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IceSynth: An image synthesis system for sea-ice segmentation evaluation

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Abstract

An ongoing challenge in automatic sea-ice monitoring using synthetic aperture radar (SAR) is the automatic segmentation of SAR sea-ice images based on the underlying ice type. Given the intractability of obtaining ground-truth segmentation data from polar regions, the evaluation of automatic SAR sea-ice image segmentation algorithms is generally limited to tests using real SAR imagery based on pseudo-ground truth data (e.g., manual segmentations) and simple synthetic tests using basic shape primitives. As such, it is difficult to evaluate automatic segmentation algorithms in a systematic and reliable manner using realistic scenarios. To tackle this issue, a novel image synthesis system named IceSynth is presented, which is capable of generating a variety of synthetic sea-ice images that are representative of real SAR sea-ice imagery. In IceSynth, SAR sea-ice textures for each ice type are synthesized via stochastic sampling based on non-parametric local conditional texture probability distribution estimates. A stochastic sampling approach based on non-parametric local class probability distribution estimates is used to generate large-scale sea-ice structures of various ice types based on ice classification priors extracted from real SAR sea-ice imagery. Experimental results show that IceSynth is capable of generating realistic-looking SAR sea-ice images that are well-suited for performing objective evaluation of SAR sea-ice image segmentation algorithms.

1. Introduction

The use of spaceborne synthetic aperture radar (SAR) imagery acquired from satellites such as RADARSAT-1/2 has become an integral part of daily monitoring of sea-ice conditions in polar regions. By operating in the microwave range (for example, RADARSAT-1 operates at 5.3 GHz), SAR allows for the acquisition of sea-ice imagery largely irrespective of time, as well as under different weather conditions such as snow and cloud cover. Based on SAR imagery, trained experts produce daily sea-ice charts that are used for a variety of operational applications such as ship navigation and and ice breaker prioritization. To analyze sea-ice conditions using SAR imagery and produce sea-ice charts manually is a very time-consuming process, since it requires the manual segmentation of ice regions and classification of ice types. Furthermore, the accuracy of the produced sea-ice charts are limited due to the intractability of performing the segmentation and classification processes by hand on a per-pixel basis.

To aid trained experts in the task of sea-ice analysis, a number of automatic techniques have been proposed for the purpose of SAR sea-ice segmentation. Current state-of-the-art automatic SAR sea-ice segmentation methods include those based on finite mixture models [1, 2, 3] and Markov Random Field (MRF) models [4, 5]. A major challenge faced in the design of automatic segmentation methods for SAR sea-ice segmentation is the lack of a common framework for systematic evaluation of such segmentation algorithms, which is important for ensuring a good transition of an algorithm from the research stage to real-world operational systems. This is largely due to the fact that it is not possible to obtain ground-truth segmentation data of sea-ice from polar regions.

The evaluation of automatic SAR sea-ice segmentation methods has been largely limited to comparisons using real SAR imagery based on pseudo-ground truth data extracted by trained experts (e.g., manual segmentations) and comparisons using simple synthetic constructed based on basic shape primitives (e.g., ellipses, circles, and rectangles). While comparisons using real SAR imagery based on pseudo-ground truth data provides a testing scenario that is representative of real-world operational tasks, the reliability of such comparisons is limited by the accuracy of the segmentations made by the trained experts, who are generally unable to provide segmentation results in a pixel level. Furthermore, given the laborious nature of producing pseudo-ground truth data, the amount of test sets is typically lim-

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ited. On the other hand, comparisons using simple synthetic images constructed from basic shape primitives are highly reliable since ground-truth data exists for the images. Unfortunately, such synthetic images are generally not representative of real SAR imagery and as such do not reflect the needs of a real-world operational system well. The underlying goal of the proposed image synthesis framework is to alleviate the issues associated with the reliability of comparisons and the realism of test data by generating synthetic sea-ice images that are representative of real SAR sea-ice imagery.

The main contribution of this paper is IceSynth, a novel image synthesis system designed to generate synthetic realistic sea-ice imagery for the purpose of systematic evaluation of automatic SAR sea-ice image segmentation methods. By utilizing sea-ice classification priors and SAR texture priors from real SAR sea-ice imagery, IceSynth is capable of generating images composed of random large-scale sea-ice structures and random SAR textures for different ice types. As such, IceSynth aims to alleviate issues associated with existing evaluation methods by allowing for the systematic and reliable comparison of automatic SAR sea-ice image segmentation methods with ground-truth data while providing testing scenarios that are representative of real-world scenarios. While SAR texture synthesis methods have been previously proposed in various research literature [6, 7, 8, 9], to the best of the authors' knowledge there are no known methods for generating SAR sea-ice textures or large-scale sea-ice structures, which are key components to the synthesis of realistic SAR sea-ice images.

This paper is organized as follows. The IceSynth image synthesis framework is described in detail in Section 2. Synthesis results using operational RADARSAT-1 SAR sea-ice imagery provided by the Canadian Ice Service (CIS) are presented and discussed in Section 3. Finally, conclusions are drawn and future work is discussed in Section 4.

2. IceSynth Image Synthesis Framework

The IceSynth image synthesis framework can be described as follows. Based on a set of texture priors, synthetic SAR sea-ice textures for each ice type is generated using stochastic sampling according to non-parametric local conditional texture probability distribution estimates. A large-scale sea-ice structural image is generated using a stochastic sampling according to non-parametric local class probability distribution estimates derived from a set of sea-ice classification priors. The generated sea-ice structural image is then combined with the set of generated SAR textures to form the final synthetic SAR sea-ice image. The generated large-scale sea-ice structural image itself acts as the ground truth for the final synthetic SAR sea-ice image. An overview of the IceSynth image synthesis framework is shown in Fig. 1.

2.1 SAR Texture Synthesis

One of the key components of the IceSynth image synthesis framework is the generation of SAR sea-ice textures for each ice type in the desired synthetic SAR sea-ice image. While there are no known texture synthesis methods in the research literature pertaining specifically to the generation of SAR sea-ice textures, the area of SAR image modelling and simulation is well established [6, 7, 8, 9]. A majority of SAR texture synthesis techniques are model-based stochastic sampling techniques, where random fields representing SAR textures are generated according to statistical models based on radar theory. Various empirical distributions have been proposed to model SAR clutter, such as log normal, Weibull, gamma, exponential, and K distributions [10]. One challenge to the use of such model-based techniques for SAR sea-ice texture synthesis is that they require the knowledge of a large number of parameters, such as the specifications of the SAR platform, imaging conditions (e.g., incidence angle), and the underlying physical properties of different sea-ice types (since the intensity of a pixel in a SAR image represents the amount of power backscattered from the target and is dependent on the target's physical properties). As such, it is very challenging to set up the parameters in such a way that realistic SAR sea-ice textures for various ice types are generated. To alleviate these issues, a different approach to SAR sea-ice texture synthesis is taken in IceSynth. Rather than utilizing model-based stochastic sampling, IceSynth utilizes an exemplar-based stochastic sampling approach where random fields representing SAR sea-ice textures are generated based on texture priors extracted from real SAR sea-ice images. The main advantage to this type of approach is that realistic textures that obey the statistical characteristics of different types of sea-ice can be generated without the need for knowledge pertaining to the SAR image platform, imaging conditions, or physical properties of the sea-ice.

The texture synthesis strategy used in the IceSynth image synthesis framework is motivated by the non-parametric stochastic sampling approach proposed by Efros and Leung [11] and can be described as follows. Suppose we wish to generate a SAR sea-ice image F characterized by n types of sea-ice. Let T_i be the synthesized SAR texture for the i^{th} ice type and $\mathrm{K}_i = \{\kappa_i^1, \kappa_i^2, \ldots, \kappa_i^m | \mathrm{K}_i \subset K_i^{\Re}\}$ be a set of texture priors, where $K_i^{\Re}$ is the real infinite texture for the i^{th} ice type. Furthermore, let S_i be the discrete lattice upon which T_i is defined, $s \in S$ be a site in the lattice, and $\aleph(s)$ be a local neighborhood around s. Finally, let SAR sea-ice textures be modeled as a Markov Random Field (MRF), where the probability distribution of $T_i(s)$

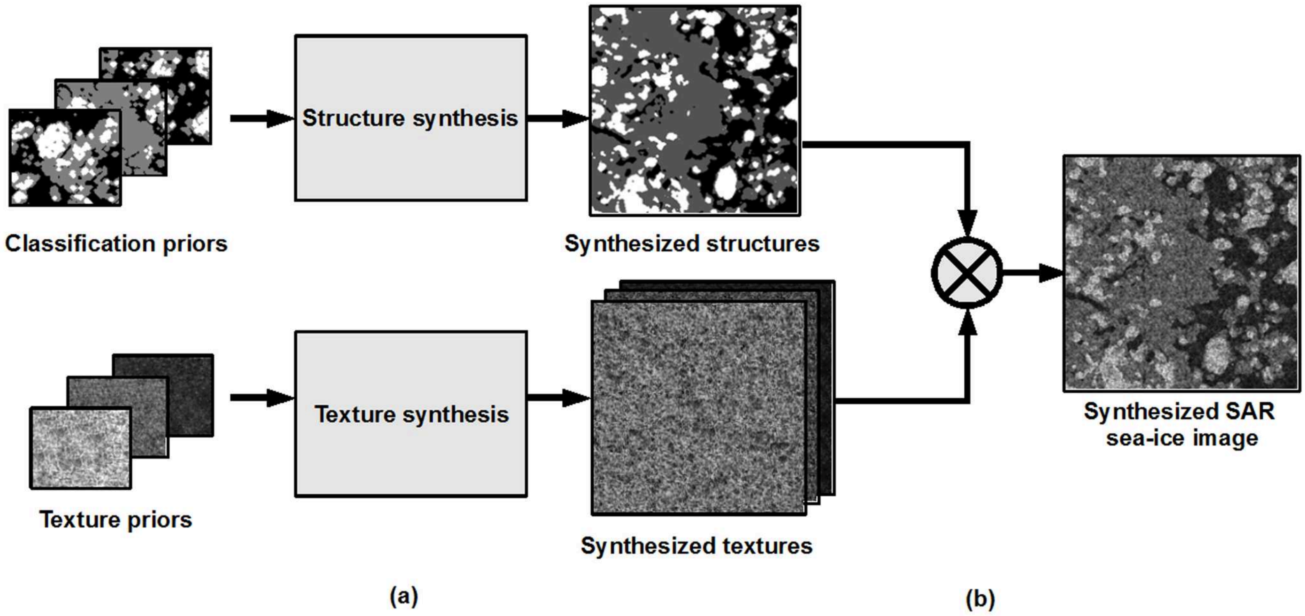

Figure 1. Overview of the IceSynth image synthesis framework: (a) Sea-ice classification and SAR texture priors are fed into the structural and texture synthesis components respectively to generate a sea-ice structural image and a set of SAR textures for each ice type. (b) The SAR textures are then applied to each type of sea-ice in the structural image to compose the final synthetic SAR sea-ice image.

given $T_i(\aleph(s))$ is independent of the rest of T_i. Based on this MRF model, $T_i(s)$ can be synthesized by drawing a random sample according to the local conditional probability distribution $P\left(T_i(s)|\aleph(s)\right)$. Given that only K_i, a subset of $K_i^{\Re}$, is known, $P\left(T_i(s)|\aleph(s)\right)$ can be estimated in a non-parametric manner with the probability distribution of all sites $\{x_1, x_2, \ldots, x_r\}$ in K_i satisfying the following condition,

$$\Psi\left(\aleph(s), \aleph(x)\right) < (1+\beta)\Psi\left(\aleph(s), \aleph(x_b)\right), \tag{1}$$

where Ψ is the cumulative Gaussian-weighted Geman-McClure [12] distance between $\aleph(s)$ and $\aleph(x)$,

$$\Psi\left(\aleph(s), \aleph(x)\right) = \sum \frac{(T_i(\aleph(s)) - K_i(\aleph(x_i))^2}{(1+(T_i(\aleph(s)) - K_i(\aleph(x_i)))^2)}, \tag{2}$$

x_b is the site in K_i that minimizes Ψ,

$$x_b = \arg\min_x \Psi\left(\aleph(s), \aleph(x)\right), \tag{3}$$

and β is the set tolerance threshold. Based on empirical tests, a suitable threshold is kept at $\beta = 0.15$. It is important to note that only a portion of the texture values in $\aleph(s)$ are known during texture synthesis process, Ψ is determined based only on the known texture values in $\aleph(s)$ and is subsequently normalized by the total number of known texture values in $\aleph(s)$. $T_i(s)$ can then be generated by sampling according to this estimate of $P\left(T_i(s)|\aleph(s)\right)$. This stochastic sampling process is repeated until all sites in SAR texture T_i has been generated.

2.2 Sea-ice Structure Synthesis

The second key component of the IceSynth image synthesis framework is the generation of large-scale sea-ice structures for the synthetic SAR sea-ice image. Due to the variety of different sea-ice structures and formations and the physical justifications that lead to such formations, it is very challenging to synthesize realistic sea-ice structures using a model-based structure synthesis approach. As such, like the SAR sea-ice texture synthesis component, an exemplar-based stochastic sampling approach is utilized in IceSynth to generate random sea-ice structures and formations based on sea-ice classification priors extracted from real SAR sea-ice images.

The sea-ice structure synthesis strategy used in the IceSynth image synthesis framework can be described as follows. Suppose we wish to generate a SAR sea-ice image F characterized by n types (classes) of sea-ice. Let Z be the synthesized large-scale sea-ice structural image, where $Z(s)$ is a random variable taking on one of n desired classes of sea-ice $\{1, ..., n\}$. Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_q\}$ be a set of sea-ice classification priors with the same n classes of ice. Finally, let S be the discrete lattice upon which Z and Ω are defined, $s \in S$ be a site in the lattice, and $\aleph(s)$ be a local neighborhood around s. To synthesize $Z(s)$, a random sample is drawn according to the local class probability distribution $P\left(Z(s)\right)$. An estimate of $P\left(Z(s)\right)$ is obtained in a non-parametric manner by taking the normalized class histogram of all sites in the local neighborhoods $\{\aleph_{\omega_1}(s), \aleph_{\omega_2}(s), \ldots, \aleph_{\omega_q}(s)\}$ for all q sea-ice classification priors. $Z(s)$ can then be generated by sampling according to this estimate of $P\left(Z(s)\right)$. This stochastic sampling process is repeated until all sites in the large-scale sea-ice structural image Z has been generated.

Once the large-scale sea-ice structural image Z has been generated, each generated SAR sea-ice texture T_i is applied to the sites in Z corresponding to the i^{th} sea-ice class to form the final synthesized SAR sea-ice image F. The large-scale sea-ice structural image Z is stored as the ground-truth data for F.

3. Experimental Results

To demonstrate the effectiveness of the proposed IceSynth image synthesis framework at generating SAR sea-ice images that are representative of real SAR sea-ice imagery, several sets of synthetic images were randomly generated based on four test sets derived from operational RADARSAT-1 SAR sea-ice imagery provided by the Canadian Ice Service (CIS). Each test set consists of five sea-ice classification priors and one set of texture priors for each ice type and can be described as follows:

Test 1: C-band HH, 100m pixel spacing, three ice types.
Test 2: C-band HH, 100m pixel spacing, three ice types.
Test 3: C-band HH, 100m pixel spacing, two ice types.
Test 4: C-band HH, 100m pixel spacing, two ice types.

The SAR sea-ice classification and texture priors contained in the test sets are characterized by various non-homogeneous sea-ice textural characteristics, as well as various sea-ice structures and formations that are difficult to recreate and synthesize using a purely model-based approach. The synthesis results for each test set are shown in Fig. 2, Fig. 3, Fig. 4, and Fig. 5. The synthesized sea-ice images from all test sets contain realistic-looking textures that capture the non-homogeneous sea-ice textural characteristics of real SAR sea-ice imagery. This is particularly noticeable in Fig. 2 and Fig. 3, where the ice floes exhibit realistic non-homogeneous textural characteristics. Furthermore, the synthesized sea-ice images from all test sets exhibit natural-looking sea-ice structures and formations. This is particularly noticeable in Fig. 2 and Fig. 5, which exhibit natural-looking ice floes and leads respectively. The synthesized sea-ice images were shown to trained experts at the Canadian Ice Service (CIS), who validated that the results exhibited natural-looking formations. This demonstrates the effectiveness of the IceSynth image synthesis framework in producing realistic-looking synthetic SAR sea-ice imagery that can be used for systematic and reliable comparison of SAR sea-ice segmentation algorithms.

4. Conclusions

In this paper, a novel image synthesis system named IceSynth is proposed for the purpose of generating synthetic SAR sea-ice images. A stochastic sampling scheme based on non-parametric local conditional texture probability distribution estimates is introduced for generating SAR sea-ice textures based on texture priors. A stochastic sampling scheme based on non-parametric estimates of local class probability distributions is introduced to generate large-scale sea-ice structures based on sea-ice classification priors. Synthesis results demonstrate the ability of IceSynth to generate realistic-looking SAR sea-ice images, thus making it suitable for use in systematic and reliable evaluation of automatic SAR sea-ice image segmentation methods. Future work involves improving the IceSynth system to allow for greater flexibility in generating SAR sea-ice images based on user-defined parameters such the proportion of different sea ice types, and floe and lead sizes.

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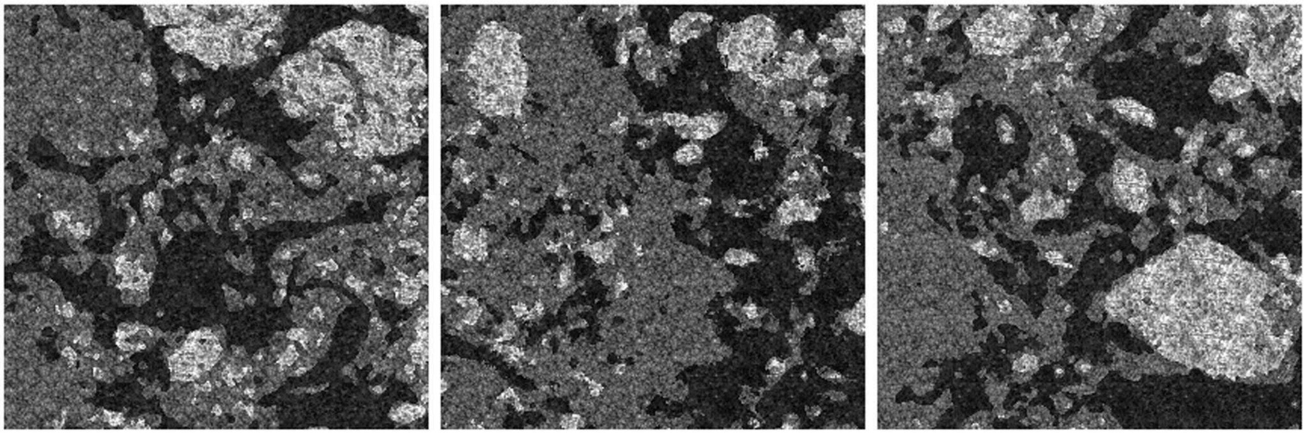

Figure 2. Synthesized sea-ice images from test set 1. The synthesized images contain natural-looking ice floes with realistic textures.

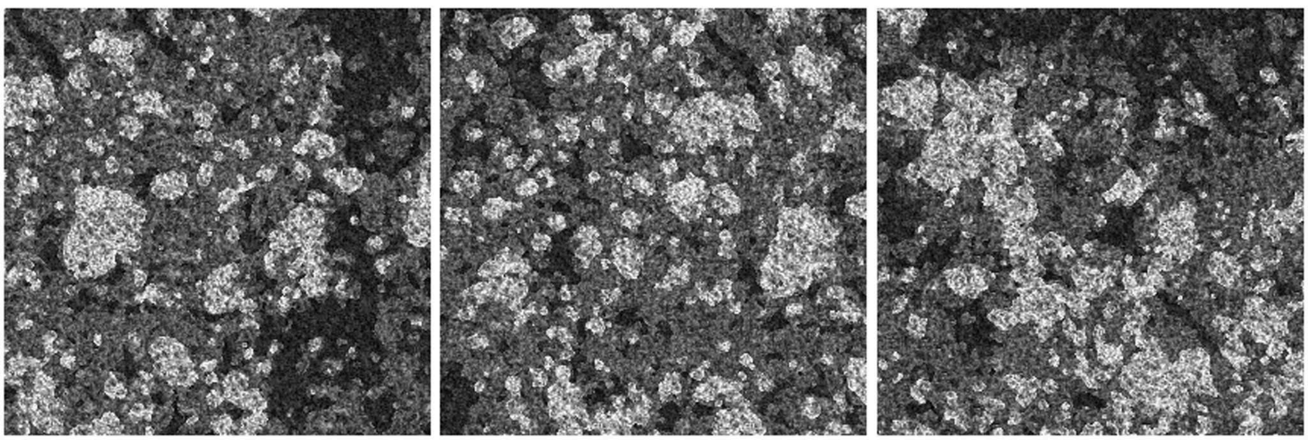

Figure 3. Synthesized sea-ice images from test set 2. The synthesized images contain natural-looking ice floes with realistic textures.

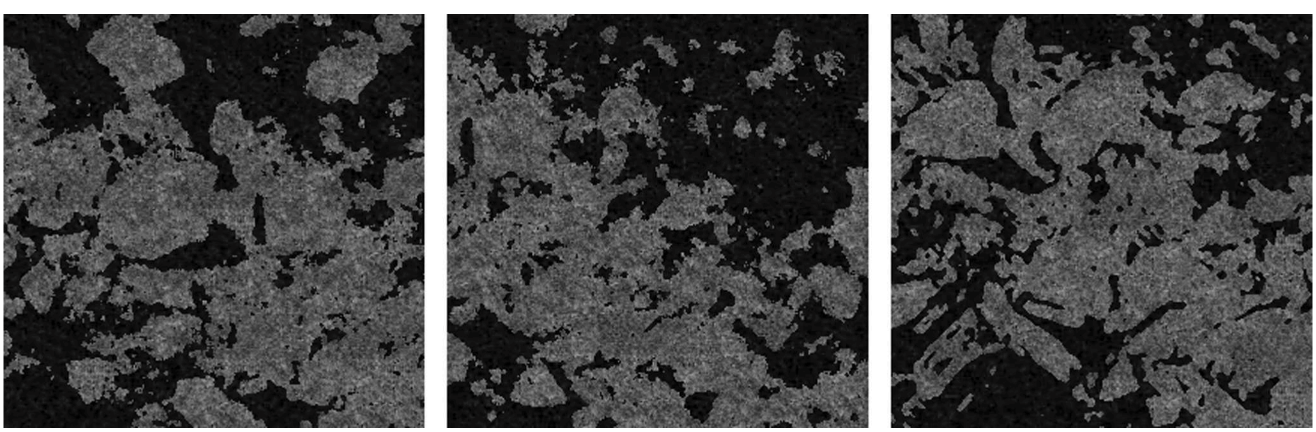

Figure 4. Synthesized sea-ice images from test set 3. The synthesized images contain natural-looking ice structures with realistic textures.

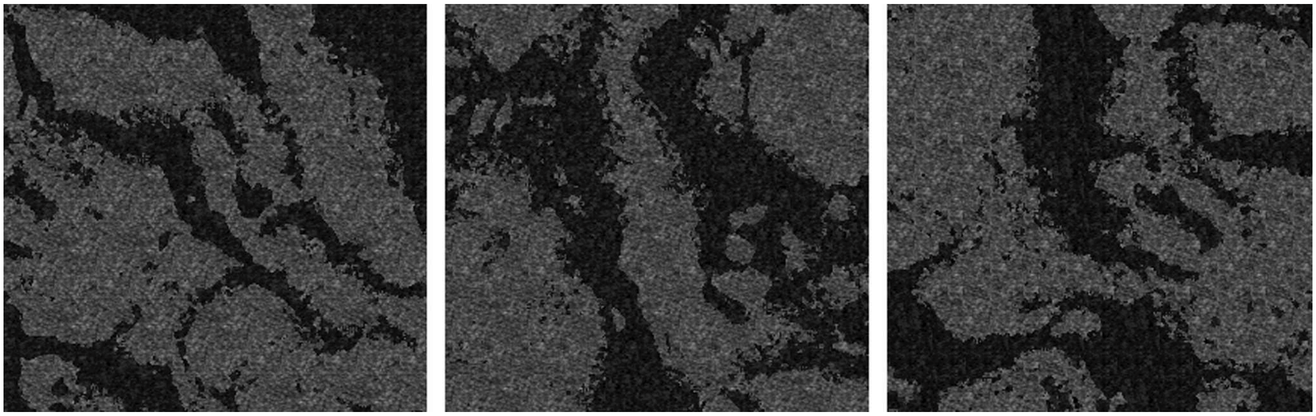

Figure 5. Synthesized sea-ice images from test set 4. The synthesized images contain natural-looking leads with realistic textures.

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