AN UNSUPERVISED METHOD FOR EQUIVALENT NUMBER OF LOOKS ESTIMATION IN COMPLEX SAR SCENES

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ABSTRACT

This paper introduces a novel unsupervised estimator of equivalent number of looks (ENL) that can be applied to an arbitrary image. It avoids the assumption that homogeneous speckle will dominate the investigated image that is followed by current unsupervised ENL estimators but not always valid, especially for the complex SAR scenes with high mixture and texture. Incorporating the statistical properties of ENL data into an automatic segmentation method, we isolate the sub-class affected least by mixture and texture and suggest taking the mean value of this class as the final ENL estimate. The proposed estimator is evaluated in the experiments performed on simulated and real data from two very different sensors. It always gives better results than the other two existing methods and possesses greater adaptability.

Index Terms—equivalent number of looks (ENL), unsupervised estimation, complex SAR scene

1. INTRODUCTION

The equivalent number of looks (ENL) is a parameter of multilook synthetic aperture radar (SAR) data, which describes the degree of averaging applied to the SAR measurements. It is an important parameter for statistical modeling of multilook SAR data and has influence on the accuracy of important classification and change detection algorithms for SAR and polarimetric SAR (PolSAR) data. The ENL is commonly estimated by manually selecting homogeneous regions in an image. However, a processing chain of PolSAR data will clearly benefit from having a robust and automatic estimation method.

Some attempts have already been made to design a fully automation estimation algorithm that avoids manual selection of a region of interest. Anfinsen et.al [1] propose an unsupervised strategy to estimate ENL for an arbitrary SAR scene. Its basic idea is that the estimator is implemented in small windows over the whole image. Then the mode value of the distribution of small sample estimates is used as the ENL. This idea is based on the assumption that no texture and fully developed speckle will dominate the population of small window estimates. The estimator, suggested by these authors, to be implemented on each window is the ML estimator in [1], which pursues the maximum likelihood estimate of ENL based on the Wishart statistical properties of the covariance matrix. We also call this unsupervised method the ML estimator in the remained part of this paper.

However, some limitations are readily observed with this estimator, just as the literature [1] admits, the above assumption is incorrect for some complex land cover regions with high texture and mixtures. Subsequently, some further research has been carried out. Liu et.al [2] basically follow the unsupervised strategy in [1], but replace the ML estimator with a new estimator, Development of Trace Moments (DTM), which cancels the textural variation based on the product model of SAR data. The disadvantage of this method is that it becomes invalid when applied to the images containing many mixtures of different classes, because mixtures do not follow the product model distributions. It is still necessary to find a more robust and unsupervised estimation for complex SAR scenes. Our work is motivated by this concern. An improved way will be addressed in this study by introducing automatic segmentation to analyse the ENL distribution.

2. METHODOLOGY

For some complex SAR scenes, such as urban regions or sea ice, many estimation windows will contain a mixture of pixels from different classes, or texture. However, those estimates from the windows only covering a single homogeneous class can still reflect the actual ENL value. Therefore, our strategy is to cluster the ENL data with a statistic model and then determine the homogeneous sub-cluster for further estimation.

First of all, we still need to implement an estimator in small windows over the whole image to obtain the ENL samples. Within the two existing estimators, we recommend the ML estimator for our algorithm. Since our idea is to find the homogeneous region through clustering based on ENL distribution, with the ML estimator, the estimate data from the homogeneous part may be easier to be isolated from other samples, as it does not deliberately overlap the influence of texture as the DTM estimator does. For the DTM estimator, its ENL distribution is relatively heavytailed, as shown in the later section of experiments. It is not easy to find a suitable statistical model for such a distribution. Besides, comparing with ML estimator, it has higher variance, which means more serious class mixing in the ENL distribution. All these factors will reduce accuracy of further clustering.

Next, an appropriate statistical model for ENL data should be found. It is worth noting that the ENL distribution, even for the homogeneous region, is not Gaussian, nor symmetric, in profile. Furthermore, ENL only has a positive value, thus its distribution is also positive only. The Fisher-Snedecor (FS) distribution [4] can cover very flexible range of non-symmetric positive distributions and therefore is quite suitable in this case. The FS distribution is a traditional F-distribution extended with a location parameter. It can be described by

$$p(t)=\frac{\Gamma(\xi+\zeta)}{\Gamma(\xi)\Gamma(\zeta)}\frac{\xi}{\mu(\zeta-1)}\frac{\left(\frac{\xi}{\mu(\zeta-1)}t\right)^{\xi-1}}{\left(\frac{\xi}{\mu(\zeta-1)}t+1\right)^{\xi+\zeta}} \quad (1)$$

where ξ and ζ are two shape parameters and μ is a location parameter and identical to the actual mean value.

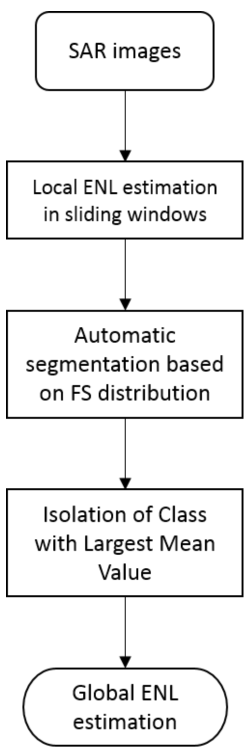


Fig. 1 workflow of new strategy

Doulgeris and Eltoft[3] have already proposed a more general segmentation algorithm, which can automatically determine how many clusters are needed to fit the data. Following the basic process framework of this segmentation algorithm, we change the fitting model to the desired FS distribution model. Then after input into the automatic segmentation, the ENL data can be divided into several classes. We choose the distribution with the largest mean as the class that is least affected by texture and mixture. Then we suggest taking the model mean parameter μ of this class as the ENL estimation of the whole image. Furthermore, the above model is just a preliminary one, as it does not fit ENL data perfectly. Other models are still worth exploring.

The workflow of the new strategy is shown in Fig. 1.

3. EXPERIMENTS

We use experiments with simulated and real data to compare our method with the two existing unsupervised estimators.

3.1. Experiment I: Simulated Multilook PolSAR data

To compare the robustness of the proposed estimator and the previous ones, we generate a four-class PolSAR images with high texture and mixtures. The simulated image is 256X256 in size. We divided the images into 32X32 blocks, each of which is 8X8 in size. To present the high mixture in the image, the four classes randomly occupy the same number of blocks in the simulation. One such test pattern is shown in Fig. 2. The class-specific covariance matrices are computed from samples of real data. Each class of data follows a matrix-variate K distribution with different degrees of texture, which increase with decreasing values of distribution parameter α_L [4]. The parameter values of the four classes ranges from that of a strongly heterogeneous environment to that of a homogeneous region. The number of looks for all classes is set to 25.

We estimated the ENL of the simulated data with the three methods. The estimation windows for all the three methods are 5X5 in size. This size can guarantee that some windows contain mixture while others cover uniform regions. All the estimates are shown in Table 1. It illustrates that only the proposed method is close to the preset number of looks. The Fig. 3 and Fig. 4 display the distribution of ENL estimates obtained by the ML and DTM estimators, respectively. We see that for the high texture and mixture, the mode values of both distributions are deviated from the preset number of looks.

For the ML estimator, it will be affected by both texture and mixture factors. The multi-peak values in its ENL distribution are mainly caused by different degrees of texture.

However for the DTM estimator, the corresponding distribution only has two peak values. As described in the literature [2], this estimator is robust for the texture effect. The underestimation peak is caused by the mixtures in the

estimation windows that do not generally follow the product texture model. Comparing the histograms in Fig. 3 and Fig. 4, we can notice that the one obtained by DTM have a relative heavy tail, which cannot be fitted well by the FS distribution. If we can find some suitable statistical model, the DTM estimator would be worth consideration for embodying in the proposed unsupervised method.
The Fig. 5 shows the classification result based on the ENL histogram for the proposed estimator. We see the relative low ENL values dominate the histogram for the high texture and mixture in the image. Though there are only four classes of simulated SAR data, the ENL values estimated from mixed area will be split as new classes. That is why there are more classes than the actual classes in the simulated image. However, there are still some small parts of image free from these two factors, which contribute to the final estimate.

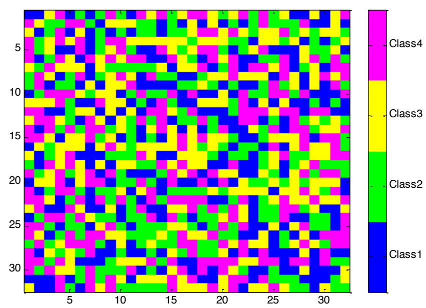


Fig. 2. Label map for test pattern, each of the 32X32 color blocks contains 8X8 pixels

Table. 1. ENL estimates for simulated data

Estimator	ML	DTM	Proposed
ENL estimates	4.9	5.3	24.3

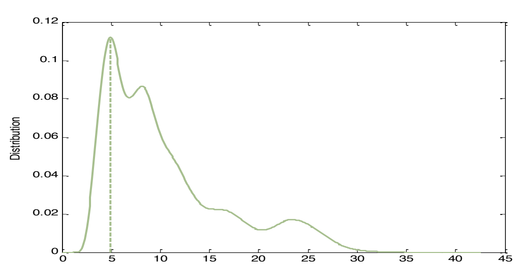


Fig. 3. Estimate distribution of ML

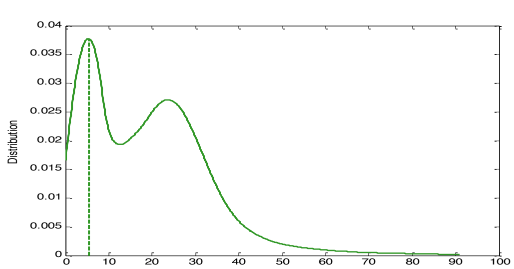


Fig. 4. Estimate distribution of DTM

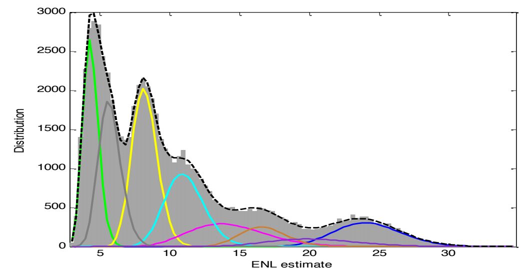


Fig. 5. Classification result on the ENL histogram

Table. 2. Time consumption of different methods

Estimator	ML	DTM	Proposed
Time consumption(s)	20.43	15.6	80.40

Here we also present the comparison on the computational complexity between the tested algorithms. All algorithms are implemented in Matlab language and the test is carried on a 2.80-GHz Intel Xeon processor. The time consumptions of the three algorithms are shown in Table. 2. From the table, we notice that DTM method has lowest computational cost, followed by the ML method, and the proposed method spends three more time than the ML. This is expected since the proposed method actually adds an automatic clustering process at the end of ML method. And the extra time cost depends on the complexity of the images. As the simulated image is much more complex than some real SAR images, therefore in practice the time consumption of the proposed method should be lower and can be even reduced if we subsample the ENL values from the sliding windows. Such cost is tolerable to get accurate ENL estimate.

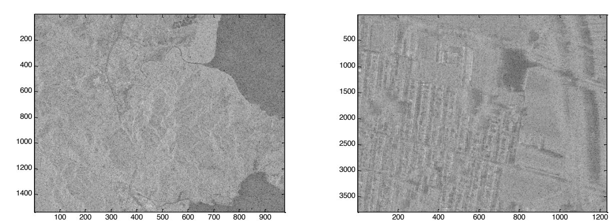
5.2. Experiment II: Real Multilook PolSAR data

We choose to use two real data sets for our experiments, which is shown in Fig. 6(a) and Fig. 6(b). The first dataset is mountainous seaside near San Francisco, acquired by Radarsat-2 Quad Polarized mode. As shown in Fig. 6(a), its landscape consists of homogeneous open water and heterogeneous mountain region. The second is the image of a village in Hebei, China, acquired by the full-polarimetric X-band airborne SAR system, CARSS (Chinese Airborne Remote Sensing System). As shown in the Fig. 6(b), a large area is covered by man-made structures. Hereinafter, we called the two image as region (a) and (b), respectively.
First, the ENL values are estimated in a sliding window of size 5X5 pixels, covering the whole images. The distributions of these estimates are shown as the gray histograms in the Fig. 7(a) and Fig. 7(b), for region (a) and (b), respectively.
From the histograms of the two images, we notice that both distributions have a wide range of estimated ENL values and their mode values are relatively low.

Then we implemented the automatic segmentation method on these two data sets. The sub-classes are shown in Fig. 7(a) and Fig. 7(b). Then the far right sub-cluster distribution, which is plotted in blue, represents the class that is affected least by mixture and texture and the mean of these distributions are taken as the ENL estimation.

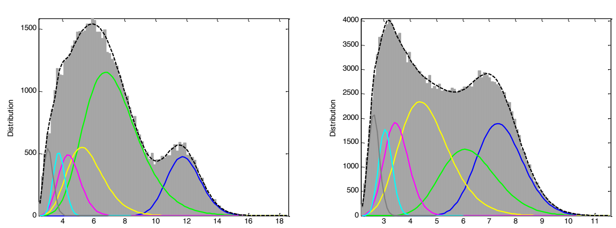
For comparing, we also implement the ML and DTM estimator on the experiment data. Furthermore, we manually choose the homogeneous region in the same images and use the ML estimator to obtain the local ENL value, which can be set as the reference ENL of the whole image. All these estimates are recorded in the Table. 3. From this table, we notice that the proposed estimator can obtain a value closer to the reference ENL for these two complex scenes.

After clustering the ENL samples, the label maps of these regions can also be provided, as shown in the Fig. 8(a) and Fig. 8(b). Here, each pixel is labeled with the corresponding color of the cluster it belongs to. Then the blue part in Fig. 8(a) and Fig. 8(b), are the samples for the sub-cluster used for ENL estimation. By interpreting the covered region, the chosen pixels represent the open water and uniform farmland, which are actually the homogeneous part of these images.



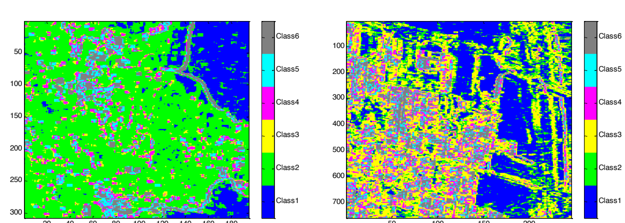
(a) (b)

Fig. 6 Two datasets for ENL estimation



(a) (b)

Fig. 7 Histograms of ENL samples and clustering results



(a) (b)

Fig. 8 Label Map of two datasets

Table. 3. ENL estimates for two real datasets

	Reference Value	ML	DTM	proposed
Region (a)	11.9	5.8	9.2	11.9
Region (b)	7.9	3.2	6.9	7.6

4. CONCLUSIONS

We have developed a novel unsupervised approach to estimate ENL for an arbitrary image. It has no limitation on the presumption of fully developed speckle dominance. By clustering the ENL data estimated from small windows over the whole image, the sub-cluster affected least by mixture and texture effects can be isolated. Therefore more precise ENL value of the whole image can be obtained automatically even for complex SAR scenes. The proposed method has been tested on two datasets from very different sensors, which verifies the generality of this method.

5. ACKNOWLEDGE

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6. REFERENCES

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