SYNTHETIC APERTURE RADAR IMAGE EFFICIENT ENCODING

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ABSTRACT

The paper investigates a practical encoding scheme applied to Synthetic Aperture Radar (SAR) imagery which provides for a reduced number of bits per pixel representation as compared to typically digitised SAR images with 8 to 16 bits per pixel.

The method of encoding described is essentially based on decorrelating sub-images of 8x8 pixels by means of a Discrete Cosine Transform (DCT), followed by non-uniform quantisation and encoding of the DCT coefficients. The quantisation level interval per coefficient and its variation with respect to the coefficient frequency value are controlled by the first and second order statistics derived from the sub-images using Kalman filter techniques. In addition, the encoder induced distortion is selected in accordance with a pre-defined image quality criterium which considers the distortion effecting the textural or "unspeckled" SAR image information (i.e. not the usual mean square error criterium).

1. INTRODUCTION

This paper describes a practical data encoding scheme specifically designed for Synthetic Aperture Radar (SAR) imagery which provides for a reduced number of bits per pixel representation as compared to typically digitised SAR images with 8 to 16 bits per pixel.

An essential feature of the applied encoding scheme is that, for a given number of bits per pixel, the detremental effect on preserving the information content of the image, expressed in terms of an adequate fidelity criterium, is minimised.

The information content of SAR imagery is essentially contained in the image texture which can be defined as the image resulting after removal of the disturbing speckle content (or by applying an infinite number of looks). Consequently the fidelity criterium concerning the preservation of texture information applied to real speckled imagery shall take the effect of speckle into account.

The condition of minimum texture distortion (in terms of rms error) for a given data rate (or number of bits per pixel) can be derived by analysing the rate distortion theoretical formulation of speckled data (ref. 1) and shows that image encoding according to a non-uniform quantisation scheme should be applied on the discrete frequency components of the SAR imagery.

As shown below depending on the image quality criterium used optimum conditions are achieved by applying quantisation level intervals defined by an inverse Wiener filter or inverse "square root" Wiener filter function.

For the determination of these filter functions we need to know the power-spectral density functions of texture and speckle image components of which only the latter is known approximately. The approach for the implementation of a practical encoding scheme taken here is to perform the quantisation and encoding on two dimensional Discrete Cosine Transform (2D-DCT) coefficients derived from consecutive sub-images of size NxN, based on parameters derived from the image data and those specific to the SAR image generation process. In addition we make the reasonable assumption that the radar reflectively signal, i.e. the signal corresponding to the ground texture content, can be modelled as a sampled first-order two-dimensional Gaussian-Markov process of which the characteristics correspond to the derived parameters.

In the sequel we first recapitulate the SAR image characteristics needed in deriving a suitable filter function. The derived filter function is then used in defining the parameters of a practical encoding scheme using synthetic SAR imagery and a given fidelity criterium. The efficiency of the encoding scheme will then be demonstrated on real SAR imagery.

2. IMAGE CHARACTERISTICS

A recapitulation of essential SAR image characteristics (ref. 1, 2, 3), needed in deriving the pre-filter transfer function is given first for the nominal case of multi-look SAR intensity image generation for which the sub-aperture filter bandwidth does not exceed half of the image bandwidth (i.e. the subsampling factor equals one in range and azimuth direction). The image bandwidth is normalized to one, i.e. $|f_1|, |f_2| \le \frac{1}{2}, \frac{1}{2}$

Effects of non-nominal SAR image generation are treated later in chapter 3.

2.1 Power spectral density (p.s.d.) functions

The p.s.d. function of the image texture component, $S_F(f_1, f_2)$ is derived from the ground texture p.s.d. function, $S_g(f_1, f_2)$, filtered by the image generation process, characterised by the linear filter operation:

$$\{A(f_1,f_2)\}^{1/2} = |k(f_1,f_2) * k(f_1,f_2)| \qquad (1)$$

where $*$ denotes convolution and

$k(f_1,f_2)$ = Two dimensional subaperture weighting function, defined for $|f_1|,|f_2| \le \frac{1}{4}, \frac{1}{4}$

Hence,

$$S_F(f_1,f_2) = S_g(f_1,f_2)\, A(f_1,f_2) \qquad |f_1|,|f_2| \le \tfrac{1}{2}, \tfrac{1}{2} \qquad (2)$$

The general form of $S_g(f_1,f_2)$ is given by:

$$S_g(f_1,f_2) = S_r(f_1,f_2) + (m_n + m_r)^2 \delta(f_1,f_2) \qquad 0 \leq |f_1|,|f_2| < \infty \tag{3}$$

where,

m_r = mean intensity of the ground reflectivity signal

m_n = equivalent thermal noise power

The p.s.d. function of the speckle component, $S_p(f_1,f_2)$ can be expressed as the sum of its texture dependent component $S_{p_1}(f_1,f_2)$ and its texture independent component $S_{p_2}(f_1,f_2)$.

Hence, $S_p(f_1,f_2) = S_{p_1}(f_1,f_2) + S_{p_2}(f_1,f_2)$ (4)

where, $$S_{p_1}(f_1,f_2) = L^{-1} \iiiint_{-1/4}^{1/4} S_r(\nu-\mu,\eta-\xi) k(\nu,\eta) k(\mu,\xi) k(f_1-\mu, f_2-\xi) k(f_1-\nu, f_2-\eta)\, d\nu\, d\mu\, d\eta\, d\xi \tag{5}$$

and $$S_{p_2}(f_1,f_2) = L^{-1}(m_n+m_r)^2 \iint_{-1/4}^{1/4} k^2(\nu,\mu) k^2(f_1-\nu, f_2-\mu)\, d\nu\, d\mu \tag{6}$$

where, L = Effective number of looks.

It can be shown (ref. 3) that for any p.s.d. function of the ground reflectivity signal and non-overlapping looks, the ratio of speckle power and image texture power is, with good approximation, given by $1/L$, hence:

$$\frac{\sigma_p^2}{M^2 + \sigma_F^2} = \frac{1}{L}$$

where,

$$\sigma_p^2 = \iint_{-1/2}^{1/2} S_p(f_1,f_2)\, df_1\, df_2$$
$$\sigma_F^2 = \iint_{-1/2}^{1/2} S_r(f_1,f_2)\, df_1\, df_2 \tag{7}$$
$$M^2 = (m_n+m_r)^2 A(0,0)$$

With (7) the image texture variance can be derived from the total image variance $\sigma_I^2 = \sigma_F^2 + \sigma_p^2$, i.e.

$$\frac{\sigma_F^2}{M^2} = \frac{\sigma_I^2}{M^2}\frac{L}{L+1} - \frac{1}{L+1} \tag{8}$$

2.2 SAR image autocorrelation function

The autocorrelation function (acf) of the image, $R_I(\tau_1,\tau_2)$ is also the sum of the autocorrelation functions of its texture and speckle components, respectively denoted by $R_F(\tau_1,\tau_2)$ and $R_p(\tau_1,\tau_2)$ i.e.

$$R_I(\tau_1,\tau_2) = R_F(\tau_1,\tau_2) + R_p(\tau_1,\tau_2) \tag{9}$$

The acf of the speckle can be derived from its p.s.d. function given by (4), (5) and (6) yielding with good approximation:

$$R_p(\tau_1,\tau_2) \simeq L^{-1}(M^2 + \sigma_F^2)\, \mathrm{sinc}^2\left(\frac{\pi\tau_1}{2}\right) \mathrm{sinc}^2\left(\frac{\pi\tau_2}{2}\right) \tag{10}$$

where τ_1, τ_2 are expressed in image sample numbers.

It is noted that the acf of the speckle depends on the texture only by its total power $M^2 + \sigma_F^2$

Consequently we can derive the acf of the image texture from the image acf, $R_I(\tau_1,\tau_2)$ and the image variance σ_I^2, using (8) and (9). The acf of the ground texture, $R_g(\tau_1,\tau_2)$ relates to the acf of the image texture, $R_F(\tau_1,\tau_2)$ through the SAR processing transfer function $A(f_1,f_2)$, defined in (1), i.e.:

$$R_g(\tau_1,\tau_2) = R_F(\tau_1,\tau_2) * [\mathcal{F}^{-1}\{A^{-1}(f_1,f_2)\}] \tag{11}$$

where $*$ and $\mathcal{F}^{-1}$ denotes respectively 2D-convolution and the 2D-Inverse Fourier Transform

3. DATA ENCODING ALGORITHM

3.1 Image generation parameters

As mentioned before the quantisation and encoding shall be performed on 2D-DCT coefficients and be defined by parameters measured from actual sub-image data and by the characteristics of the image generation process.

The parameters derived from the sub-image (i) being processed are estimates of:

- Mean value ($\hat{M}_i$)
- Image and texture variance, respectively $\hat{\sigma}_{Ii}^2$ and $\hat{\sigma}_{Fi}^2$
- Image autocorrelation function $\hat{R}_i$ (1,1) and texture autocorrelation function $\hat{\rho}_{Fi}^2$

Parameters specific to the image generation process are:

- Subaperture weighting function,
- Effective number of looks L (dependent on look overlap)
- Image subsampling ratio's (a_1 and a_2 in respectively range and azimuth
- Method of look summation and detection i.e.
  a) Summation of per look intensity images
  b) Summation of per look amplitude images
  c) Square root of a)

The data reduction processing exists of encoding the 2D-DCT coefficients with identical uniform quantizers per coefficient, the required variation of quantization level intervals with frequency being implemented by applying a pre-encoding filter. The reconstructed image with essentially the same spatial resolution as the original image can be obtained by applying a post-encoding filter, being the inverse of the pre-filter.

In case the image is subsampled e.g. as a means of data reduction, the speckle p.s.d. funtion S_p shall be modified to take two dimensional aliasing into account while the processing transfer function (A) given by (1) is truncated due to the reduced image bandwidth. Hence for a subsampling factors a_1, a_2 it follows:

$$S_p(f_1,f_2,a_1,a_2)\begin{cases} = S_p(f_1,f_2) + \text{2D aliasing terms for} & |f_1|,|f_2| \leq \frac{1}{2a_1},\frac{1}{2a_2} \\ = 0 \quad \text{otherwise.} \end{cases}$$

and

$$A(f_1,f_2,a_1,a_2)\begin{cases} = A(f_1,f_2) \text{ for} & |f_1|,|f_2| \leq \frac{1}{2a_1},\frac{1}{2a_2} \\ = 0 \quad \text{otherwise} \end{cases}$$

The speckle autororrelation function $R_p(\tau_1,\tau_2,a_1,a_2)$ is for the case of $a_1=a_2=2$ well approximated by:

$$R_p(\tau_1,\tau_2,2,2) \simeq L^{-1}(M^2+\sigma_F^2)\,\mathrm{sinc}(\pi\tau_1)\,\mathrm{sinc}(\pi\tau_2) \tag{12}$$

If the image is generated by an amplitude detector the image is converted to an intensity image for the purpose of determining the adaptive statistical parameters for encoding. It can be shown that the statistics of the squared amplitude image generated by the type (b) look summation, mentioned above, is almost identical to the statistics of an intensity image generated by type (a) look summation. This is obviously also true for the type (c) look summation.

In order to establish the boundary conditions of the applied encoding scheme, the variances of the parameter estimates need to be derived.

It can be shown that due to the speckle statistics the variances of the estimates derived from a single subimage (i) of size NxN are respectively given by:

$$\mathrm{Var}.\hat{M}_i = \frac{\hat{M}_i^2}{N^2L}\left(1+\gamma_i^{-1}\right) \tag{13}$$

$$\mathrm{Var}.\hat{\sigma}_F^2 \leq \frac{8M_i^4L}{N^2(L+1)^2}\left(1+\gamma_i^{-1}\right)^2 \tag{14}$$

$$\mathrm{Var}.\hat{\rho}_{Fi}^2 = \frac{4}{(N-1)^2L}\left(1+\gamma_i\right)^2 \tag{15}$$

where,

M_i = speckle averaged mean value

γ_i = M_i^2/σ_{Fi}^2

σ_{Fi}^2 = subimage texture variance

$$\hat{\rho}_{Fi}^2 = \frac{\hat{R}_i(1,1) - R_p(1,1,a_1,a_2) - \hat{M}_i^2}{\hat{\sigma}_{Fi}^2}$$

With γ_i varying between 1 and ∞ (no texture) it is apparent that for the small size of subimage (N=8) abd say L=4, the image correlation coefficient estimate $\hat{\rho}_{Fi}^2$ becomes very unreliable, i.e. varying from 0.3 rms to ∞
However, we can improve the accuracy of the estimate by using Kalman filter techniques applied on the texture correlation between subimages. In order to apply this technique the mean variation of the values γ^{-1} and ρ_F^2 from one subimage to the next need to be determined.

From actual image statistics, urban areas, for which $\gamma = 1 \div 2.5$, show the largest fluctuation in γ^{-1} and ρ_F^2, respectively $\sigma^2(\gamma^{-1}) = 0.02$ and $\sigma^2(\rho_F^2) = 0.04$. These values have been taken as "state noise" variances in the corresponding Kalman filters which reduce the error in the correlation coefficient ρ_F^2 estimate to about 0.3 rms for $\gamma \approx 3$. Due to the boundary values of $\min(\rho_F) < \rho_F < 1$ the measured value of $\hat{\rho}_F^2$ is not a "maximum likelihood" estimate. This estimate can be computed for a given subaperture filter and subsampling rates and shall be taken into account in defining the quantization interval of the encoder (see para. 3.4).

The value of $(\hat{\gamma}_i)^{-1} = \{\max(0, \hat{\sigma}_{Fi}^2/\hat{\mu}_i^2)\}^{-1}$ is quantized at equal intervals in the range of $0 < (\hat{\gamma}_i)^{-1} < 1$, yielding 15 lower bounded values of $\hat{\gamma}_i^{-1}$ denoted by $\hat{\gamma}_{ci}$. This value is used in defining the pre-filter H_{oi} (See para. 3.3.).

3.2 Image fidelity criterium

Here two ways of expressing the effect of encoder induced distortion are considered, related to two possible ways of reconstructing the original image:

a) A combination of pre-filter (H) and post-filter (P) is applied which equals the Wiener filter ( ) operation and provides for minimum total distortion (i.e. due to speckle, filtering and encoding) of the texture data as compared to all other filter combinations at equal rate (Ref. 1).
Also as shown in Ref. 1 the total distortion (d_T) and the encoder induced distortion (d_{ca}) is minimised if the pre-filter equals the Wiener filter (and hence P=1) where:

$$d_{ca} = d_T - d_{To} \tag{16}$$

and d_{To} = image distortion due to speckle and filtering only.

Analysis using synthetic SAR where the texture data is modelled according to a to a first order two dimensional Gaussian-Markov process shows that for $\alpha \le H \le 1$ the encoder induced distortion is lower and upper bounded by respectively $H=\alpha$ and H=1 but that the encoder distortion increases rapidly with increasing filter attenuation beyond the Wiener filter condition (i.e. $H<\alpha$).

For the condition of $HP=\alpha$, it follows for the encoder distortion (Ref. 1), omitting the variables f_1, f_2 for brevity:

$$d_{ca} = \frac{1}{M^2} \iint_{-1/2}^{1/2} \min\left\{\theta \frac{\alpha^2}{H^2}, \alpha S_F\right\} df_1 df_2 \tag{17}$$

and

$$d_{To} = \frac{1}{M^2} \iint_{-1/2}^{1/2} (1-\alpha) S_F \, df_1 df_2 \tag{18}$$

where,

$$\alpha \triangleq \alpha(f_1,f_2) = S_F(f_1,f_2)\{S_F(f_1,f_2) + S_p(f_1,f_2)\}^{-1}$$

$\theta^{1/2}$ = rms quantization error

b) A combination of pre-filter (H) and post-filter (P) is applied which equals unity (i.e. HP=1). The fidelity criterium in this case is defined as the encoder induced distortion of the reconstructed image texture (d_{cb}). The image texture after encoding and post filtering ($\hat{f}$) is defined as the average of the reconstructed image ($\hat{i}$) with respect to the remaining speckle ($\hat{p}$) i.e.

$$\hat{f} = E_{\hat{p}}[\hat{i}] \qquad (19)$$

It can be shown that in terms of p.s.d. functions

$$d_{cb} = \frac{1}{N^2} E[f-\hat{f}]^2 = \frac{1}{N^2} \iint_{-1/2}^{1/2} \min \{\Theta \frac{\alpha}{H^2}, S_F\} df_1 df_2 \qquad (20)$$

The distortion measure d_{cb} is minimum at a given rate if the distortion induced by encoding of the DCT coefficients is the same for each coefficient i.e.

$$H = \alpha^{1/2} \quad \text{"square root" Wiener filter} \qquad (21)$$

An additional quality measure is the texture to speckle ratio after encoding $(TPR)_C$ as compared to the one before encoding $(TRP)_O$.
This relationship is given by:

$$(TPR)_c = (TPR)_o \, (1 - d_{cb}\gamma)\{1 - \frac{L(d_o - d_{cb})}{1+\beta^{-1}}\}^{-1} \qquad (22)$$

where,

$d_o \triangleq$ total image distortion for HP=1

Due to the spectral composition of the speckle and texture components of actual data and the filtering applied there will be always an **increase** of the texture to speckle ratio due to encoding, which actually suppresses the speckel more than the texture.
The behaviour of the distortion measure d_{ca} and d_{cb} as function of the pre-filter value is shown schematically in Fig. 1.

3.3 Pre-filter definition

With the observation that the encoder induced distortion d_{ca} resulting from a specific pre-filter/encoder combination for a given rate is upper and lower bounded by respectively the condition H=1 and H=α, if $\alpha \leq H \leq 1$, it follows that a pre-filter which fulfils this condition is given by

$$H_o(f_1, f_2) = Max\{\alpha(f_1, f_2)\} \qquad (23)$$

where the max. is taken over the set of possible ground texture p.s.d. functions yielding a given image texture variance.
Note also that the second distortion measure d_{cb} does not deviate much from its minimum value for this definition of the pre-filter.(See Fig. 1).

In order to achieve numerical results the set of ground texture p.s.d. functions $S_g(f_1, f_2)$ is modelled according to a first order two dimensional sampled Gaussian-Markov process:

$$S_g(f_1,f_2)_{0<\rho<1} = \frac{\sigma_r^2 a_1 a_2 (1-\rho^2)^2}{(1+\rho^2-2\rho\cos 2\pi f_1 a_1)(1+\rho^2-2\rho\cos 2\pi f_2 a_2)} + m_r^2\,\delta(f_1,f_2) \quad (24)$$

for $|f_1|,|f_2| \leq \frac{1}{2a_1}, \frac{1}{2a_2}$

where:

ρ = texture correlation coefficient in range and azimuth

σ_r^2 = ground texture variance.

A rather lengthy but straight forward deriviation of (23), which is beyond the scope of this paper, leads to the following formulation of the pre-filter H_{0i} in terms of the image generation parameters $\hat{\gamma}_{ci}$: L, a1, a2 defined in para. 3.1.

$$H_{0i}(k,\ell) = A(k,\ell)\left[A(k,\ell) + X_i(k,\ell)\, C(k)\, C(\ell)\right]^{-1} \quad (25)$$

where:

$k,\ell \triangleq$ 2D-DCT coefficient numbers in respectively range and azimuth (k,ℓ = 0, 1, ... N-1)

$$X_i(k,\ell) = \max.\{1, \hat{\gamma}_{ci}\, P(k,\ell)\}\, S_{P_2}(k,\ell,a_1,a_2)\,(m_n + m_r)^{-2}\,(a_1 a_2)^{-1}$$

$$P(k,\ell) = a_1 a_2\, A(0,0)^{-1} \int_{-1/2a_1}^{1/2a_1}\int_{-1/2a_2}^{1/2a_2} A(k,\ell)\, F_1(\rho_k, f_1)\, F_2(\rho_\ell, f_2)\, df_1\, df_2$$

$$F_j(\rho_x, f_j) = \frac{1-\rho_x^2}{1+\rho_x^2 - 2\rho_x \cos 2\pi f_j a_j} \qquad j = 1,2$$

$$\left.\begin{array}{l}
\rho_x \begin{cases} = \dfrac{1-\sin\left(\frac{\pi x}{N}\right)}{\cos\left(\frac{\pi x}{N}\right)} & \text{for} \quad 0 < x < \frac{N}{2} \\ = 0 & \text{for} \quad \frac{N}{2} \leq x \leq N-1 \end{cases} \\[2ex]
A(k,\ell) = A\left(\dfrac{k}{2a_1 N}, \dfrac{\ell}{2a_2 N}\right) \\[2ex]
C(x) \begin{cases} = \sin\left(\frac{\pi x}{N}\right) & \text{for} \quad 0 < x < \frac{N}{2} \\ = 1 & \text{for} \quad \frac{N}{2} \leq x \leq N-1 \end{cases}
\end{array}\right\} x = k, \ell$$

$$S_{P_2}(k,\ell,a_1,a_2) = S_{P_2}\left(\frac{k}{2a_1 N}, \frac{\ell}{2a_2 N}, a_1, a_2\right) \qquad \text{aliased speckle spectrum}$$

An example of the pre-filter function is depicted in Fig. 2 for typical sub-image parameters of $\gamma = 1{,}5$ and a1=a2=2.

3.4 Encoder quantization interval

The value of the quantization interval Q_i of sub-image (i) is directly related to the image distortion after encoding and filtering expressed by:

$$d_{0i}(\rho_{Fi}, \gamma_i) = \frac{1}{M_i^2} E\left[(i-\hat{i})^2\right] = \frac{1}{M_i^2} \int\int_{-1/2}^{1/2} \min.\left\{S_{F_i} + S_{P_i}, \frac{Q_i^2}{12 H_{0i}^2}\right\} df_1\, df_2 \quad (26)$$

The functional relationship of the distortion measure d_{ca} or d_{cb} given respectively by (17) and (20) with d_{oi} can be established by using synthetic SAR image for which the p.s.d. functions are known as function of the sub-image dependent parameters $\gamma_i = \frac{M_i^2}{\sigma_{F_i}^2}$ and the correlation coefficient ρ_i.

For example, by approximating the actual results to a well fitted analytical expression, this relationship using the distortion measure d_{cb} is for the case of L=4 and subsampling ratio's $a_1=a_2=2$, given by:

$$\log_{10} d_{oi} \simeq \log_{10} d_{cb} + 0.44 + 1.33\rho_i + 0.63 \log_{10} \gamma_i \tag{27}$$

Taking into account the non-linear relationship between the measured correlation coefficient ρ_{Fi} and the corresponding ground texture correlation coefficient ρ_i and the accuracies of the estimates $\hat{\rho}_{Fi}$ and $\hat{\gamma}_i$, the following conservative estimate of d_{oi} is actually used in defining the quantization interval Q_i:

$$\log_{10} \hat{d}_{oi} = \mathrm{Max.}\left\{-1.46, \log_{10} d'_{cbi} + 0.24 + 1.1\hat{\rho}_{Fi} - 0.26 \log_{10} \hat{\gamma}_{ci}\right\} \tag{28}$$

where

$$d'_{cbi} = \gamma_i d_{cb} \triangleq \frac{\text{texture distortion power}}{\text{texture variance}}$$

and Q_i is determined either by iteration to obtain $\hat{d}_{oi} = \frac{1}{M_i^2} \sum_k \sum_\ell \{i(k,\ell) - \hat{i}(k,\ell)\}^2$ a measurable quantity, or by an approximate solution of (26) e.g.

$$\log_{10} Q_i = -0.1 + \log_{10} \hat{M}_i + 0.5 \log_{10} \hat{d}_{oi} + 0.25\hat{\rho}_{Fi} - 0.5 \log_{10} \hat{\gamma}_{ci} \tag{29}$$

A block diagram of the encoder operations is depicted in Fig. 3. Note that for sub-image reconstruction the values of $(\hat{\gamma}_{ci})^{-1}$ and $\hat{\rho}_{Fi}$ are transmitted to the decoder along with the encoded data.

4. RESULTS

Fig.P1 shows examples of applying the encoding technique described to SAR imagery generated by summation of four amplitude detected looks and using "Kaiser weighted" sub-aperture filtering with a sub-sampling ratio of two in range and azimuth (i.e. L=4 and $a_1=a_2=2$).
The values for $\hat{\gamma}_c$ and $\hat{\rho}_F$ averaged over the picture are $E(\hat{\gamma}_c)=3$ and $E(\hat{\rho}_F)=0.64$. For these values the picture distortion measure can be estimated together with the speckle reduction (see Table below).

The distortion introduced by the encoding is depicted in Fig. P2 , where it is clearly seen that for a distortion of 0.08 and 0.12 the distortion is mainly due to speckle reduction, hence a desirable feature. For a total distortion of 0.3 texture distortion is clearly observed.

From this test case it can be concluded that for image representations of 2 to 3 bits/pixel, texture distortion is almost invisible.

R bits/pixel	d_o	d_{cb}	Speckle reduction (dB)
2.8	0.08	0.02	1.0
1.7	0.12	0.05	1.4
0.7	0.30	0.20	4.3

Table - Statistical data of "Isle of Wight" image encoding

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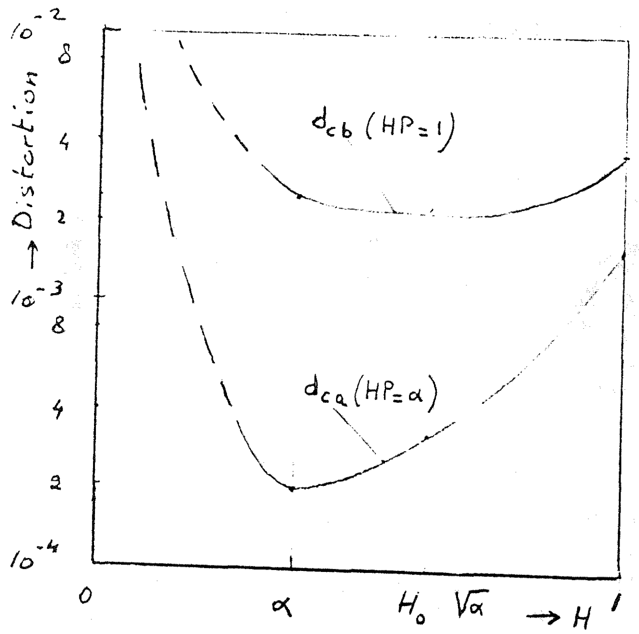
2) R.K. Raney "Transfer functions for partially coherent SAR systems". IEEE Trans. on Aerospace and Electronic Systems, Vol. AEG-19, No. 5, Sept. 1983.

3) Final Report on "Study of SAR data compression and encoding", MLR TR 85085L, ESA Contract No. 5829/84/NL.



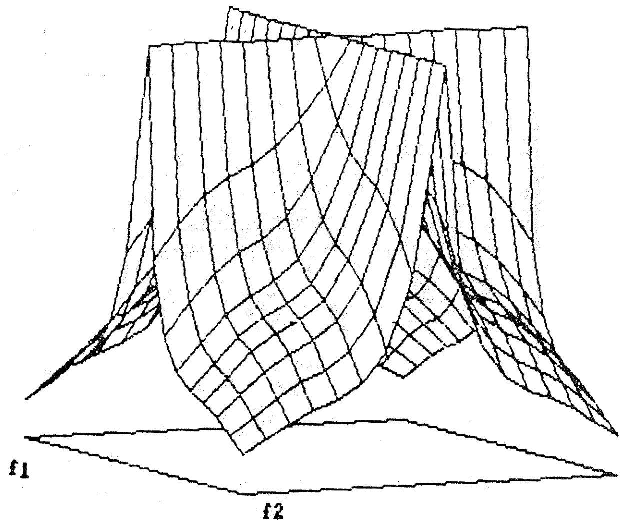
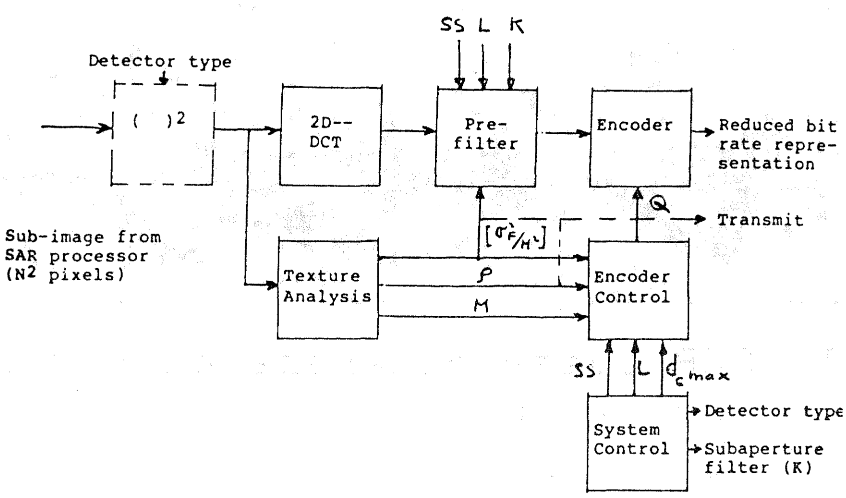
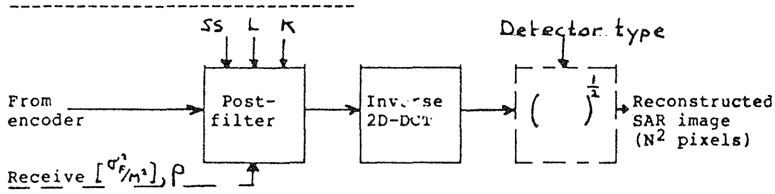


Fig.1 Distortion measures vs pre-filter transfer function H
R=2 bits/pixel, γ =6, ρ =0.6

Fig.2 Prefilter transfer function H_0 for γ =1.5, a_1=a_2=2

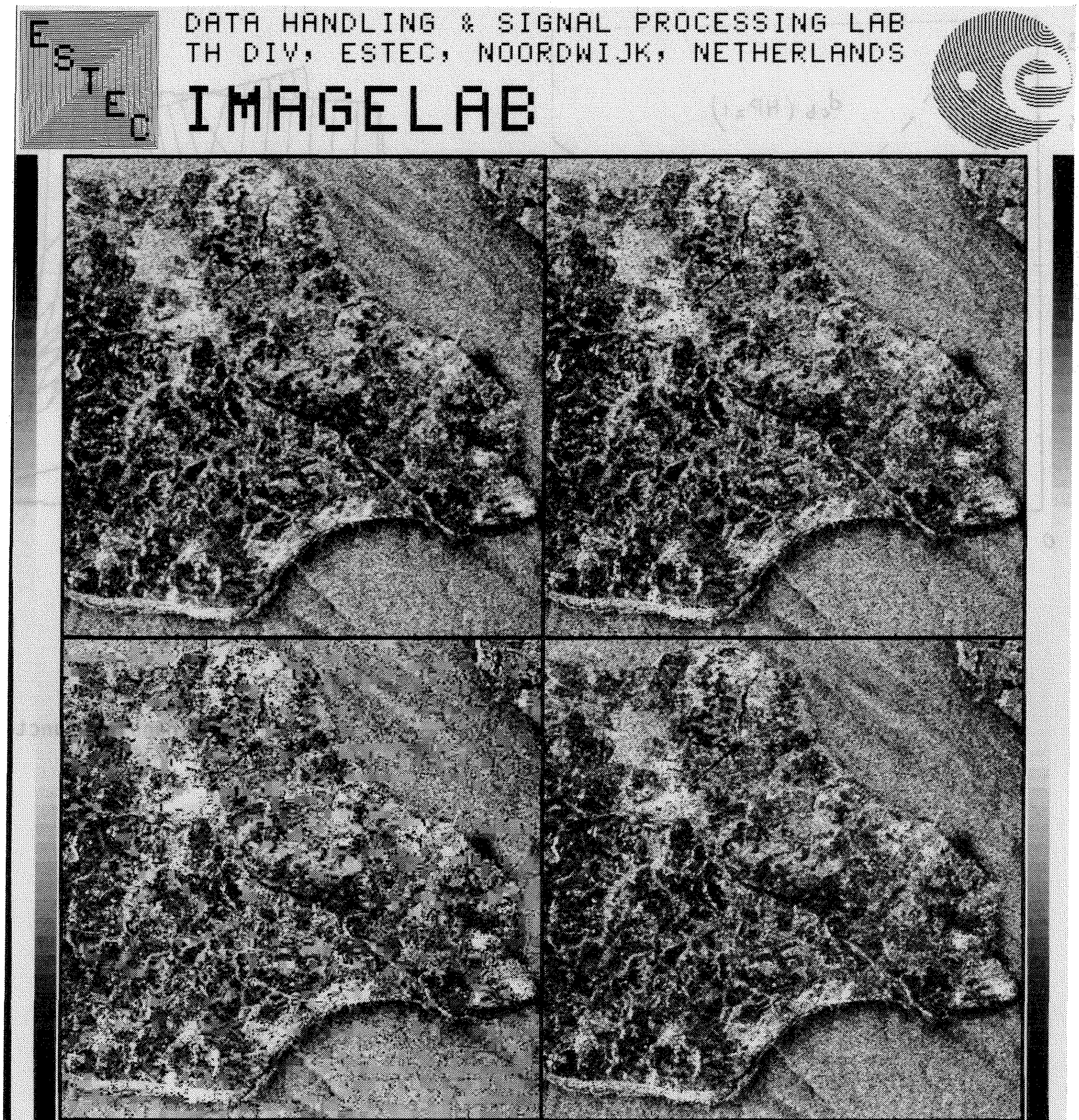


a) SAR image data reduction scheme



b) SAR image reconstruction scheme

Fig.3 Practical SAR image reduction and reconstruction schemes operating on consecutive subimages of N^2 pixels.



P 1. SAR image compression results

TL : Original SAR scene - Isle of Wight
TR : Reconstructed image, compression rate 8:2.8, dist 8%
BR : Reconstructed image, compression rate 8:1.7, dist 12%
BL : Reconstructed image, compression rate 8:0.7, dist 30%

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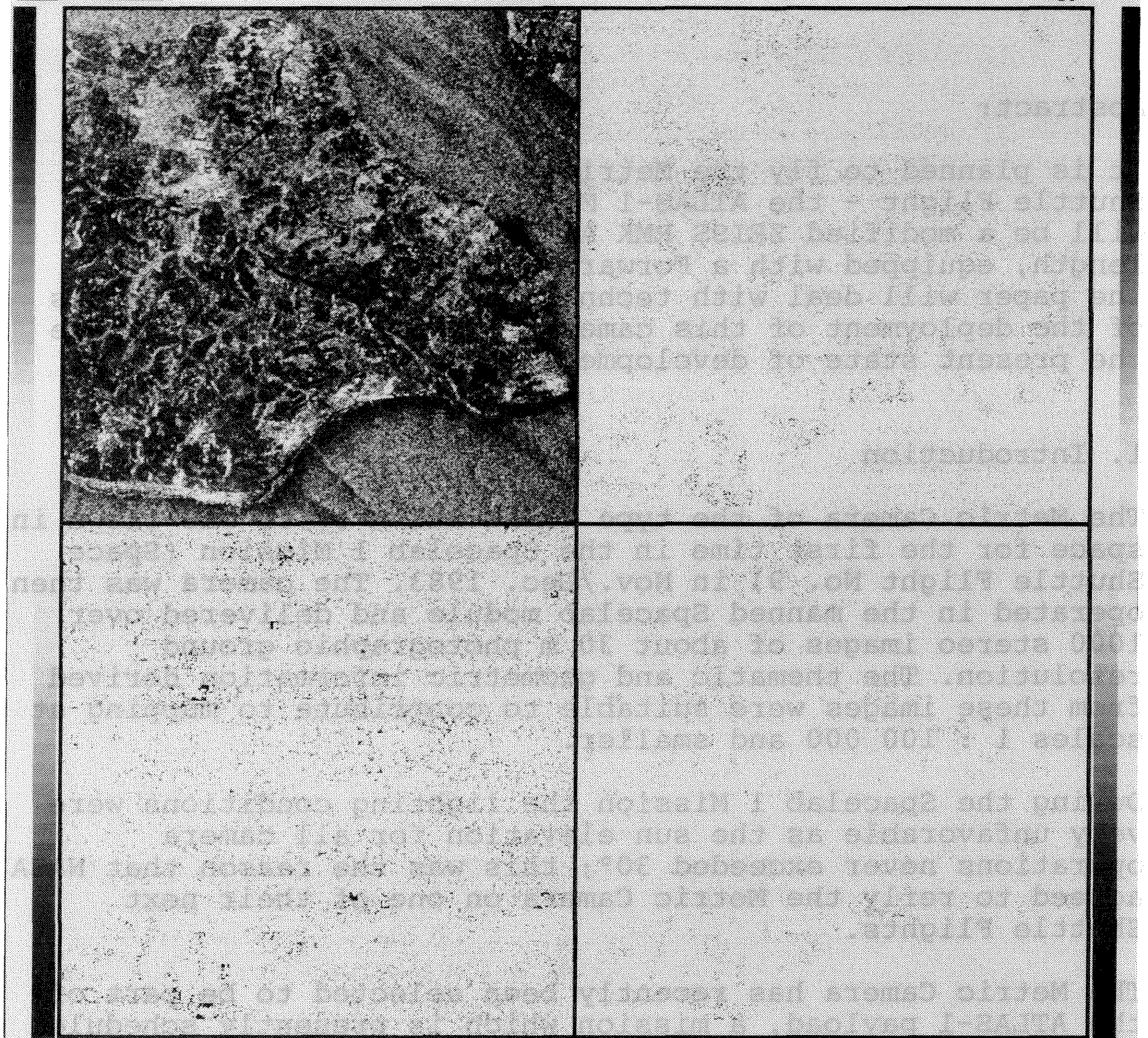
IMAGELAB



P 2. SAR image compression results

TL : Original SAR scene - Isle of Wight
TR : Error image for 2.8 bit/pixel
BR : Error image for 1.7 bit/pixel
BL : Error image for 0.7 bit/pixel
(Error data are biased by 127 and scaled by a factor of 2).