SYNTHETIC APERTURE RADAR IMAGE ENHANCEMENT USING PARTICLE FILTERS*

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ABSTRACT

In this paper, we propose a novel approach to reduce the noise in Synthetic Aperture Radar (SAR) images using particle filters. Interpretation of SAR images is a difficult problem, since they are contaminated with a multiplicative noise, which is known as the "Speckle Noise". In literature, the general approach for removing the speckle is to use the local statistics, which are computed in a square window. Here, we propose to use particle filters, which is a *sequential Bayesian technique*. The proposed method also uses the local statistics to denoise the images. Since this is a Bayesian approach, the computed statistics of the window can be exploited as *a priori* information. Moreover, particle filters are sequential methods, which are more appropriate to handle the heterogeneous structure of the image. Computer simulations show that the proposed method provides better edge-preserving results with satisfactory speckle removal, when compared to the results obtained by Gamma *Maximum a posteriori* (MAP) filter.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) imagery has been widely used in many areas from earth observation to space exploration. Since it is not dependent on weather conditions, it is widely preferred to optical satellite imagery. Moreover, its ability to penetrate through clouds make it an invaluable tool both for earth observations and planet explorations, such as the case in Magellan mission of NASA, where the surface of planet Venus is mapped by the SAR of Magellan probe, which can penetrate the dense, sulphurous clouds shielding the planet's surface.

Despite its advantages, SAR imagery suffers from the multiplicative noise, which is also known as the "speckle". In literature, generally the speckle noise is transformed from a multiplicative one to an additive one using logarithmic transformation [1, 2]. Additionally, there are also some adaptive filtering techniques, such as the Kuan [3], Lee [4], Frost [5] filters, which are based on computing the local statistics of the image in a fixed window. One of the major problems of these techniques is the trade-off between the image resolution and the speckle removal, arising from the selection of the window size. If the window size is taken to be large, the speckle removal becomes more effective with the price of the degradation in the image resolution [2, 6]. In [6], the Gamma filter, which is a MAP estimator, is proposed, where the texture and the speckle are modelled by Gamma distributions. There are also some wavelet denoising techniques [2, 7], as well as different modelling methods [8], which are used in the literature.

In this work, we propose a novel approach, utilizing the use of particle filters for speckle removal. To the best of authors' knowledge, this is the first application of particle filters to the denoising of SAR imagery. Particle filters are Bayesian methods, where the *a priori* information is taken into account and the disadvantages of the MAP estimation techniques are avoided [9,10]. Moreover, since particle filters are sequential methods [9,10], they are very suitable for non-stationary applications [11, 12]. In this case, the heterogeneity of the image can be thought of as a spatial non-stationarity. Computer simulations show that the proposed particle filter approach removes the speckle noise satisfactorily, while preserving the spatial resolution better compared to the Gamma filter.

The rest of the paper is organized as follows: First, brief background information on SAR image models and the particle filters are given, which are followed by the detailed information on the proposed method. Then, computer simulations are shown and the conclusions are drawn.

2. SAR IMAGERY AND THE GAMMA FILTER

An observed SAR image y, can be modelled as a multiplication of the texture x (radar reflectivity) with the speckle noise n, as follows:

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$$y_k = x_k n_k \quad , \quad k = 1,2,..., N^2 \qquad (1)$$

where, k denotes the relevant pixel index in the vector, which is formed by concatenating the rows of the two dimensional window of size NxN. In literature, various probability density functions (pdf) are used to model the statistical properties of the observation, texture and the speckle. One possible model for both texture and speckle are Gamma distributions [6]:

$$p(n_k) = L^L \exp(-Ln_k) n_k^{L-1} / \Gamma(L) \qquad (2)$$

$$p(x_k) = \frac{\alpha^\alpha}{\langle x \rangle^\alpha} \frac{1}{\Gamma(\alpha)} \exp\left(-\alpha \frac{x_k}{\langle x \rangle} \right) x_k^{\alpha-1} \qquad (3)$$

In Eqs. 2-3; L, α, $\langle . \rangle$ denote the number of looks, the heterogeneity parameter and the mean operator, respectively [6]. The mean and variance are defined in the fixed window as follows:

$$\langle x \rangle = \frac{1}{N^2} \sum_{k=1}^{N^2} x_k , Var(x) = \sigma_x^2 = \frac{1}{N^2} \sum_{k=1}^{N^2} \left(x_k^2 - \langle x \rangle^2 \right) \qquad (4)$$

where $k = 1, 2, \ldots, N^2$. In Eq. 2, the mean of the noise is taken to be unity, i.e. $\langle n \rangle = 1$. Thus, the variance of the speckle becomes: $\sigma_n^2 = 1/L$. The heterogeneity parameter, α, is a measure of the correlation of the texture, which is given by the following equation:

$$\alpha = 1 / \langle C_x \rangle^2 \qquad (5)$$

where $\langle C_x \rangle$ is known as the coefficient of variation of the texture and given as follows:

$$\langle C_x \rangle = \sigma_x / \langle x \rangle \qquad (6)$$

Using the definitions given above, the Gamma-Gamma MAP estimate of the texture can be found by the following equation [2, 6]:

$$\hat{x}_k = \frac{(\alpha - L - 1)\langle y \rangle + \sqrt{\langle y \rangle^2 (\alpha - L - 1)^2 + 4\alpha L y_k \langle y \rangle}}{2\alpha} \qquad (7)$$

where, the heterogeneity parameter can be estimated from the observed intensity image, as follows [2]:

$$\alpha = \frac{L+1}{L(\sigma_y / \langle y \rangle)^2 - 1} \qquad (8)$$

3. PARTICLE FILTERS

Particle filters are used in order to sequentially update *a priori* knowledge about some predetermined state variables by using the observation data. In general, these state variables are the hidden variables in a non-Gaussian and nonlinear state-space modelling system. Such a system can be given by the following equations:

$$\begin{aligned} \mathbf{x}_t &= f_t(\mathbf{x}_{t-1}, \mathbf{v}_t) \\ \mathbf{y}_t &= h_t(\mathbf{x}_t, \mathbf{n}_t) \end{aligned} \qquad (9)$$

where $\mathbf{x}_t$ and $\mathbf{y}_t$ represent the hidden state and the observation vectors at current time t, respectively. Here, the process and observation noises are denoted by $\mathbf{v}_t$ and $\mathbf{n}_t$, respectively. f_t and h_t are respectively known as the process and observation functions and in their most general case, they are nonlinear. Also, the noise processes in (9) can possibly be non-Gaussian. Here, the objective is to sequentially compute the *a posteriori* distribution of the state variables obtained via the observation data gathered up to that time, i.e. $p(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t})$. If both the process and the observation noise processes have Gaussian distribution and the corresponding functions f_t and h_t are linear, then the desired *a posteriori* distribution is also Gaussian and sequentially estimating the mean and variance is sufficient instead of the whole pdf. In this situation, the optimal solution can be obtained by the Kalman filter [9]. Instead of using temporal non-stationarity, this can also be used for the spatial non-stationarity. Then, index t can be replaced by k, in Eq. 9, to express spatial indexing. In this case, for the processing of images, two dimensional version of the Kalman filter is proposed in literature [12]. In general non-Gaussian situations we may not always have analytical expressions for distributions. Thus, the distributions are expressed in terms of samples, to approximate them. These samples are called as the particles. The expression for the *a posteriori* pdf can be given in terms of particles as follows:

$$p(\mathbf{x}_{0:k} \mid \mathbf{y}_{1:k}) \approx \sum_{i=1}^{K} w_k^i \delta(\mathbf{x}_{0:k} - \mathbf{x}_{0:k}^i) \qquad (10)$$

where w_k^i, $\mathbf{x}_{0:k}^i$, $\delta(.)$ denote the weight, i^{th} particle and the Kronecker delta operator, respectively. Here, the major problem is to draw samples from an analytically inexpressible non-Gaussian distribution. The particles in

Eq. 10 are drawn by a method known as the "Importance Sampling" [9, 10]. Here, instead of drawing samples from p(.), another distribution q(.) is used and the corresponding "Importance Weight" for each of them is estimated as follows:

$$w_k^i \propto \frac{p(\mathbf{x}_{0:k}^i \mid \mathbf{y}_{1:k})}{q(\mathbf{x}_{0:k}^i \mid \mathbf{y}_{1:k})} \tag{11}$$

where q(.) function is called as the "Importance Function" and drawing samples from this pdf is easier than that of original distribution [9 ,10]. However, importance sampling shown in (11), can be used in batch processing techniques and should be modified as follows for the sequential applications [9, 10]:

$$w_k^i \propto w_{k-1}^i \frac{p(\mathbf{y}_k \mid \mathbf{x}_k^i)\, p(\mathbf{x}_k^i \mid \mathbf{x}_{k-1}^i)}{q(\mathbf{x}_k^i \mid \mathbf{x}_{0:k-1}^i \mathbf{y}_{1:k})} \tag{12}$$

But, as a consequence of this sequential modification, a phenomenon, known as "Degeneracy", arises as a problem and causes the importance weight of each particle, but one, to converge to zero as time evolves [9, 10]. In order to avoid the degeneracy problem, "Resampling" is performed as an additional step and by this procedure, particles with high importance weights are replicated, while the others are discarded. By doing so, we can approximate the desired pdf.

4. THE PROPOSED METHOD

In this work, we propose using particle filters in order to estimate the marginal pdf of the texture. For this purpose, first, the whole observed image is convolved by a two dimensional mask, with all elements equal to 1 and then an informative *a priori* distribution is obtained for each pixel in the image by using the local statistics of each, two dimensional window, consisting of N^2-1 neighbouring pixels. This estimated pdf is denoted by $\hat{p}(x)$. Then, particle filter is applied by scanning each column of the image in a one dimensional way and the *a posteriori* marginal pdf of the texture is obtained. After finding its pdf, any expectation of it, such as the Minimum Mean Square Error (MMSE) estimate can be found [9]. Here, the current pixel is taken as the state variable, i.e. x_k . Then, the Bootstrap Particle Filter is utilized, where the a priori state transition pdf is taken to be the importance function [9, 10]:

$$q(x_k^i \mid x_{0:k-1}^i y_{1:k}) = p(x_k^i \mid x_{k-1}^i) \tag{13}$$

The approximation in Eq. 13 is generally performed in most particle filtering schemes, since the exact importance function $q(x_k^i \mid x_{0:k-1}^i y_{1:k})$ is unknown [9, 10]. However, assuming that the speckle can be modeled by a unit mean process with variance $\sigma_x^2 = 1/L$, we can take the mean of the texture, equal to the mean of the observed intensity image, i.e. $\langle x \rangle = \langle y \rangle$. Moreover, within the fixed window, the heterogeneity parameter can also be estimated from the observed intensity image *y*, by Eq. 8. Thus, for each fixed window, samples from the estimate of the original pdf *p(x),* can be drawn by using Eq. 3, given the *a priori* information about the value of *L*. So, instead of using a Markov transition model for the states, we propose to draw samples from this estimated pdf, namely $\hat{p}(x)$, which can be treated as an informative *a priori* pdf for each pixel (state). Here, the absolute value of the heterogeneity parameter is taken in order to be able to draw samples from a Gamma distribution. Therefore, the importance function of the Bootstrap particle filter turns into the following form:

$$q(x_k^i \mid x_{0:k-1}^i y_{1:k}) = p(x_k^i \mid x_{k-1}^i) \approx \hat{p}(x_k^i) \tag{14}$$

If the *a priori* transition pdf is chosen as shown in Eq. 13, the importance weight calculation of each particle takes the following form, which is the likelihood function:

$$w_k^i \propto w_{k-1}^i\, p(y_k \mid x_k^i) \tag{15}$$

By using Eqs. 1 and 2, the likelihood function can be expressed as follows [6]:

$$p(y_k \mid x_k^i) = \frac{L^L}{\Gamma(L)(x_k^i)^L} \exp\left(-\frac{L y_k}{(x_k)^i}\right)(x_k^i)^{L-1} \tag{16}$$

The pseudo-code of the proposed method is given below:

1. For each pixel of the observed image *y*, take a neighbourhood of NxN pixels (2D convolution by an NxN mask with all elements equal to 1) and calculate the following statistics for *each* of them:
   a) $\langle y \rangle = \langle x \rangle$
   b) $\sigma_y^2 = \frac{1}{N^2}\sum_{k=1}^{N^2}\left(y_k^2 - \langle y \rangle^2\right)$
   c) $\alpha = \left|\frac{L+1}{L(\sigma_y/\langle y \rangle)^2 - 1}\right|$
2. Start the particle filtering scheme with the first pixel.
3. Draw K samples for the texture from the following pdf with the aforementioned statistics a, b, c:

$$\hat{p}(x_k) = \frac{\alpha^\alpha}{\langle x \rangle^\alpha} \frac{1}{\Gamma(\alpha)} \exp\left(-\alpha \frac{x_k}{\langle x \rangle} \right) x_k^{\alpha-1}$$

i.e. $x_k \sim \langle x \rangle Ga(\alpha,\alpha)$

For each particle,

4. Calculate the importance weight:

$$w_k^i \propto p(y_k \mid x_k^i) = \frac{L^L}{\Gamma(L)(x_k^i)^L} \exp\left(-\frac{Ly_k}{(x_k)^i} \right) (x_k^i)^{L-1}$$

for $i = 1,2,\ldots\ldots,K$

5. Normalize the importance weights:

$$\tilde{w}_k^i = w_k^i \Big/ \sum_{i=1}^{K} w_k^i$$

6. Resample and make the unnormalized importance weights equal to each other

7. Go to the next pixel and repeat 3-7 for that.

Table.1. Pseudo-code of the proposed method

5. EXPERIMENTS

In order to test the performance of the proposed method, synthetic SAR images are formed by multiplying an aerial image with different speckles having various number of looks. The mean of the speckles are taken to be unity, while their variances are chosen to be the reciprocals of their number of looks. The results are compared by the Gamma filter. In order to estimate 1a, 1b and 1c of the Table 1, 7x7 mask, having all elements equal to 1, is convolved with the observation image. Also, for numerical comparison, the following measure, which is known as the Signal to Mean Square Error Ratio (S/MSE) is used:

$$S/MSE = 10\log_{10}\left[\sum_{pixels} y_1^2 \Big/ \sum_{pixels} (y_2 - y_1)^2 \right] \quad (17)$$

where y_1 and y_2 denote the denoised and noisy images, respectively [2]. This measure corresponds to the standard Signal to Noise Ratio (SNR) in case of additive noise [2]. Finally, the histograms are also plotted, for a better comparison. Fig. 1 shows the original texture image. Figs. 2-4 show the results for different number of looks.

Fig.1a. Original Image (Texture)

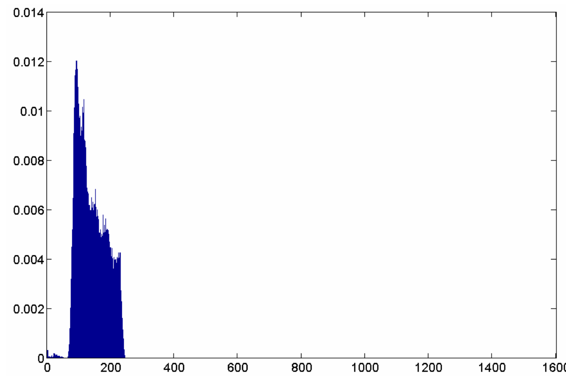

Fig.1b. Histogram of the original image

6. CONCLUSIONS

In this work, a novel approach for SAR image enhancement is proposed, where particle filter is utilized. As a result of the computer simulations, it is observed that the proposed method provides a satisfactory speckle removal and preserves the edges of the image better than the Gamma filter. Thus, the spatial resolution is increased when compared to the Gamma Filter. It is also noted that the quality of the speckle removal becomes much more effective during the small values of the number of looks, which are relatively more severe cases. These can also be observed from the histograms, where the number of outliers is decreased much more efficiently by the proposed method. These results are very promising for developing more sophisticated methods, utilizing the particle filters, such as the ones where the dependencies between the pixels are modelled by Markov Random Fields.

L	S/MSE (dB)	
	Particle Filter	Gamma Filter
3	0.8409	0.0084
5	1.5351	0.0109
10	2.4266	0.0215

Table 2. S/MSE value comparisons for different number of looks (L)

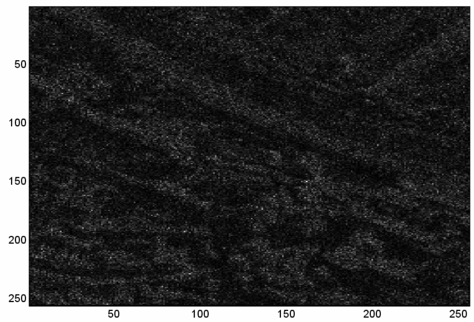

Fig.2a. Observation Image , L = 3

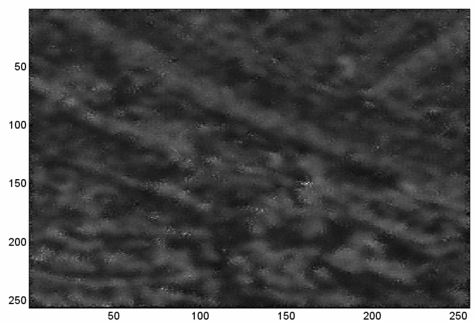

Fig.2b. Enhanced image (Particle Filter), L = 3

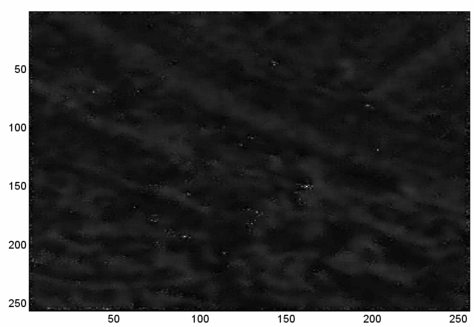

Fig.2c. Enhanced image (Gamma Filter), L = 3

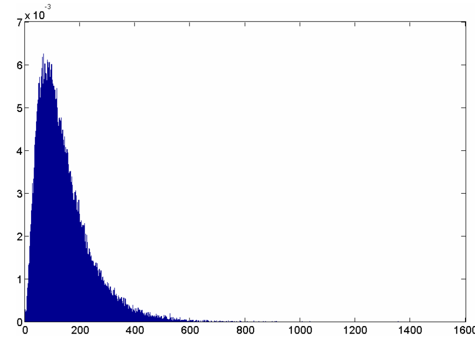

Fig.2d. Histogram of Fig.2a

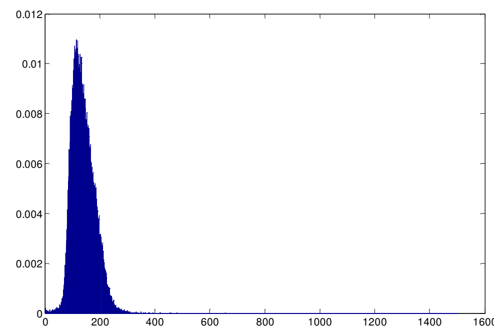

Fig.2e. Histogram of Fig.2b

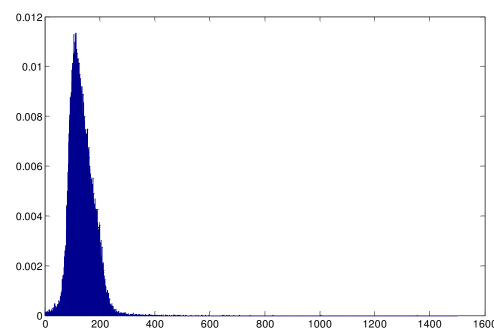

Fig.2f. Histogram of Fig.2c

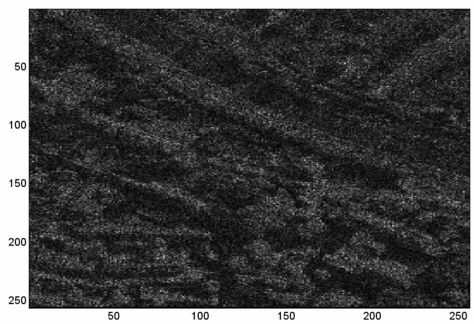

Fig.3a. Observation Image , L = 5

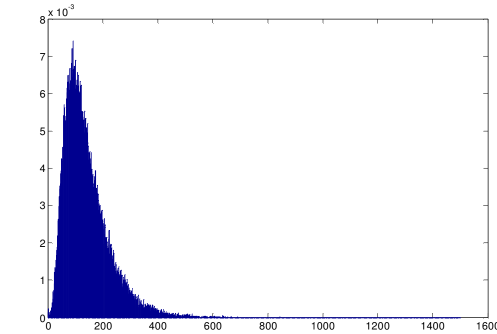

Fig.3d. Histogram of Fig.3a

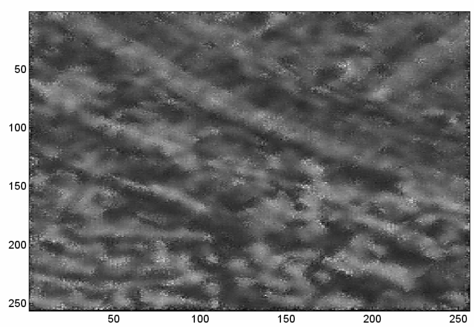

Fig.3b. Enhanced image (Particle Filter), L = 5

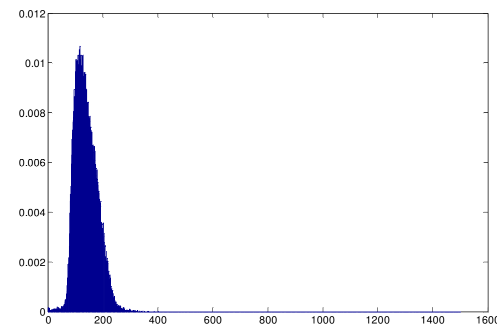

Fig.3e. Histogram of Fig.3b

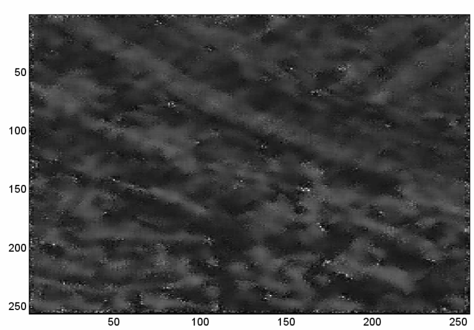

Fig.3c. Enhanced image (Gamma Filter), L = 5

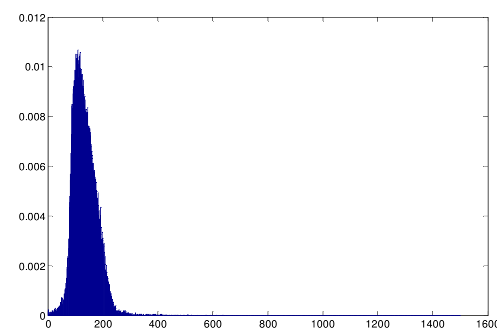

Fig.3f. Histogram of Fig.3c

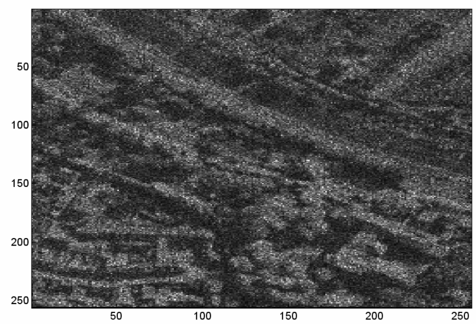

Fig.4a. Observation Image , L = 10

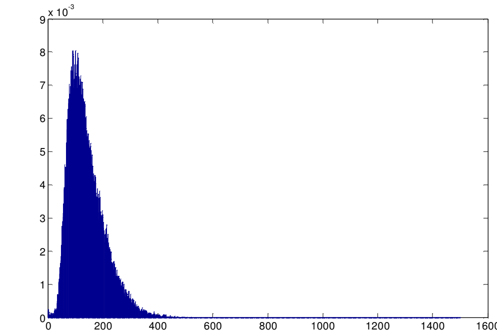

Fig.4d. Histogram of Fig.4a

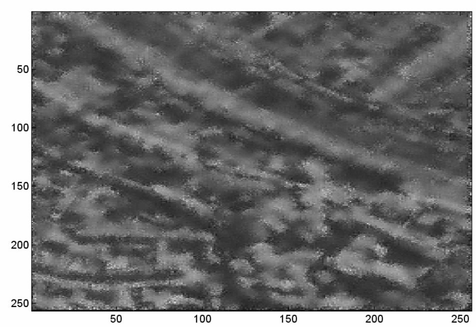

Fig.4b. Enhanced image (Particle Filter), L = 10

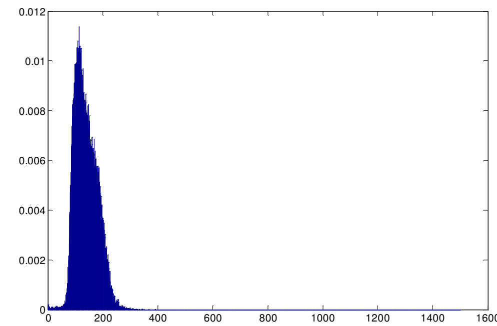

Fig.4e. Histogram of Fig.4b

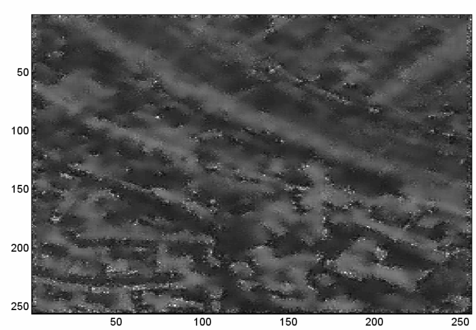

Fig.4c. Enhanced image (Gamma Filter), L = 10

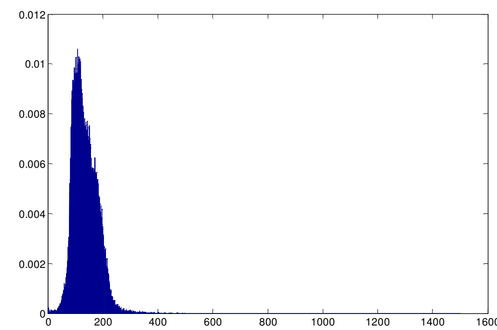

Fig.4f. Histogram of Fig.4c

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