not included in our previous work. Similar to our previous work, we have restricted to Radarsat-1 ScanSAR Wide mode data only. SAR data over
the winter seasons 2004–2005 and 2005–2006 were used in this study and the corresponding ITC’s were produced. The number of the acquired SAR images during the ice season 2004–2005 was 96 and during the ice season 2005–2006 160. We have used data of February and March 2005 (87 SAR images) as a training data set and the data of February–April 2006 (111 SAR images) as a test set. In order to estimate ice thickness evolution more accurately, particularly in the melting season, the HIGHTSI ice model was updated by incorporating a more sophisticated albedo scheme. The heat and mass balances at the ice-ocean interface were improved by applying a parameterization of oceanic heat flux associated with the ice concentration. HIGHTSI was forced with the ECMWF data has a resolution of 11 km \times 11 km \text{m}^2, which also defines the model resolution.

Ice motion is estimated from two successive SAR images by performing a phase correlation between registered SAR image pairs over the common areas of an image pair [5]. The algorithm is applied in a multi-resolution pyramid to cover larger areas and to capture larger ice motions. The computed ice motion information is utilized to improve the resulting ITC in several ways. First, the fast ice regions are recognized, based on the ice motion from SAR images and the fact the areas which stay continuously in a stationary state, and a different ice thickness estimation parametrization is applied for detected fast ice and drift ice areas.

The areas of uniform motion, including the areas with no motion, are also located. Assuming that only small changes in the local ice conditions have occurred during the few days period (short time scale compared to the fast ice detection) between the SAR images over these areas moving as a uniform field, we have several SAR measurements of the same ice field available, and we now use the median value of these values for each such segment in the ice thickness estimation. We also use the cross (phase) correlation between each pair of two SAR images as input for the ice thickness estimation for the latter image.

The inputs currently used in the estimation of a SAR segment are ice thickness values produced by the HIGHTSI ice model, $H_h$, median value of the available measurements of the same ice field (segment), $I$, and a product term between HIGHTSI thickness and the SAR pixel median value, $H_h I$. The product term $H_h I$ is included to take into account the terms of the form $(a_1 H_h + b_1)(a_2 I + b_2)$ in the estimation, i.e. that $H_h$ is modulated by $I$. The multiple linear regression analysis showed that the product term is of essential significance. We have also studied the use of cross correlation (if available), $C_c$, and local SAR autocorrelation, $C_a$, as features in the ice thickness computation. It seems that their contribution to the estimate is neglectable. However, we are currently using the temporal minimum $(C_c)$ of the cross-correlation.

We are studying of more useful ways to utilize $C_c$ and $C_a$.

We used two methods to estimate the output, i.e. the ice thickness based on the inputs: a linear model and a nonlinear model. The linear model weights were define based on a least squares fit using the training data set. The LS-solution for the linear coefficient vector $A$ with the linear model $H = FA$ is

$$A = F^\dagger H,$$  

(1)

where $F$ is a feature matrix, the kth line of the matrix contains the feature vector $F_k = [H_{hk} I_k H_{hk}I_k 1]$, $H$ contains the ice thickness values from the operational model, and $F^\dagger$ is the Moore-Penrose pseudoinverse of $F$:

$$F^\dagger = (F^TF)^{-1}F^T.$$

The nonlinear method was a two layer Multi-Layer Perceptron (MLP) neural network trained by using the error backpropagation algorithm with the same training data set, except that only $H_h$ and $I$ were used as input variables. The hidden layer nonlinearities were implemented using the hyperbolic tangent (tanh) function and the output layer with one output (the estimated thickness) was linear. Feed-forward neural networks, such as MLP, with a single hidden layer of sigmoidal units are capable of approximating uniformly any continuous multivariate function, to any desired degree of accuracy [6]. According to our experiments the estimation error did not significantly reduce with more than five hidden units, and we used five hidden units in our tests. The weights were initialized randomly, and the parameters used in tests were simply selected by running the algorithm 100 times with different random initializations and selecting the weight set giving the smallest estimation error for the training data set. The advantage of the MLP-model is that we can feed the input variables into the network and train it with the desired output values without building a model of the relation between the inputs and the output(s). Open water areas were detected based on a dual-thresholding of the local autocorrelation [7]. Open water is not allowed to appear in areas with an estimated ice thickness higher than a given threshold.

Unfortunately we do not have sufficiently good enough in-situ measurements available to train and test the algorithm properly. We have a limited set of EM measurements made during the winter 2004–2005, but it was impossible to extract the level ice thickness from the distributions of the EM measurements over SAR segments. Therefore we regarded the operational ice thickness charts as the ground truth in our training data set.

### 3. EXPERIMENTAL RESULTS

We used data from February–March 2005 for training the algorithm. These data mostly represent dry snow conditions. Results for this new algorithm were computed over the period February–April 2006 and were compared with existing point measurements and ice thickness values of the operational ITC’s. Without the ice motion information [4], the ice...
thickness of the model-based ITC’s were typically overestimated for the drift ice and underestimated for the land-fast ice. The new algorithm performs better than the previous algorithm without the ice motion estimation, compared to the in-situ measurements.

The training data consisted of 87 SAR images and their areal distribution was 49 images over the Bay of Bothnia, 6 images over the Gulf of Bothnia (Quark area), 4 images over the Archipelago sea, and 28 images over the Gulf of Finland. The corresponding numbers for the test data are 48, 25, 7, and 31, respectively (totally 111 test set images). The Gulf of Riga is visible in most of the images of Gulf of Finland and in about half of the images cover the Archipelago Sea. It should be noted that the area of Gulf of Riga is clearly smaller than that of the Gulf of Finland, and again the area of Gulf of Finland is smaller than the area of Bay of Bothnia or Gulf of Bothnia. This means that the training data are dominated by the data from Gulf of Bothnia and Bay of Bothnia.

Table 1. Comparison of the operational product and measurements made by ice breakers. Also comparisons to the values produced by the operational system are made. The values are in cm. The corrected values are computed by correcting the systematic error between the measured values and the estimates.

<table>
<thead>
<tr>
<th>Comparison</th>
<th>L1 error</th>
</tr>
</thead>
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<tr>
<td>Operational ITC vs. measured</td>
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</tr>
<tr>
<td>HIGHTSI+SAR linear vs. measured</td>
<td>8.51</td>
</tr>
<tr>
<td>HIGHTSI+SAR nonlinear vs. measured</td>
<td>9.09</td>
</tr>
<tr>
<td>HIGHTSI+SAR linear vs. oper. ITC</td>
<td>7.60</td>
</tr>
<tr>
<td>HIGHTSI+SAR nonlinear vs. oper. ITC</td>
<td>7.37</td>
</tr>
<tr>
<td>HIGHTSI+SAR linear (corr.) vs. measured</td>
<td>8.25</td>
</tr>
<tr>
<td>HIGHTSI+SAR nonlinear (corr.) vs. measured</td>
<td>8.39</td>
</tr>
</tbody>
</table>

Fig. 1. The operational ice thickness on March 11th 2006 (upper left) and the ice thickness produced by HIGHTSI (upper right), estimation by the proposed method, linear (lower left) and nonlinear (lower right) methods. The values are in cm, the colorbar at the bottom is showing the color mapping.

Comparison of both the methods to measured ice thicknesses (35 measurements in February-April 2006) gave very promising results. The mean $L_1$ error for the linear method was about 8.5 cm and little more for the nonlinear method, the corresponding error for the operational method was about 8 cm. On the other hand the difference between the methods and the operational method were about 7.5 cm, meaning that they behave differently from the operational method. Subtracting the systematic error (only for this test set) the error of the new methods was very close to that of the operational method. However, we have not studied yet, whether there exists such systematic deviations in the training dataset. For detailed results, see Table 1 and Fig. 2.

We also compared the two new methods with the operational method in different areas of the Baltic Sea. These results are presented in table 2. It can be seen that the algorithm performs the best in the Bay of Bothnia (BoB) and Gulf of Bothnia (GoB). The relationship between SAR $\sigma^0$ and ice thickness is complicated and can be described only statistically. In addition, these statistical models are valid only locally [8]. Because in our case most of the training samples originated from the Bay of Bothnia and Gulf of Bothnia, the model works also with best accuracy in these areas. The statistical dependence between the radar response and ice thickness must be defined separately for each climatologically different sea areas. We note that there is a significant latitude difference between BoB, GoB and Gulf of Finland (GoF) and
Gulf of Riga (GoR). Hence, the local climate and the resulting ice cover significantly deviate from each other in these areas. Also the relative errors in the GoR and GoR are higher than in the GoB area, because the mean ice thicknesses in Gulf of Finland and Gulf of Riga are smaller. During the melting period the SAR-based ice thickness estimation did not improve the thickness values given by the model significantly. This is due to the low \( a^0 \) contrast between different ice types in wet snow conditions. Possibly this can be improved to some extent by performing a separate training for wet snow conditions.

Table 2. Comparison of the operational product and the new product in different areas of the Baltic Sea. BoB=Bay of Bothnia, GoF=Gulf of Bothnia, Quark area and the Archipelago Sea, GoF=Gulf of Finland, GoR=Gulf of Riga. L1 errors (L1) and cross-correlations (CC).

<table>
<thead>
<tr>
<th>Area</th>
<th>February-March 2006</th>
<th>April 2006 (melting period)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Brightest L1 Lin. L1</td>
<td>Brightest CC Lin. CC</td>
</tr>
<tr>
<td>GoB</td>
<td>14.86 8.13 9.17 0.279</td>
<td>15.50 11.02 11.69 0.331</td>
</tr>
<tr>
<td>GoF</td>
<td>10.22 10.70 9.28 0.595</td>
<td>11.57 9.72 10.27 0.413</td>
</tr>
<tr>
<td>GoR</td>
<td>11.57 9.72 10.27 0.413</td>
<td>11.77 11.46 10.57 0.626</td>
</tr>
<tr>
<td>BoB</td>
<td>15.50 11.02 11.69 0.331</td>
<td>16.94 22.74 15.66 0.393</td>
</tr>
</tbody>
</table>

It seems that, in general, the linear model produced slightly better results for our test data compared to measurements, but in some cases also the nonlinear model performs better. This behavior may be due to over-fitting of the nonlinear model to the training data set.

4. CONCLUSION

The results yielded by the current algorithm were clearly better than those produced by our earlier algorithm [4], the mean \( L_1 \) error for the earlier algorithm compared to the measurements was 11.8 cm. The results clearly show that this new ice thickness algorithm has potential for operational use in the area of the Baltic Sea.

There seems to be clear differences between the algorithm performance in different areas of the Baltic Sea. This suggests that the training should be performed separately for different sea areas, at least for the Gulf of Bothnia and Gulf of Finland, possibly also for the archipelago sea and Gulf of Riga. The performance during the melting period was not improved by utilizing SAR data. Applying a separate training for melting period will be studied performed to improve this situation.

With the current parameter setting the linear and nonlinear models produced rather similar results. However, the linear modulation model assumes a rather simple linear relationship between the inputs and the output, and with more input variables a more complicated model will probably be required, e.g. a generalized additive model. Another alternative for modeling the input-output relationships is to use the MLP training for learning the relationships. The optimization of the nonlinear estimation algorithm parameters will be studied and also the use of hybrid model combining the results of linear and nonlinear model will be studied. The training and test data sets will be extended to cover several years. We have SAR images and operational ITC’s for this purpose available, and we are able to make the model runs, using the also archived forcing data, for all the ice seasons with available ITC’s and SAR data.

The use and computation of the features derived from the ice motion will be studied more carefully, and also including other additional features (e.g. segment size and shape) into the classification will be studied. We also aim to study how to utilize the divergence (computed from ice motion) in open water detection. Also the usability of the algorithm in other sea areas than Baltic Sea will be studied, especially sea areas with poor or missing ice charting are in our interest.

5. REFERENCES


