Adaptive Multiresolution Quantization for Contextual Information Gain in SAR Sea Ice Images

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Abstract – In this paper we describe an adaptive multiresolution technique that quantizes SAR sea ice images to improve contextual information such as the spatial, relational make up of ice types in a region. First, we use dynamic local thresholding to extract regional intensity threshold values from which a histogram is constructed. Next, we blur the threshold histogram with varying window sizes to build a multiresolution contour map. We identify peaks based on a cumulative distribution function and track each peak on the contour map to assess its significance. Then, for each significant peak identified, we cluster the threshold values extracted during dynamic local thresholding using nearest-neighbors to establish sets of threshold values. Finally, we assign a pixel its quantization value by comparing its original intensity to the set that it belongs to. The technique handles noise and preserves contexts, ensuring a consistent and smooth quantization of the image. We have applied the technique to a large number of ERS-1, ERS-2, and RADARSAT images to obtain quantized representation of the images for contextual information gain. We have also embedded the technique in an unsupervised sea ice segmentation tool that has been installed at the National Ice Center and the Canadian Ice Service.

INTRODUCTION

SAR sea ice images contain noise that might hinder computer-based image understanding and pixel values that can be omitted without loss of useful intrinsic information and with gain of desired contextual information. Hence, our adaptive multiresolution quantization technique has been designed to re-represent images to highlight their contexts and suppress their non-essential details. The technique increases the visual interpretability of the image and allows image compression for more efficient storage.

Briefly, we employ dynamic local thresholding [1] to extract regional intensity threshold values from which a histogram is constructed. Then, we blur the histogram several times with varying window sizes (scales) to obtain a multiresolution contour map. We track peaks on this map to measure each peak's significance. Given the set of significant peaks, we cluster around each significant peak a set of non-significant peaks. Next, we perform adaptive quantization using these clusters for regional and pixelwise interpolations.

Our technique can be used as either an assistant to human operators or a standalone module for a certain stage of the operations. As part of our sea ice segmentation tool [2], the technique reduces the computational burden on subsequent modules and enhances the results as well.

In the following, we first describe the methodology of our technique. Second, we discuss the multiresolution peak detection algorithm in greater detail. Third, we demonstrate through an example how the technique performs. Finally we conclude the paper.

Note that we see contexts as regional compositions of ice types. Different contexts are found as different ice types co-exist in different situations due to different geographical locations and seasonal temperatures. Compared to surface textures, these contexts are more reliable properties for image manipulation since they are of a second-order perception level of sea ice features and thus more resistant to noise-corruption.

METHODOLOGY

Our design is based on dynamic local thresholding, data reduction [3], and multiresolution processing [4]. Dynamic local thresholding allows us to handle local contexts within the image's global constraints, while enabling information to be preserved across local regions adaptively. Dynamic local thresholding has been used in SAR sea ice segmentation [5]. Image analysis at a fine resolution yields noise and unnecessary details and at a coarse level distorts local deviations. Thus, multiresolution processing is used to fuse information at various scales of resolution [4].

Dynamic Local Thresholding

First, to extract data points to build a histogram that holds contextual information, we divide the image into smaller, overlapping regions. For each bimodal region, we derive an adaptive threshold via maximum likelihood. These threshold values hold the bisector value of each region, encrypting certain local contextual information of the image. We collect the thresholds and build a histogram, from which significant peaks will be extracted using multiresolution processing. Readers are referred to [5] for a detailed discussion of this algorithm.

Multiresolution Processing

Next, we blur the histogram of threshold values with varying window sizes to construct a contour map, identify peaks based on a cumulative distribution function, and track each peak through the scale space to assess each peak's

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significance. For each significant peak identified, we then cluster non-significant thresholds using nearest-neighbors to create a set. When traversing the map, we evaluate the significance of each peak based on several observations: (1) low-resolution peaks are more significant, (2) high-resolution peaks are more accurate, (3) neighboring peaks suggest a significant peak, and (4) the significance of a peak is proportional to its height. The underlying single-resolution peak detection design is based on the data reduction technique detailed in [3].

Adaptive Quantization

Each regional threshold falls within a set. For N peaks, we have N sets. For each set, we perform a regional interpolation to assign to each region without a derived threshold value an interpolated threshold value. Next, we perform a pixelwise interpolation to assign each pixel of each region a threshold value. Thus, after performing the interpolations for N sets, each pixel will have N thresholds. We assign a pixel, p, a new value of $c(p) = j \cdot 256/Q$, $t_{p,j} \leq g(p) < t_{p,j+1}$, where Q is the number of quantization levels, $g(p)$ is the original gray level of p, and $t_{p,i}$ is the ith-threshold value of the pixel. Note that our quantization scheme does *not* necessarily assign same-intensity pixels to the same quantization level or class. The decision depends on the local context that surrounds the pixel, thus taking into account possible intensity range and contrast inconsistencies in the image.

MULTIRESOLUTION PEAK DETECTION

Histogram-based peak detection techniques inherently do not handle noise well. Our multiresolution peak detection addresses the problem by blurring the histogram at various window sizes and then collecting significant peaks by traversing the contour map. Our peak detection design is based on using the cumulative distribution function (CDF) of the histogram [3]. First, we generate a peak detection signal from the histogram. Then, we locate the histogram peaks using the zero-crossings of the peak detection signal and the local extrema between the zero-crossings. To obtain the peak detection signal, we convolve the histogram's CDF with a kernel of size Ω. Different sizes of Ω result in different degrees of blurring.

Given the image histogram, H_T, for each Ω, we compute $\overline{cdf}_{T,\Omega}(t) = \left(\sum_{i=t-(\Omega-1)/2}^{t+(\Omega-1)/2} cdf_T(i) \right) \Big/ \Omega$ and the peak detection signal as $\eta_\Omega(t) = cdf_T(t) - \overline{cdf}_{T,\Omega}(t)$. Given the signal, we proceed to find the peaks, represented by a triplet $\left\langle \omega_i^s, \omega_i^m, \omega_i^e \right\rangle$, for the starting point, maximum point, and the ending point of a peak, respectively. We also register each peak in the set P_Ω. The local weight of a peak is:

$$W_\Omega(\omega_i^m) = \frac{\eta_\Omega(\omega_i^m) - \eta_\Omega(\omega_i^m - 1)}{1 + \eta_\Omega(\omega_i^m) - \eta_\Omega(\omega_i^m - 1)} + \frac{H_T(\omega_i^m)}{M \cdot N_{scale}},$$

where M is the highest bin frequency, and N_{scale} is the number of resolution levels. The first term in the above equation measures the dominance of the peak—the magnitude of the positive cross over. The second term measures the significance of the peak—the frequency of the bin in the original threshold histogram.

To track peaks, we analyze the contour map. For a peak situated at t in the set of peaks, P_Ω, we modify its weight:

$$W_\Omega'(t) = W_\Omega(t) + \sum_{j=t-(\Omega-1)/2}^{t-1} \frac{P_\Omega(j)}{|j-t|} + P_\Omega(j) + \sum_{j=t+1}^{t+(\Omega-1)/2} \frac{P_\Omega(j)}{|j-t|}.$$

The two summation terms collect the neighboring peaks as evidence for t as a peak, weighted by the distance of those peaks from t. The single term $P_\Omega(t)$ serves as a self-assurance weight. Next we sum the weights together across all resolution levels. When consecutive peaks are found, we merge the peaks and create a new peak at the heaviest location in the continuum. Finally, we select peaks with a weight greater than 0.5 N_{scale} as quantization peaks, requiring an isolated peak to survive at least half the number of blurring levels.

AN EXAMPLE

Here we show an example of the application of our adaptive multiresolution quantization technique on SAR sea ice images. Fig. 1 shows an original ERS-1 image.

Fig. 1 An ERS-1 image (Mar 26, 1992, 72.86N, 143.84N). Copyright ESA.

Fig. 2 shows the multiresolution map of the thresholds. Numbers before the parentheses indicate the bin or threshold values detected as peaks at each scale. Numbers in parentheses denote the accumulated weights for the corresponding peaks. For example, for the peak value at 32, its weight gradually improved from 1.09 to 6.43.

Ω=13: 32(1.09) 39(1.08) 47(1.29) 52(1.32) 83(1.47) 89(1.44)
Ω=11: 32(2.17) 39(2.37) 44(1.62) 47(2.91) 52(2.64) 83(2.77) 89(2.72)
Ω=9: 32(3.26) 39(3.70) 42(1.92) 44(3.54) 47(4.36) 52(3.77) 69(1.19) 83(4.08) 89(3.99)
Ω=7: 32(4.35) 39(5.54) 41(2.92) 42(4.75) 44(5.71) 47(5.78) 52(4.90) 57(1.90) 61(1.14) 69(2.38) 83(5.38) 89(5.49) 91(1.83)
Ω=5: 32(5.43) 39(7.04) 41(5.42) 42(7.25) 44(7.21) 47(6.90) 52(6.03) 57(2.21) 61(2.28) 65(1.14) 69(3.56) 79(1.21) 83(6.68) 86(1.77) 88(2.71) 89(7.99) 91(3.66) 94(1.28) 99(1.21) 108(1.12)
Ω=3: 32(6.43) 39(8.04) 41(7.42) 42(9.25) 44(8.21) 46(2.09) 47(8.90) 52(7.15) 55(1.09) 57(3.33) 61(3.43) 65(2.29) 69(4.73) 74(1.21) 78(2.24) 79(3.21) 83(7.98) 86(3.04) 88(4.71) 89(10.25) 91(4.98) 94(2.56) 97(1.23) 99(2.42) 108(2.23)

Fig. 2 The multiresolution map of the thresholds. At the highest resolution level (Ω=3), all threshold values with a weight higher than 3 (half of the number of resolution scales) were selected as significant peaks. Peaks at 41 and 42 were merged, so were peaks at 88 and 89.

After peak merging and filtering, 14 significant thresholds and thus 15 quantization levels were found. Fig. 3 shows the result of our adaptive multiresolution quantization technique.

Fig. 3 The quantized image of Fig. 1. There are only 15 quantization levels and the contextual information of the image has been improved visually.

As observed, the contexts of the image are more clearly defined, compared to the original image. The multiyear class which dominates most of the image is now identified as a single intensity class, eliminating the need to process various pixel values and noise effects computationally and enhancing visual inspection. Moreover, the original image in GIF requires 935460 bytes to store, while the quantized image in GIF requires only 160116 bytes to store—an improvement of 82.88% in memory storage space.

CONCLUSIONS

We have applied our quantization technique to more than 300 ERS-1, ERS-2, and RADARSAT images and have found it to be effective in improving the contextual information while reducing the computational burden (time and speed) for later stages of image processing. We have embedded the technique in our sea ice segmentation tool called ASIS (Automated Sea Ice Segmentation) [2]. The technique acts as a pre-processing module before ASIS performs computation-intensive tasks on clustering the image pixels into segmentation classes.

In conclusion, we have described a technique that combines dynamic local thresholding, data reduction, and multiresolution processing—a synergism that allows our algorihtm to consider local details and disregard noise effects. It is adaptive because the pixels are allocated to quantization bins based not only on their intrinsic gray levels, but also their surrounding regions and pixels. This allows the selection of thresholds to follow the activities of the image across local regions, thus achieving contextual information gain for better visual interpretability and more efficient computer analysis.

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