Towards a Novel Approach for Texture Segmentation of SAR Sea Ice Imagery

David A. Clausi†‡, M. Ed Jernigan†
Department of Systems Design Engineering†
Department of Geography (Earth Observation Laboratory)‡
University of Waterloo, Waterloo, Ontario N2L 3G1
dclausi@monet.uwaterloo.ca (519)885-1211 x5342

Abstract: Texture is an important aspect of identifying sea ice types in SAR imagery. The traditional grey level cooccurrence matrix has limitations that prevent its use for segmentation purposes. The Gabor filter, based on characteristics of the human visual system, is an alternative approach that can generate an improved texture feature set. Texture segmentation applied to a difficult image demonstrates the versatility and appropriateness of the Gabor approach when compared to the cooccurrence features.

I. INTRODUCTION

Exceptional volumes of data transmitted from satellite and aerial radar platforms demand the automated interpretation of remotely sensed imagery in a cost and time-effective manner. There is no known algorithm capable of performing consistent identification of the various visually distinct formations found in SAR sea ice imagery. The remote sensing community recognizes that texture is an important aspect of automated segmentation of such imagery.

A common texture feature approach for this application is the grey level cooccurrence matrix (GLCM). A grey level cooccurrence linked list (GLCLL) [3] is used to alleviate the computational demands of the GLCM. Even though the linked list dramatically reduces the computational demands, the cost of computing cooccurrence probabilities is still quite expensive. Also, the method has not been demonstrated to be sufficiently robust to solve the SAR sea ice segmentation problem. Is there any method that could generate texture features that are more reliable for discriminating SAR sea ice imagery with a reduced computational load?

[1]Funding for the primary author provided by Natural Sciences and Engineering Research Council of Canada and the Faculty of Engineering, University of Waterloo.

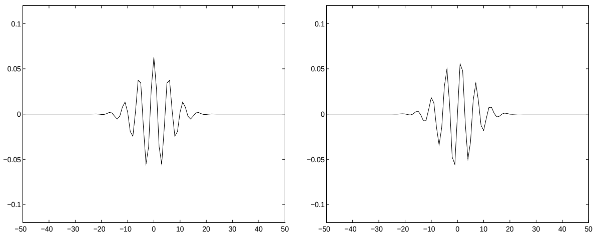
One common theme in texture analysis is the generation of features at multiple resolutions, a methodology based on known characteristics of the human visual system (HVS). A filter that is often used to perform multi-resolutional analysis is the Gabor function. This paper will first motivate and describe the use of Gabor filters. Then, Gabor filters are compared to cooccurrence probabilities in the context of a difficult texture segmentation problem.

II. BACKGROUND

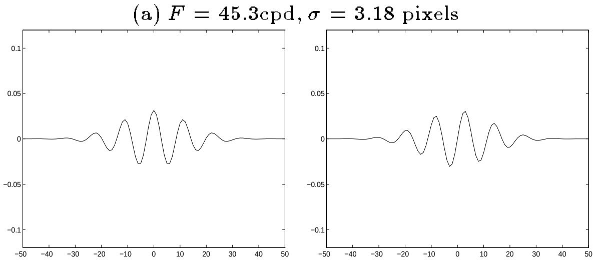
Investigations into the biological vision response to textural patterns have lead to the following fundamental understandings. Hubel and Wiesel [4] determined that vision systems are tuned to distinguish different orientations. Campbell and Robson [2] extended this model to include frequency sensitivity as well. This lead to their hypothesis that the HVS is based on multiple independent filters each tuned to a different orientation and frequency pair. Recently, research dealing specifically with texture perception has substantiated these observations. Rao and Lohse [6] determined that only three major characteristics are required for texture identification: repetition (ie. frequency), directionality (ie. orientation), and complexity (based on the regularity of the observed texture).

Gabor filters are the filter of choice for texture segmentation algorithms [1, 5]. Functionally, the Gabor filter is the product of a sinusoid with a Gaussian function. Practically, the Gabor filter can be "tuned" to specific orientations (θ) and frequencies (F). The finite effective extent of the filter is controlled by the standard deviations (σ_x,σ_y) of the 2-d dimension Gaussian. A 2-d Gabor filter is expressed as:

$$h(x, y) = g(x, y) \exp(2\pi j(Ux + Vy))$$



(a) F = 45.3cpd, σ = 3.18 pixels



(b) F = 22.6cpd, σ = 6.36 pixels

Fig. 1: 1-d Gabor functions with real and imaginary components.

where $F = \sqrt{U^2 + V^2}$, $\theta = tan^{-1}(U/V)$, and $g(x, y)$ is a two-dimensional Gaussian:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left\{\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right\}\right].$$

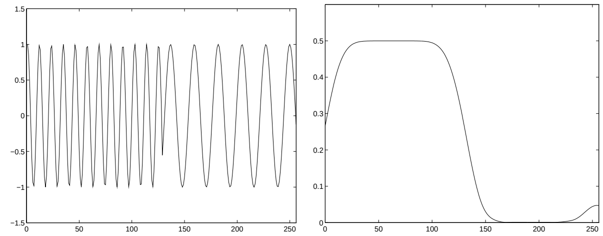
The complex exponential may be divided into real $[h_r(x, y)]$ and imaginary $[h_i(x, y)]$ components. Examples of 1-d Gabor filters are illustrated in Fig. 1. All frequencies (cycles per dimension or cpd) are based on a dimension of 256 pixels. In the frequency domain, the Gabor filter is represented by a Gaussian centred on (F,θ) with extensions inversely proportional to (σ_x,σ_y).

For a Gabor filter to work optimally, the input signal $f(x)$ is a pure sinusoid. In this case, only one Gabor filter tuned to the correct frequency is required for identification. For example, given a signal comprised of sequential sinusoids (Fig. 2) a single filter can be tuned to identify one part of the signal. This response is based on calculating the magnitude following filtering with both the real and imaginary components of the Gabor signal, ie.

$$y(x) = \sqrt{[h_r(x) * f(x)]^2 + [h_i(x) * f(x)]^2}$$

where '$*$' denotes the convolution operator. Since the DC gain of these Gabor filters is nearly zero they generate sufficiently scale invariant measurements.

Unfortunately, pure sinusoids do not make up the textural characteristics of natural imagery such as SAR sea ice imagery. Typically, SAR sea ice imagery has



(a) Sequential pure sinusoids: 22.6 and 11.3 cpd [f(x)].
(b) Response [y(x)] of (a) to filter represented in Fig. 1(b).

Fig. 2: Tuned filter response.

a more stochastic appearance, encompassing possibly more than one dominant F. Also, within the same texture, the value of F may may change gradually within local regions. In these cases, it is necessary to use multiple filters in order to capture the true essence of the texture.

III. METHODS

Given that an overwhelming number of (F, θ, σ_x, σ_y) combinations can be used, a method to reduce the number of filters is required. This can be done by implementing the Gabor function in the form of a wavelet filter bank [5]. In this form, filter center frequencies are separated by one octave (a doubling of frequency). Orientations can be set according to the four fundamental directions {0,45,90,135 degrees}. Bandwidths are set to allow full coverage in the frequency domain with minimal overlap. Thus, with increasing centre frequency, the bandwidths in the frequency domain increase causing their spatial extents to be decreased. This is an appealling characteristic since shorter time intervals are mapped to higher frequencies and longer time intervals are mapped to lower frequencies. In Fig. 1, doubling of the frequency leads to doubling the spatial extent (σ) which maintains preferred spatial localization.

When segmenting a SAR sea ice image, this mapping has tremendous potential. A wavelet transform could be applied so that compressed wavelets would identify multi-year ice types and dilated wavelets would identify smooth ice types. The characteristic line patterns of pressure ridges would have oriented frequency components that a filter could be "tuned" to isolate. Generally, the wavelet approach can take a signal, break it down into component pieces, and the manipulation of these pieces can yield features that represent characteristics of the various textures that appear in the image. Such multi-resolutional filtering gives the opportunity to dissect an image and isolate the essential

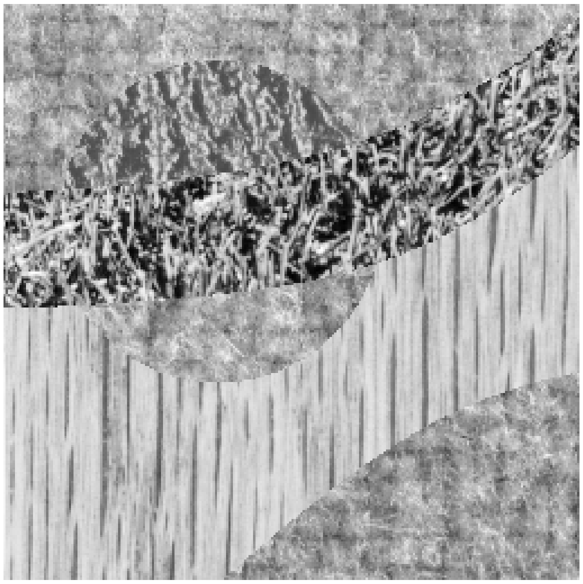


Fig. 3: Original 256x256 image.

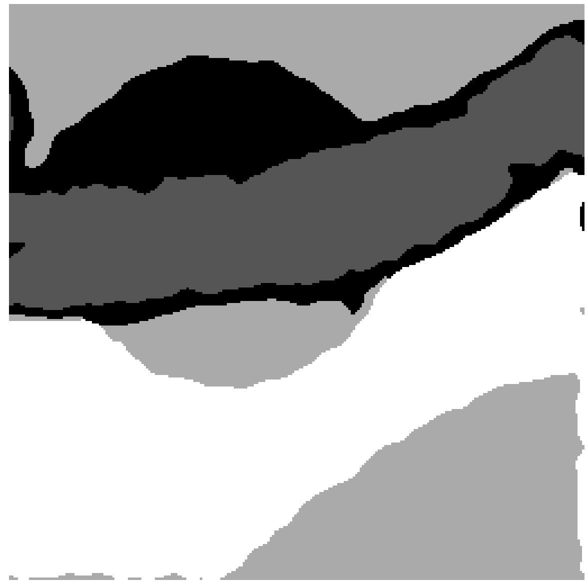


Fig. 4: Gabor wavelet segmentation.

details necessary for segmentation.

IV. TESTING AND RESULTS

In order to compare the Gabor and cooccurrence probability methods, an image comprised of Brodatz textures is used (Fig. 3). This image is difficult to segment for a number of reasons: boundaries are not geometrically regular, different resolutions are required to recognize the different textures, and one of the textures is represented at three separate spatial locations. These characteristics mimic conditions often found in SAR sea ice imagery.

The cooccurrence probabilities were determined for $\theta = \{0,45,90,135\}$ degrees, a pixel separation distance of one, and grey level quantization level of 64. Contrast, correlation, and entropy are the statistics of choice since these measurements utilize the essential information found in the cooccurrence probabilities [3]. Trials using different window sizes were used: 8x8, 16x16, and 32x32. The Gabor filters were set up in a wavelet fashion following the functionality in [1] and the configuration in [5]. Gaussian smoothing was performed on the image feature maps. Thus, each pixel in the image is represented by a N-dimensional feature vector where N represents the number of filters. The K-means algorithm is used to cluster the feature vector data. Then, an iterative Fisher linear discriminant is used to improve the classification.

The results for the Gabor segmentation is found in Fig. 4. All four texture classes are recognized. Although some boundary problems are noticed, the results are quite successful.

The best results for the cooccurrence probabilities occurred with a 16x16 window (Fig. 5). However, all the boundaries in the image were erroneously determined to belong to the same class. The 8x8 window result was too detailed and could not resolve the resolution of the wood texture since darker grains were classified to a different class than the lighter portions of this texture. Using a 32x32 window resolved this resolution problem but completely destroyed boundary identification due to considerable blurring. Both the 8x8 window and 32x32 window did not identify the class represented with the smallest area. In order to capture the best of both resolution worlds, the 8x8 and the 16x16 feature sets were combined, however, this feature set also generated poor results.

V. DISCUSSION AND CONCLUSIONS

The Gabor wavelet filtering and the cooccurrence probability approaches for texture feature extraction can be compared in a number of different ways.

- Gabor frequency domain filtering is computationally faster. For the above implementation, the cooccurrence features (with 16x16 windows) took approximately three times as long per feature when compared to the Gabor technique.

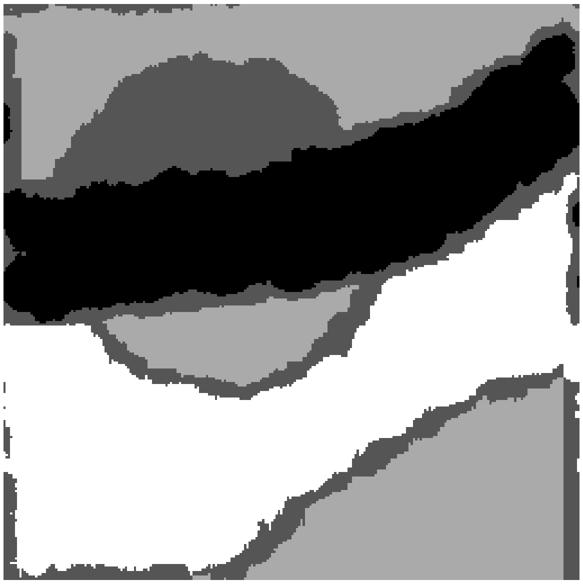


Fig. 5: Cooccurrence segmentation (16x16 window).

- The Gabor function mimics critical aspects of the HVS. The moment statistics of the cooccurrence probabilities can perform a similar task [3].
- The identical Gabor filter configuration can be successfully applied to a wide variety of imagery. In contrast, there is considerable uncertainty about which parameters to choose for the cooccurrence probabilities from image to image.
- To implement the cooccurrence technique with anything but $\{0,45,90,135\}$ degrees of orientation is awkward. The Gabor filters can easily operate using any orientation. This is important because the resolving capacity of the HVS is estimated to be about 30 degrees [4].
- Gabor filters use a Gaussian weighting. The uniform distribution used by the cooccurrence approach leads to poorer boundary identification. A Gaussian neighbourhood could be used, however, the updating ability of the GLCLL approach could not be used simultaneously [3].
- The Gabor wavelet filtering is inherently multi-resolutional. The cooccurrence technique could use multiple windows, but *a priori* selection of window sizes would be difficult.
- In order to run at a reasonable speed, cooccurrence probabilites require grey level quantization which may destroy important information. Gabor filters operate at the same speed for any grey level quantization.

The Gabor filtering approach holds considerable promise for the texture segmentation of SAR sea ice imagery. Further research is required in order to generate improved texture features based on these filters as well as dedicated, completely unsupervised methods to classify the feature vectors.

ACKNOWLEDGEMENT

Santhana Krishnamachari is thanked for providing the Brodatz collage used for testing.

REFERENCES

[1] A.C. Bovik, M. Clark, and W.S. Geisler. Multichannel texture analysis using localized spatial filters. *IEEE Trans. Pattern Anal. Machine Intell.*, 12(1):55–73, Jan 1990.

[2] F.W. Campbell and J.J. Kulikowski. Orientational selectivity of the human visual system. *J. Physiol.*, 187:437–445, 1966.

[3] D.A. Clausi and M.E. Jernigan. A fast method to determine cooccurrence texture features and its applicability to image interpretation. In *26th Symposium on Remote Sensing of Environment and 18th Annual Symposium of the Canadian Remote Sensing Society*, Mar 1995.

[4] D.H. Hubel and T.N. Wiesel. Receptive fields and functional architecture in two nonstriate visual areas (18 and 19) of the cat. *J. Neurophysiol.*, 28:229–289, 1965.

[5] A.K. Jain and F. Farrokhnia. Unsupervised texture segmentation using Gabor filters. *Pattern Recognition*, 24(12):1167–1186, 1991.

[6] A.R. Rao and G.L. Lohse. Identifying high level features of texture perception. *CVGIP: Graphical Models and Image Processing*, 55(3):218–233, May 1993.