Multi-sensor image fusion with the steered Hermite Transform

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ABSTRACT

The steered Hermite Transform is presented as an efficient tool for multi-sensor image fusion. The fusion algorithm is based on the Hermite transform, which is an image representation model based on Gaussian derivatives that mimic some of the most important properties of human vision. Moreover, rotation of the Hermite coefficients allows efficient detection and reconstruction of oriented image patterns in reconstruction applications such as fusion and noise reduction.

We show image fusion with different image sensors, namely synthetic aperture radar (SAR) and multispectral optical images. This case is important mainly because SAR sensors can obtain information independently of weather conditions; however, the characteristic noise (speckle) present in SAR images possesses serious limitations to the fusion process. Therefore noise reduction is a key point in the problem of image fusion. In our case, we combine fusion with speckle reduction in order to discriminate relevant information from noise in the SAR images. The local analysis properties of the Hermite transform help fusion and noise reduction adapt to the local image orientation and content. This is especially useful considering the multiplicative nature of speckle in SAR images.

Keywords: Image fusion, Hermite transform, steerable transforms, local orientation analysis, speckle reduction, remote sensing.

1. INTRODUCTION

Image fusion improves interpretation and provides better analysis capability. Image fusion provides a tool to combine information sources with different spectral, spatial and temporal resolutions. Recent multiresolution techniques such as image pyramids and wavelet transforms have been used in image fusion. Several authors have showed that, for image fusion, the wavelet transform approach obtains good results [1]. A methodology for image fusion based on the Hermite transform (HT) is presented in this paper. The tool shown here is appealing for different fusion applications, this is, it can be used to fuse images from the same sensor such as optical imagery, or from different sensors, such as synthetic aperture radar (SAR) images with optical imagery.

HT fusion schemes take advantage of the fact that Gaussian derivatives are good operators to detect relevant image patterns [2]. Moreover, the HT can be locally rotated, adapting to the local dominant orientation which results in significant energy compaction [3],[4],[5]. In this paper we concentrate in multisensor image fusion, namely SAR and multispectral Landsat 7 TM. This case is important since SAR sensors can obtain information independently from weather conditions; however noise present in SAR images (speckle) possesses limitations to the fusion process. We tackle the problem by combining fusion with speckle reduction in order to discriminate relevant information from noise in the SAR image. The fusion algorithm is based on the directional oriented Hermite transform, which is an image representation model based on Gaussian derivatives that mimic some of the most important properties of human vision. The local analysis properties of the Hermite transform help fusion and noise reduction adapt to the local orientation and image content. This is especially useful considering the multiplicative nature of speckle in SAR images.

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Optical and Digital Image Processing, edited by Peter Schelkens, Touradj Ebrahimi, Gabriel Cristóbal,
Frédéric Truchetet, Proc. of SPIE Vol. 7000, 70002A, (2008) · 0277-786X/08/$18 · doi: 10.1117/12.783872

2. HERMITE TRANSFORM

In this section we will briefly discuss the basic principles of the Hermite transform. The HT is a special case of a polynomial transform. First, windowing takes place at several positions over the input image, resulting in a sampling lattice S. In the second step, the local information contained within every window is expanded in terms of a set of orthogonal polynomials $G_{m,n-m}(i,j)$. In the case of the HT, a 2-D Gaussian function is used as local analysis window [2]:

$$\omega(i,j)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i^2+j^2)}{2\sigma^2}\right) \tag{1}$$

Windowing takes place at several positions *(p,q)* that conform the sampling lattice S over the entire image. In order to fully recover the original image from the localized information, a periodic weighting function *W(i,j)* must be defined:

$$L(i,j)=\frac{1}{W(i,j)}\sum_{p,q\in S}L(i,j)\omega(i-p,j-q) \tag{2}$$

where $W(x,y)=\sum_{(p,q)\in S}\omega(i-p,j-q)$. The signal content within the window function is described by a weighted sum of orthogonal polynomials $G_{m,n-m}(i,j)$ of order m in i and order $n-m$ in j. For the case of the Gaussian window, the corresponding orthogonal polynomials are the Hermite polynomials:

$$G_{n-m,m}(i,j)=\frac{1}{\sqrt{2^n(n-m)!m!}}H_{n-m}\left(\frac{i}{\sigma}\right)H_m\left(\frac{j}{\sigma}\right) \tag{3}$$

where $H_n(i)$ denotes *nth* Hermite polynomial

The polynomial coefficients $L_{m,n-m}(p,q)$ are calculated by convolution of the original image $L(x,y)$ with the function filter $D_{m,n-m}(i,j)=G_{m,n-m}(-i,-j)V^2(-i,-j)$ followed by subsampling at positions *(p,q)*, i.e.,

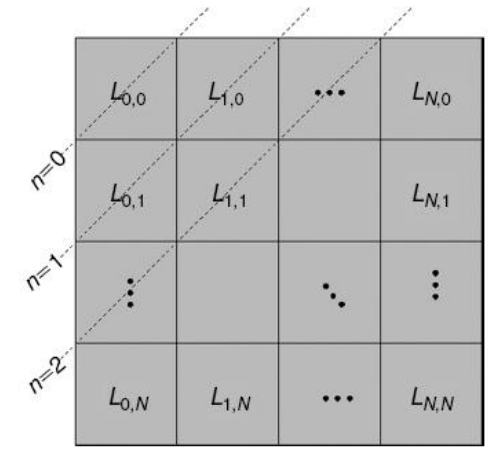
$$L_{m,n-m}(p,q)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}L(i,j)D_{m,n-m}(i-p,j-q)\,didj \tag{4}$$

The inverse polynomial transform is defined by an interpolation process with pattern functions $P_{m,n-m}(i,j)$:

$$\hat{L}(i,j)=\sum_{n=0}^{\infty}\sum_{m=0}^{n}\sum_{(p,q)\in S}L_{m,n-m}(p,q)P_{m,n-m}(i-p,j-q) \tag{5}$$

where $P_{m,n-m}(i,j)=\frac{G_{m,n-m}(i,j)\omega(i,j)}{W(i,j)}$ for a $m=0,\dots,n$ and $n=0,\ 1,\dots,\infty$

In practice, HT implementaion using a Gaussian window requires the choice of some parameters, i.e. the size of the Gaussian window spread (σ) and a subsampling factor that defines the sampling lattice *S*. Resulting Hermite coefficients


$L_{0,0}$
$L_{1,0}$
$L_{N,0}$
$L_{0,1}$
$L_{1,1}$
$L_{N,1}$
$L_{0,N}$
$L_{1,N}$
$L_{N,N}$
$n=0$
$n=1$
$n=2$

$$g_{m,n-m}\left(\theta-\theta_0\right)=\sum_{k=0}^{n} c_{m,k}\left(\theta_0\right) g_{n-k,k}\left(\theta\right) \tag{9}$$

where $c_{m,k}^{(n)}\left(\theta_0\right)$ is the rotated coefficient. Fig 2. shows the directional Hermite decomposition over an image. First, a Hermite transform was applied and then the coefficients of this transform were rotated toward the estimated local orientation, according to a criterion of maximum oriented energy at each window position. For local 1D patterns, the steered Hermite transform provides a very efficient representation. This representation consists of a parameter θ that indicates the orientation of the pattern and a small number of coefficients that represent the profile of the pattern perpendicular to its orientation. For such pattern, steering over θ results in a compaction of energy into the coefficients $L_{n,0}^{\theta}$, while all other coefficients are set to zero. Using Hermite coefficients, the energy content can be expressed as (Parseval Theorem)

$$E_{\infty}=\sum_{n=0}^{\infty}\sum_{m=0}^{n}\left[L_{n-m,m}\right]^2 \tag{10}$$

The steered Hemite transform offers a way to describe 1D patterns on the basis of their orientation and profile. We can define the 1D energy and the 2D energy measures of the signal contained within each local position as

$$E_N^{1D}\left(\theta\right)=\sum_{n=1}^{N}\left[L_{n,0}^{\theta}\right]^2, \tag{11}$$

$$E_N^{2D}\left(\theta\right)=\sum_{n=1}^{N}\sum_{m=1}^{n}\left[L_{n-m,m}^{\theta}\right]^2 \tag{12}$$

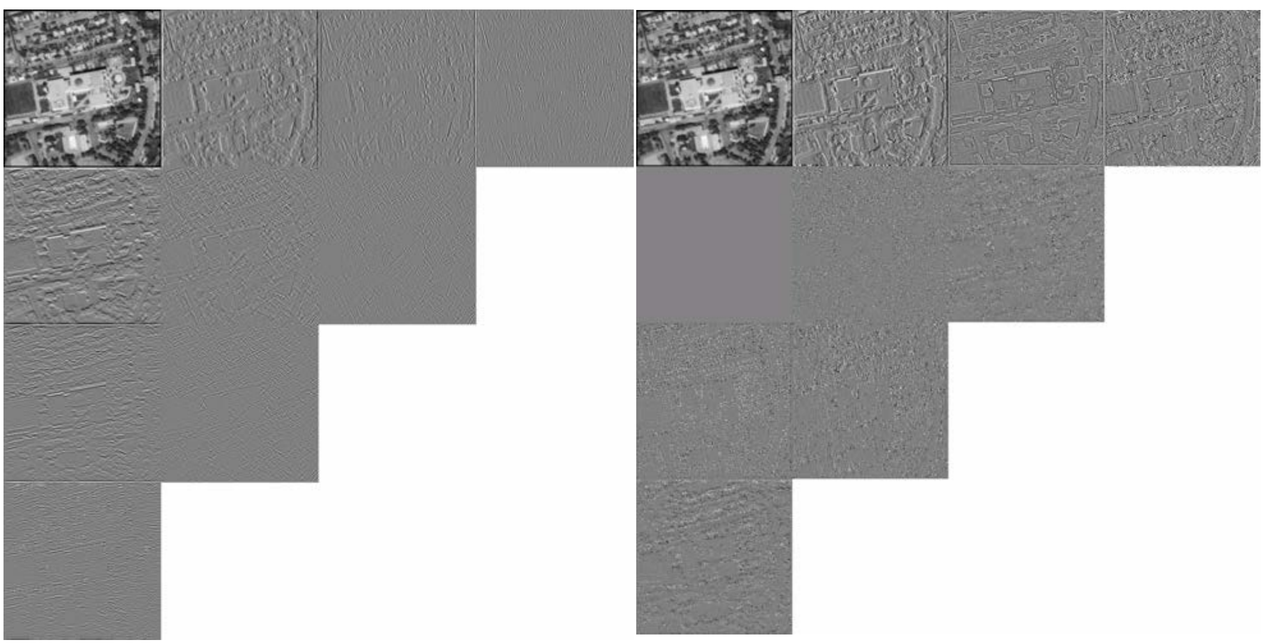


Fig. 2. Steered Hermite transform. Left: Original coefficients, Right: Steered coefficients.

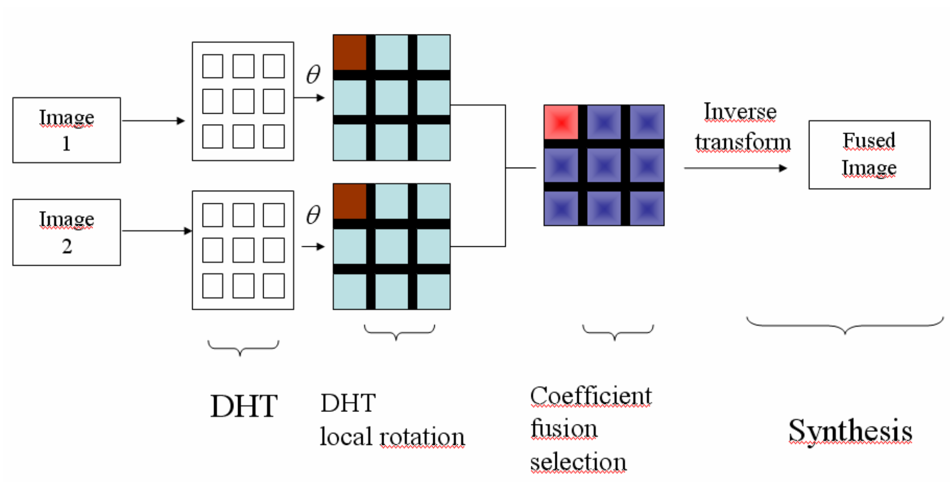


Image 1
Image 2
θ
θ
Inverse transform
Fused Image
DHT
DHT local rotation
Coefficient fusion selection
Synthesis

SAR images have a Rayleigh distribution and the signal-to-noise ratio (SNR) is approximately 1.9131. Second, in general, the SNR of multilook SAR images does not change over the whole image.
The threshold is calculated by:

$$T = \frac{2\alpha}{\mathrm{SNR}^2 N_{look}} \ln\left(\frac{1}{P_R}\right) L_{00}^2 \tag{13}$$

where SNR is the signal to noise ratio, equal to 1.9131; N_{look} is the number of looks of the image; P_R is the probability (percentage) of noise left on the image and will be set by the user; L_{00} is the zero-order Hermite coefficient; $\alpha = \left| R_L(x,y) * D_{1,0}(x,y) * D_{1,0}(-x,-y) \right|_{x=y=0}$, R_L is the normalized autocorrelation function of the input noise, and $D_{1,0}$ is the filter used to calculate the HT first-order coefficient.

A careful analysis of this expression reveals that this threshold adapts to the local content of the image because of the dependence of the noise variance on the local mean value, the latter being approximated by the Hermite coefficient L_{00}.

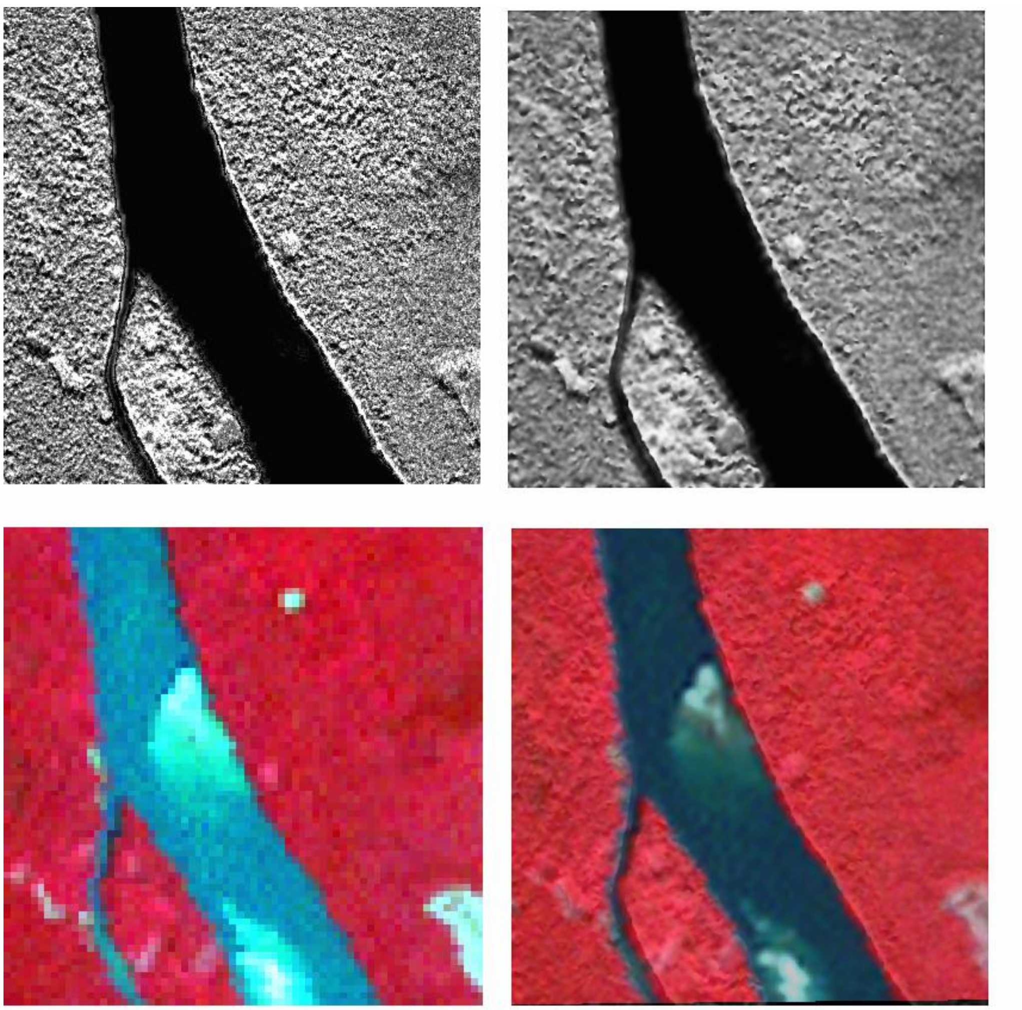
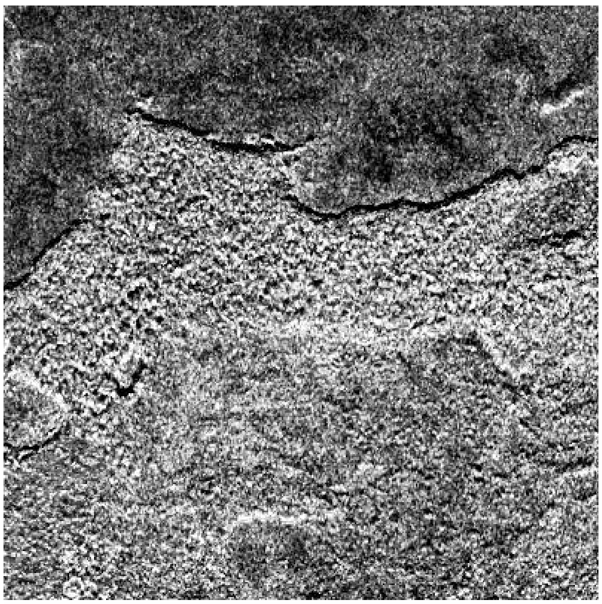
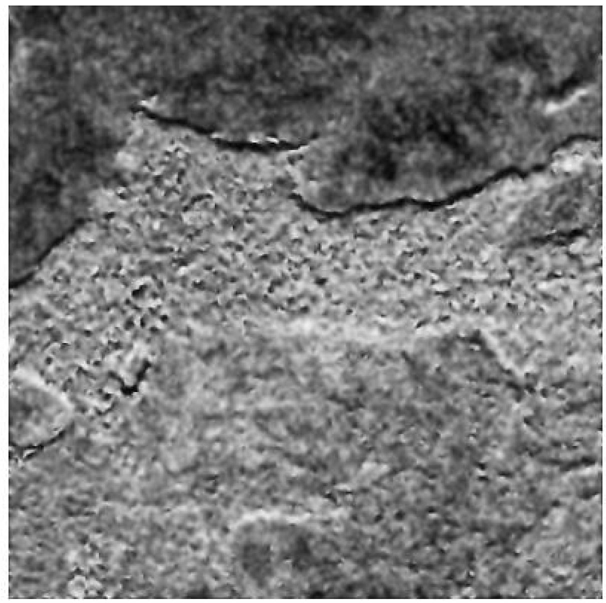
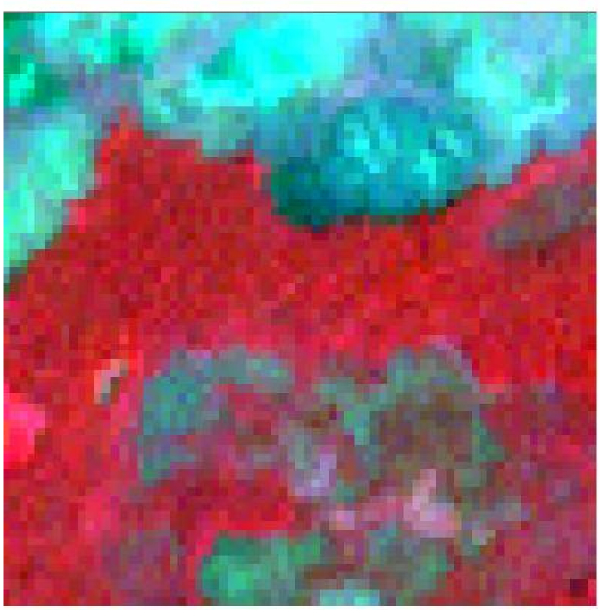
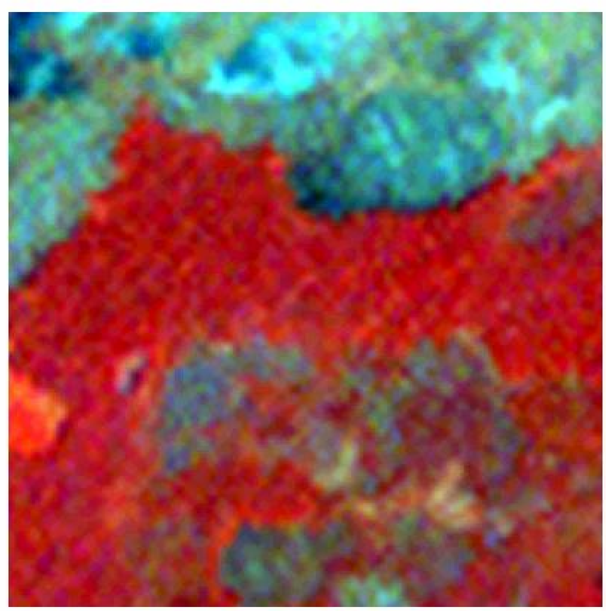


Fig. 4. Top left, SAR AeS-1 image with speckle. Top right, SAR image with speckle reduction. Bottom left, RGB composition of multispectral Landsat-7 ETM+. Bottom right, Resulting fused image fusion with noise reduction









5. CONCLUSIONS

In this work we presented the HT as an efficient tool for image fusion in remote sensed data. The use of Gaussian derivatives as basis functions of the HT makes this transform especially suitable to represent relevant image structures such as edges. Moreover, the rotation property of the HT presented here is an important feature that allows detecting the orientation of relevant image structures.

This translates into an energy compaction into few coefficients of the transform. Furthermore, the local orientation property of the HT is a key factor for the reconstruction of oriented patterns. We profit from this property in the proposed speckle reduction algorithm for SAR images.

The proposed scheme for fusion between MS and SAR images also shows very good performance, since the higher resolution and relevant texture of the SAR image are incorporated into the MS image without loosing spectral integrity

ACKNOWLEDGMENTS

This work was sponsored by UNAM PAPIIT grant IN106608 and the Center for Geography and Geomatics Research Ing. Jorge L. Tamayo.

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