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AN EDGE PRESERVING MULTIRESOLUTION FUSION USING CURVELET TRANSFORM AND MRF PRIOR

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ABSTRACT

Satellites used for remote sensing are, in general, capable of acquiring two different types of images: multispectral (MS) images and a panchromatic (Pan) image. The MS sensors provide multiband images with accurate spectral (color) information but with low spatial resolution. In this project, we propose an edge preserving multiresolution fusion by using subsampled as well as nonsubsampled CT. a close approximation (initial estimate) to the final fused image is first obtained using the available Pan, MS image, and the CT/NSCT, which is then used in deriving the relation between LR and HR MS images and also the edges in the final fused image. The final fused MS image is obtained by using regularization for which we use a homogenous MRF prior that requires simple gradient based optimization in order to obtain the final solution.

INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans). In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance.

EXISTING SYSTEM

In the last few years, multiresolution analysis has become one of the most promising methods for the analysis of images. Several approaches for MS image fusion have been proposed using wavelet transform (WT) method. In these techniques, the high-frequency components of the MS images are replaced by that of the Pan image in the wavelet domain. Multiresolution transforms such as "a trous" wavelets and Laplacian pyramid (LP)-based approaches are used in image fusion community. Similar to WT, the temporal Fourier transform (TFT) is also used to obtain the fused image. Due to the limited directional edge extraction in WT, the injected details may not exactly correspond to those in the true HR MS images.

WAVELET TRANSFORM

Wavelet transforms are classified into discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs). Note that both DWT and CWT are continuous-time (analog) transforms. They can be used to represent continuous-time (analog) signals. CWTs operate over every possible scale and translation whereas DWTs use a specific subset of scale and translation values or representation grid.

Wavelet transform applied to the rows and columns of the benchmark image lena with reflection at the boundaries On the left the well known benchmark image lena1 is shown. To the right of it we have applied the wavelet transform to the rows of the image. The corresponding result is interpreted as image again and is composed of a coarse and scaled version of the original and the details, which are necessary to reconstruct the image under consideration. On the right we have illustrated this interpretation as low and high frequency coefficients blocks, denoted by L and H, respectively. Remark that most of the high frequency coefficients are shown in grey color, which corresponds to small values around zero. The one dimensional wavelet transform can be applied to the columns of the already horizontal transformed image as well. The result is shown and is decomposed into four quadrants with different interpretations. LL: The upper left quadrant consists of all coefficients, which were filtered by the analysis low pass filter h˜ along the rows and then filtered along the corresponding columns with the analysis low pass filter h˜ again. This subblock is denoted by LL and represents the approximated version of the original at half the resolution. HL/LH: The lower left and the upper right blocks were filtered along the rows and columns with h˜ and g˜, alternatively. The LH block contains vertical edges, mostly. In contrast, the HL blocks shows horizontal edges very clearly. HH: The lower right quadrant was derived analogously to the upper left quadrant but with the use of the analysis high pass filter g˜ which belongs to the given wavelet. We can interpret this block as the area, where we find edges of the original image in diagonal direction.

ADAPTIVE IHS METHOD

In model-based approach to enhance the hyperspectral images using the Pan image. Their framework takes care of enhancement of any number of spectral bands. They also estimate the regularization parameters adaptively with the use of spectral response of the sensor. A linear image formation model and solve the fusion problem by applying a prior constraint under the regularization framework. An inhomogeneous Gaussian Markov random field (IGMRF) is used as a prior and its parameters are estimated using the Pan image that has high spatial resolution. Since the learning of the spatial relationship is entirely based on the Pan data, it adds to the spectral distortion in the fused image. The fusion performance of this method is also affected due to the approximate parameters estimation using maximum likelihood. It is also computationally taxing as a number of IGMRF parameters are estimated at every location in the image. fusion problem using an image degradation model and solved it using the Bayesian data fusion framework. They obtained the final fused image using the adaptation of visual and spectral details.

PROPOSED SYSTEM

The block schematic of our proposed multiresolution fusion is shown in Fig. 4.1, in which an *m*th low-resolution MS image and the Pan image are fused giving *Zm* as the fused image. The initial approximation of fused image (initial estimate) obtained using the Curvelet is used to recover the high-frequency details for the fused MS image. Using this initial estimate and the given LR MS image, the degradation matrix entries are estimated by posing it as a least squares problem. This degradation matrix gives us the relationship between the LR and HR MS images. The discontinuities in the final fused image correspond to the edge pixels in the initial estimate. A Canny edge detector is used to extract these edge details from the initial estimate. The fina solution is obtained by using the MAP-MRF formulation, in which the MRF prior parameters are estimated using the initial estimate. With this MAP framework, the final cost function consists of data-fitting term and the MRF prior term. This cost function is optimized using gradient-based optimization technique in order to smooth the non edge regions only. The use of WT in the fusion process preserves the edge details present in the horizontal, vertical and diagonal directions only. One can overcome this limitation using more recently proposed multiresolution and directional transforms called Curvelet. Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing. Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms in that the degree of localisation in orientation varies with scale.

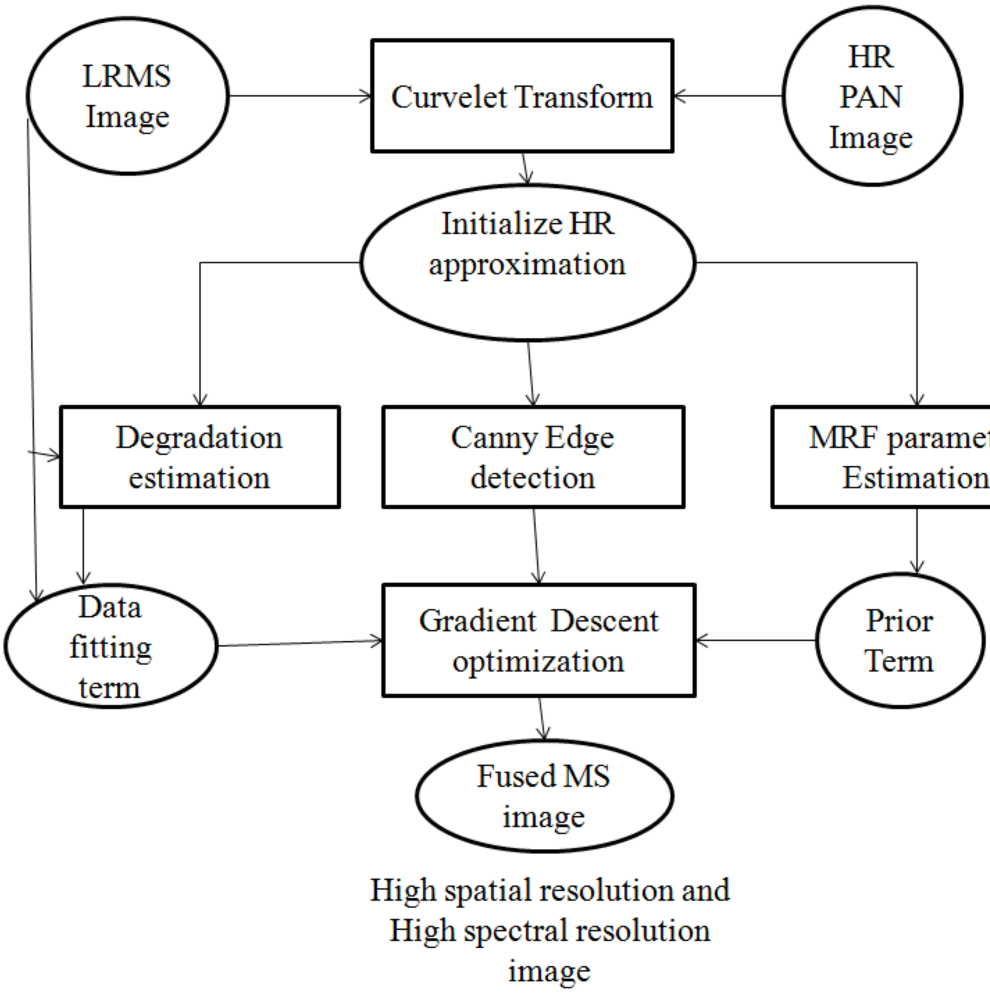

Fig 1 Block schematic of the multiresolution fusion process for fusing an mth MS and the Pan image

These missing frequencies can be obtained from the Pan data by using our learning approach. In order to do this, the low-frequency details are duplicated in the initial estimate from the MS image the Curvelet Transform decomposition. The missing high-frequency details, i.e., CT coefficients of level 3 and 4 are obtained by copying the CT coefficients of the Pan image that correspond to the third and fourth levels of the initial estimate. Once the the Curvelet Transform coefficients of the initial estimate are obtained, the inverse the Curvelet Transform is taken to obtain initial estimate in spatial domain. This process is repeated for all the MS image bands. It is worth to mention here that it is not possible to obtain the true edge details of final fused image. Hence, one has to look for those edge details that better approximate the edges in the final solution. Since the the Curvelet Transform gives better edge details, it is reasonable to assume that the edges in the initial estimate correspond to true edges. A Canny edge detector is then used to obtain the edges from this initial estimate. Here, one may argue on the selection of the Canny edge filter for edge preservation. However, it is well known that the Canny edge detector represents an optimum edge detector, and it performs better under noisy conditions.

FORWARD MODEL AND DEGRADATION ESTIMATION

Since we cast our problem in a restoration framework, solving such a problem needs a forward model that represents the image formation process. Let l be the number of low resolution MS images y_m ($m = 1, 2, . . . l$), each captured with a different spectral band, of size $M \times M$ and Z_m be the corresponding fused HR MS image of size $qM \times qM$, where q is the decimation factor representing the spatial resolution difference between the LR and HR fused images. The forward model for the image formation can be written as

$$y_m = A_m z_m + n_m, \quad m=1,2,\ldots l$$

In (1), $\mathbf{y}_m$ and $\mathbf{z}_m$ represent the lexicographically ordered vectors of size $M^2 \times 1$ and $q^2M^2 \times 1$, respectively. A_m is the degradation matrix of size $M^2 \times q^2M^2$, which accounts for aliasing and blur. In (1), $\mathbf{n}_m$ is the independent and identically distributed noise vector with zero mean and variance σ^2_{nm} and has same size as $\mathbf{y}_m$.

MRF PRIOR MODEL AND MAP ESTIMATION

In order to obtain a regularized estimate of the high resolution fused image, we define an appropriate prior term using MRF modeling. MRF provides a convenient and logical approach to model context-dependent entities such as pixel intensities, depth of the object, and other spatially correlated features. In this paper, we prefer to use an MRF model, which does not require the LR observations for parameter estimation. Also, the computational complexity is additionally reduced by the use of homogeneous MRF, where a single MRF parameter is estimated. An MRF prior for the unknown fused HR image can be described by using a energy function expressed as Gibbsian density. One can choose this energy function as a quadratic form with a single global parameter, assuming that the images are globally smooth.

A method of specifying MRF prior involves considering the pair wise cliques c on a neighborhood and imposing a quadratic cost that is a function of finite-difference approximations of the first-order derivative at each pixel location. This constitutes a homogeneous and non edge preserving smoothness prior. By using first order neighborhood, the energy function corresponding to the MRF prior can be written aswhere γ_m represents the MRF parameter that indicates the penalty for departure from smoothness in $\mathbf{z}_m$. C is the set of all cliques. The MRF parameter γ_m is known if the fused image is known. In our work, since the initial estimate is already available, we make use of the same to estimate γ_m. We use maximum pseudo-likelihood for estimating it. The MRF model on the fused image serves as the prior for the MAP estimation, in which the prior parameter is already known. The data-fitting term contains the degradation matrix estimated using the initial estimate. In order to use MAP estimation to HR fused image, we need to obtain the estimate as Using the Bayes' rule and the different steps.

RESULTS AND DISCUSSION

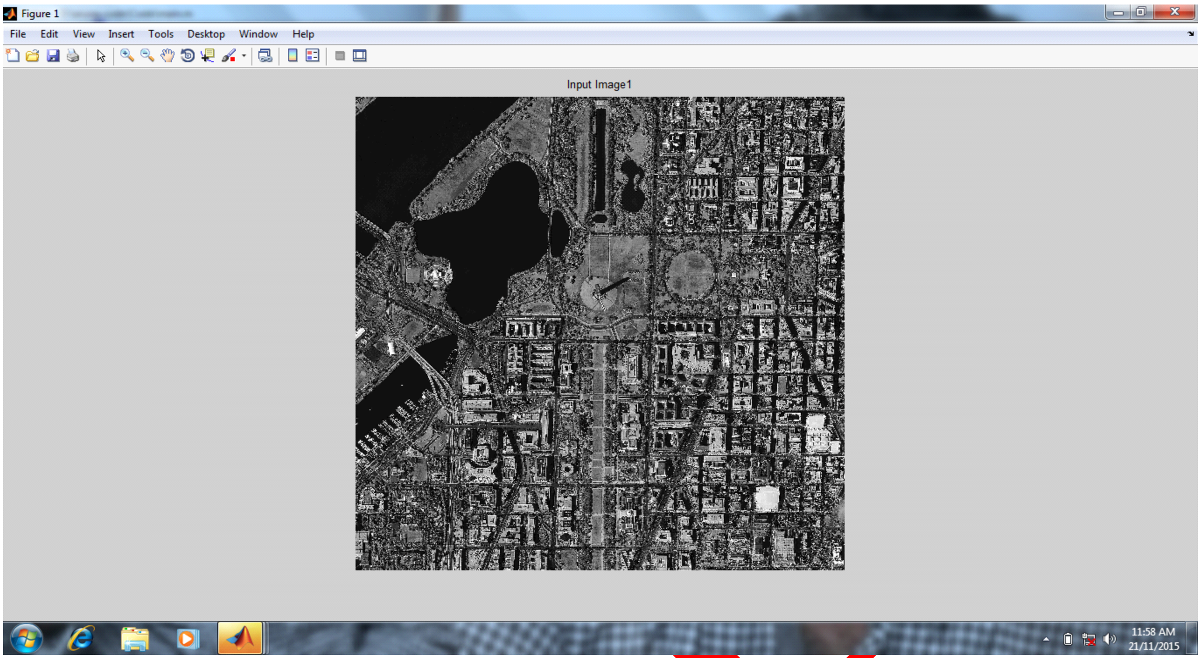

Fig 2 INPUT IMAGE 1

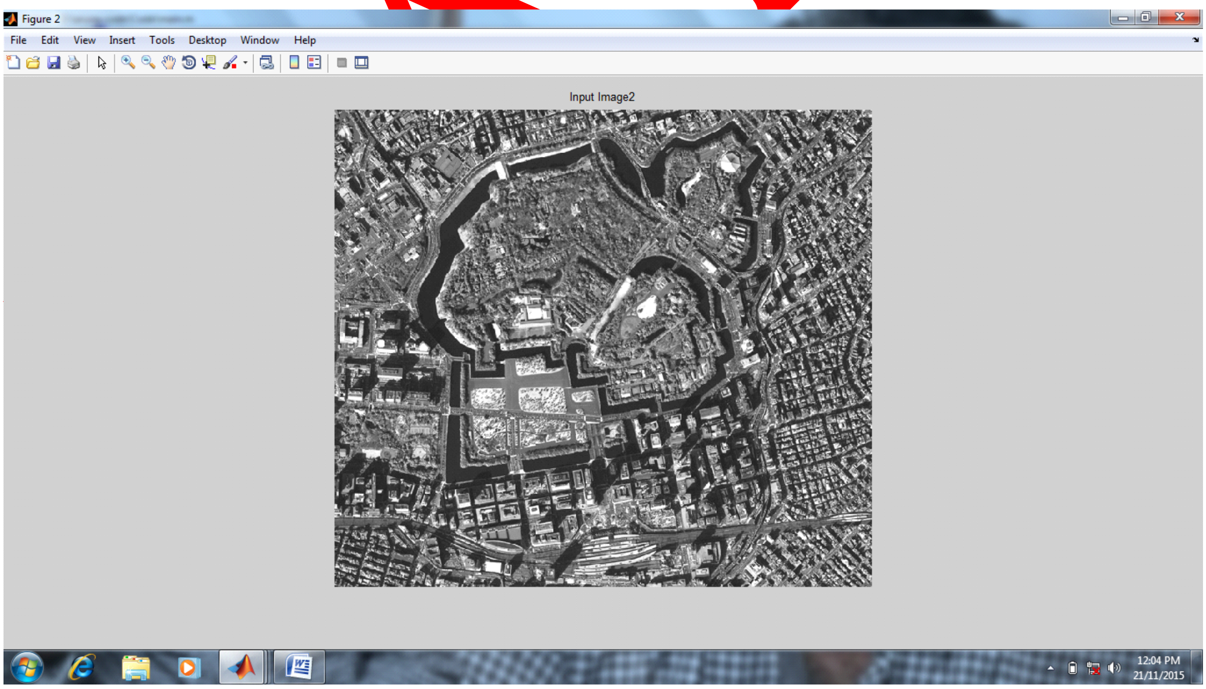

Fig 3 INPUT IMAGE 2

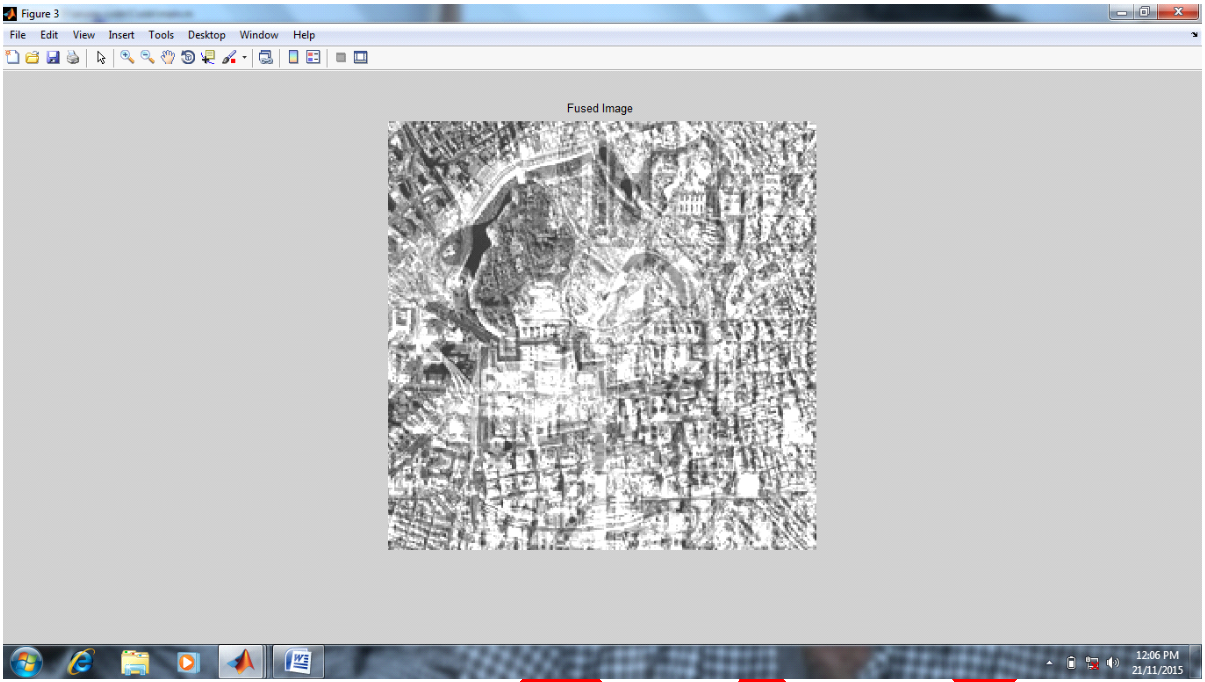

Fig 4 OUTPUT IMAGE

CONCLUSION

This project presents a new technique for multiresolution image fusion using curvelet-based learning and MRF prior. In the proposed method, we first obtain the initial high-resolution MS image by the available Pan image and the test MS image. Since the initial estimate has high spatial and spectral resolutions, it is used to obtain the degradation between fused MS and test MS image, where the blur is assumed to be a nonidentity matrix. We cast the fusion problem in the restoration framework and obtain the final solution by using the regularization framework. The final cost function is obtained using the MAP-MRF approach, where MRF smoothness prior is used to regularize the solution. The edge details in the final fused image are obtained by applying Canny edge detector on the initial estimate. The MRF parameter is also estimated using the initial estimate image, which is used during optimization. Experimental results demonstrate that the proposed method recovers the finer details with minimum spectral distortion. In addition, the perceptual and the quantitative analysis show that the proposed technique yields better solution when compared with the state-of-the-art approaches.

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