Wavelet-curvelet-contourlet based remote sensing data mining model

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Abstract: Remote sensing applications such as change detection, multispectral classification, environment monitoring, image mosaicking, weather forecasting, super resolution images and integrating information into geographic information system (GIS), image registration is a required process. Such natural images contain intrinsic geometrical structures that form the key features in visual information. Satellite data thus delivered/received in the form signals/images have a wide coverage with multi-temporal and multispectral capabilities. In such problems, a prime objective is to improve the quality of transmitted signals/images composed of desired signal plus additive random/Gaussian noise, by employing efficient feature extraction and denoising techniques with efficient representation of visual information. The experimental results and performance factor analysis based on of each of the multiresolution transforms show that contourlet transform produces relatively better result in terms of capturing directional information, reconstruction, noise restraints.

The modelling and simulation: The feature extraction and denoising process is aimed at removing the noise with the help of a matched filter (either using wavelet, curvelet or contourlet), and is composed of three major steps viz. Decomposition of the transmitted signal, Thresholding to demise noisy elements, and Reconstruction of the processed signal. Signal is represented as $x(t)$: $x(t) = s_i(t) + n_i(t)$, having the general series expansion in $\{\varphi\}_{n=1}^{\infty}$ with either of the wavelet, curvelet or contourlet as basis: $x(t) \approx f = \sum_{n=1}^{\infty} x(t)\varphi_n$,where $s_i(t)$ represent signal of interest (e.g. object) and $n_i(t)$ represents noise factor characterised by Gaussian distribution. The decomposition of the signal with matched filter, $h(t)$ yields the output, $y(t) = s_0(t) + n_0(t)$. The matched filter maximizes the peak signal to noise ratio (PSNR), the ratio of the power of $s_o(t)$, and the power of $n_o(t)$ according to the Schwarz inequality. Decomposition process begins with application of a wavelet filter (with low-pass filter$h$, high-pass filter$g$, and down sampling by a factor of 2 at each stage of the filter bank), as a result of which, the given signal, $x(t)$, is decomposed into low and high frequency components. The low pass and high filters are given by

$$h(n) = 2^{\frac{-1}{2}}\langle\varphi(t), \varphi(2t-1)\rangle,\ g(n) = 2^{\frac{-1}{2}}\langle\psi(t), \varphi(2t-1)\rangle = (-1)^n h(1-n)$$

Next, a thresholding is performed by selecting the transform coefficients below a certain threshold and setting them to zero as $c_\lambda = \begin{cases} c_\lambda, & |c_\lambda| \geq t_\lambda \\ 0, & |c_\lambda| < t_\lambda \end{cases}$, where $c_k$are the curvelet coefficients, $t_\lambda$is the threshold, λ the index.

The thresholding process leads to shrinking the noisy coefficients in the threshold interval $[-t_\lambda, t_\lambda]$, and retaining the detail coefficients. Finally, the signal $x(t)$ is reconstructed using inversion of analysing transform. Simulations are performed on noisy mixed sample signal data on Matlab® R 7.9 on a core i7 2.2 GHz PC using the USFFT software package. The results (PSNR in dB) along with RMSE are shown in the table.

Image	Signal data	Wavelet filter	Curvelet filter	Contourlet filter	RMSE
Sample I	20.01(m=0, σ^2=0.01)	24.89	26.15	26.89	0.1214
Sample II	21.09 (m=0, σ^2=0.01)	26.89	27.14	27.84	0.1234
Sample III	19.77(m=0, σ^2=0.01)	27.70	29.15	29.67	0.0764

Keywords: *Remote sensing, wavelet, curvelet, contourlet, thresholding*