Investigation of the Dual-Tree Complex and Shift-Invariant Discrete Wavelet Transforms on Quickbird Image Fusion

Styliani Ioannidou and Vassilia Karathanassi

***Abstract*—In the current survey, the performance of the shift-invariant discrete wavelet transform and dual-tree complex wavelet transform (DT-CWT) for Quickbird image fusion is investigated. For this purpose, a DT-CWT fusion algorithm is developed and implemented on high-resolution multispectral and panchromatic Quickbird images of Heraclion, Crete, Greece. In order to point out the effectiveness of the aforementioned transforms, the resulting imagery is visually (through photointerpretation) and computationally (through index computations) compared to fusion products derived by other commonly used methods, such as the intensity hue saturation transform (IHS), the discrete wavelet transform, and the crossbred wavelet and IHS transform. The DT-CWT has been proved to provide a complete and effective tool for Quickbird image fusion.**

***Index Terms*—Dual-tree complex wavelet transform (DT-CWT), fusion, Quickbird, shift-invariant discrete wavelet transform (SIDWT), wavelets.**

I. Introduction

MULTISENSOR image fusion is the procedure of implementing appropriate algorithms that associate, correlate, and combine datasets derived from various satellite systems to produce remotely sensed images with desirable features, i.e., images that accumulate the spectral characteristics of the initial multispectral bands and the geometry of the very high-resolution panchromatic band.

Quickbird, for example, is a very high-analysis multispectral and panchromatic satellite sensor acquiring imagery with 8- and 2-ft resolution, respectively. Thus, fusion methods producing multispectral bands with 2-ft resolution are of significant importance for remote-sensing applications.

Among data-fusion methods, the discrete wavelet transform (DWT) [3] is a flexible tool capable of both time and frequency analyses of input signals in a multiresolution environment basis. Apart from its various advantages, two main drawbacks of the DWT [1] are the existence of shift variance and the directional constraint in diagonal feature extraction (45° plane).

One of the oldest transforms compensating the DWT disadvantages is the shift-invariant DWT (SIDWT), which is based on the fact that not all shifts are necessary for perfect signal reconstruction [5], [6].

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The authors are with the Laboratory of Remote Sensing, School of Rural and Surveying Engineering, National Technical University of Athens, 157 80 Zographos, Greece (e-mail: si01613@survey.ntua.gr; karathan@survey.ntua.gr).

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A near-shift independent wavelet-oriented method is the dual-tree complex wavelet transform (DT-CWT) [1], which deals with the shift variance phenomenon using parallel wavelet filtering with directionality support (six planes). This filtering provides a 1/2 sample delay in the wavelet branches of the dual trees allowing near-shift invariance and perfect reconstruction.

In this letter, a DT-CWT-based fusion algorithm is developed. This algorithm and the existing algorithm based on the SIDWT are for the first time applied on Quickbird imagery. Their results are compared to the results produced by conventional fusion algorithms such as those based on the DWT, the intensity hue saturation (IHS), and the crossbred wavelet and IHS (WIHS) transform.

II. SIDWT and DT-CWT Related Theory

Once the DWT is implemented, every second wavelet coefficient at each decomposition level is discarded, resulting in components highly dependent on their location in the subsampling vector and with great uncertainty as to when they occurred in time. This unfavorable property is referred to as shift variance and can be avoided by implementing a transform known as the SIDWT. Contrary to the simple DWT fusion method, no subsampling occurs, leading to highly redundant wavelet decomposition [5].

Rockinger [5] proposed a shift-invariant wavelet algorithm by oversampling the plain DWT.

Disregarding the severe computational cost ($(3^{*}J+1)$ coefficients for J analysis levels) and its overcompleteness, the use of an undecimated SIDWT would, yet, not solve the output directionality constraint mentioned in the Introduction [2].

The DT-CWT idea is based on the use of two parallel treelike filter series that implement complex wavelet filtering on the input signals. These trees provide the signal delays necessary for every level of multiresolution analysis, so as to eliminate aliasing effects and achieve shift invariance [2].

As far as the DT-CWT is concerned, since complex wavelets can discriminate positive from negative frequencies, the diagonal subbands can be distinguished into more directions than the ones that the simple DWT produces ($2^{*}J$ DWT coefficients for J analysis levels). The two-dimensional (2-D) DT-CWT produces $2^{2*}J$ coefficients of analysis.

III. DT-CWT Fusion Algorithm

The DT-CWT fusion algorithm (Fig. 1) first implements a forward DT-CWT to the input satellite data, decomposing the

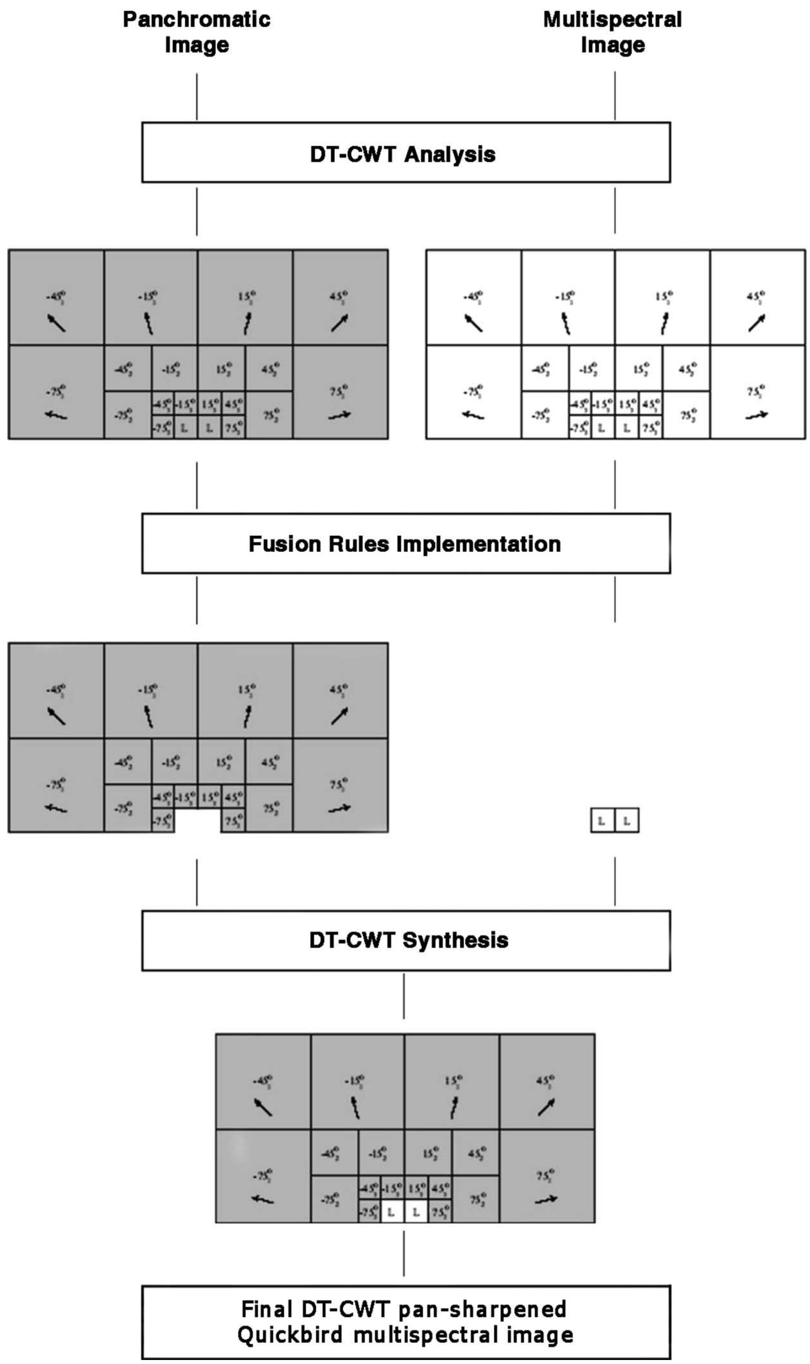

Fig. 1. DT-CWT fusion algorithm developed.

panchromatic and multispectral bands into the coefficients of wavelet analysis. This is achieved by a near-symmetric 13–19 tap filter with a 14–14 shift filter.

Having decomposed the initial datasets, their multiresolution and multidirectional descriptions are derived, along with respective magnitudes. Wavelet and scaling coefficients are extracted from each of the multispectral and panchromatic bands. Wavelet coefficients express the detail coefficients, and scaling coefficients are approximations of the initial bands. After the complex wavelet-based analysis, the fusion rule occurs.

The rule suggests the combination of the panchromatic band's wavelet coefficients with the multispectral bands' scaling coefficient. That is, the outcome of successive lowpass filtering on the multispectral bands and the outcomes of successive highpass filtering on the panchromatic image (all six directional planes) are combined (Fig. 1). After the implementation of the fusion rule, an inverse DT-CWT is generated between selected features. The final fused image has accumulated the geometry of the panchromatic band (2-ft analysis) and the spectral analysis of the multispectral bands.

IV. Implementation of Fusion Algorithms

A. Datasets

The data consist of two sets of images: the first representing a peri-urban area and the second depicting an offshore urban one.

Both are parts of a multispectral and panchromatic Quickbird image of Heraclion, Crete, Greece.

Subsets have been selected in order to include a variety of land-use categories, i.e., buildings, roads, sea, vegetation, grass, and bare soil, delimited by many multioriented edges. The land-use variety implies a variation in spectral signatures, which should be respected in the fused spectral bands, independently of the spectral range of the panchromatic band that is used during the fusion procedure. Moreover, edges on the fused images should be as clear as possible, independent of their orientation.

B. Preprocessing

Since the majority of the applied fusion algorithms (apart from IHS) have been developed on a DWT basis, preprocessing has been set to meet DWT requirements. Given that each level of wavelet analysis produces a digital image with half the spatial resolution of the initial one, for a successful pixel-based wavelet image fusion, the ratio of the spatial resolutions of the input imagery must be a power of two. High-resolution multispectral and panchromatic satellite sensors (i.e., Quickbird, IKONOS, and SPOT-5) meet this requirement, therefore from this point of view, no resampling is needed. Due to the fact that the grids of the panchromatic and multispectral images are not coincident, a pixel from the first image does not fully match its twin in the second image. Thus, in this letter, resampling has been implemented for subpixel coregistration-accuracy purposes.

C. Processing

The 2-D SIDWTs proposed by Rockinger and the DT-CWT have been applied on the datasets. For evaluation purposes, the DWT, the IHS, and the WIHS transforms have also been implemented. Since the spatial resolution of Quickbird panchromatic imagery is four times the spatial resolution of Quickbird multispectral imagery, three levels of analysis are needed for all wavelet-based fusion algorithms. In this letter, the Haar wavelet—which is the most commonly used and is included in most software packages—has been implemented for all image case studies apart from the DT-CWT, which uses complex-based wavelets.

All computations have been performed on a Pentium IV personal computer, using a 3.00-GHz processor, running Windows 2000. The MATLAB codes implementing the forward and inverse DT-CWT are courtesy of Dr. Nick Kingsbury, and for all wavelet-based methods, the Image Fusion Toolbox for MATLAB developed by Oliver Rockinger has been used. For IHS-based methods, ER Mapper was used.

V. Fusion Results

The fusion algorithms were applied on the two datasets. The results for the peri-urban area are presented in Fig. 2(a)–(g).

VI. Evaluation

Since human perception uses the most integrated mechanisms that include spectral statistical and spatial criteria for evaluating fusion results, photointerpretation evaluation has taken place first. Photointerpretation of the final fused images has shown that the IHS fusion transform is obviously prone to spectral distortions, although it produces excellent spatial characteristics. The wavelet-based fusion algorithms (DWT, DT-CWT, and SIDWT) have ascribed the initial spectral information satisfactorily, with minor visual differences. However, the DWT and WIHS fusion algorithms have produced objects with obvious jagged edges, a sign of spatial distortion (Fig. 3).

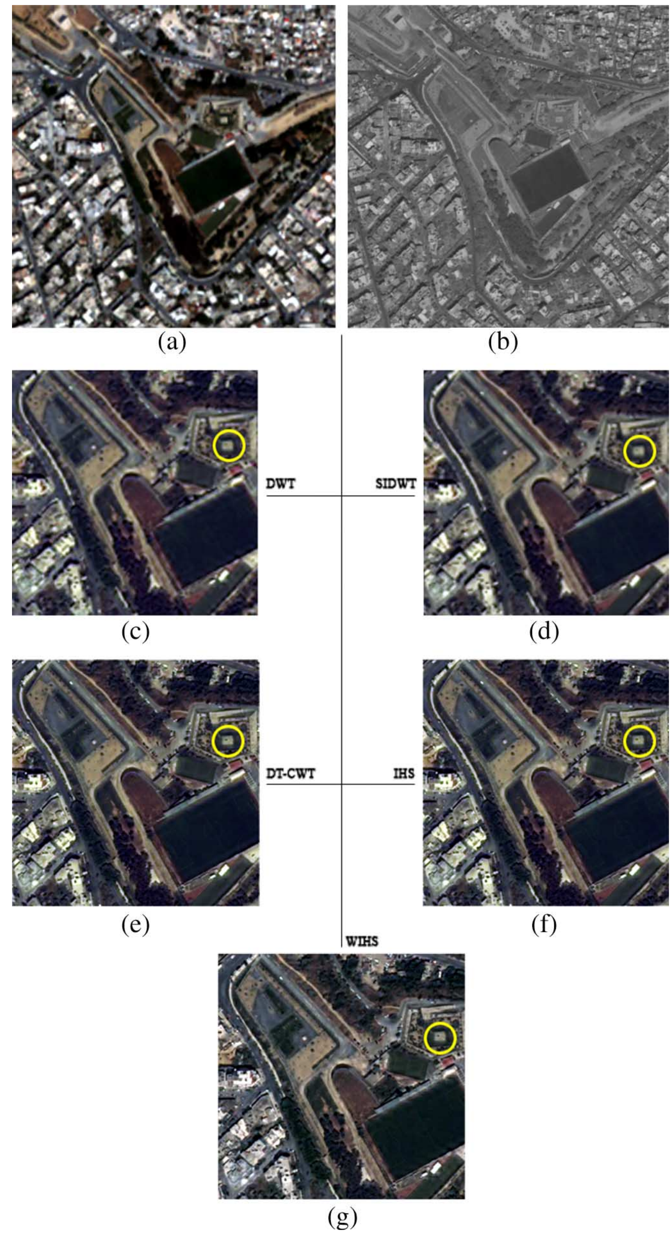

Fig. 2. (a) Original true-color composite. (b) Original panchromatic Quickbird image. (c) DWT fused image. (d) SIDWT fused image. (e) DT-CWT fused image. (f) IHS fused image. (g) WIHS fused image of Quickbird imagery of a peri-urban area of Crete, Greece.

The SIDWT produces fused results with satisfactory spectral characteristics but relatively ambiguous object edges (moderate spatial attribution), whereas the DT-CWT has produced well-balanced results with adequate both spectral and spatial details (Fig. 3).

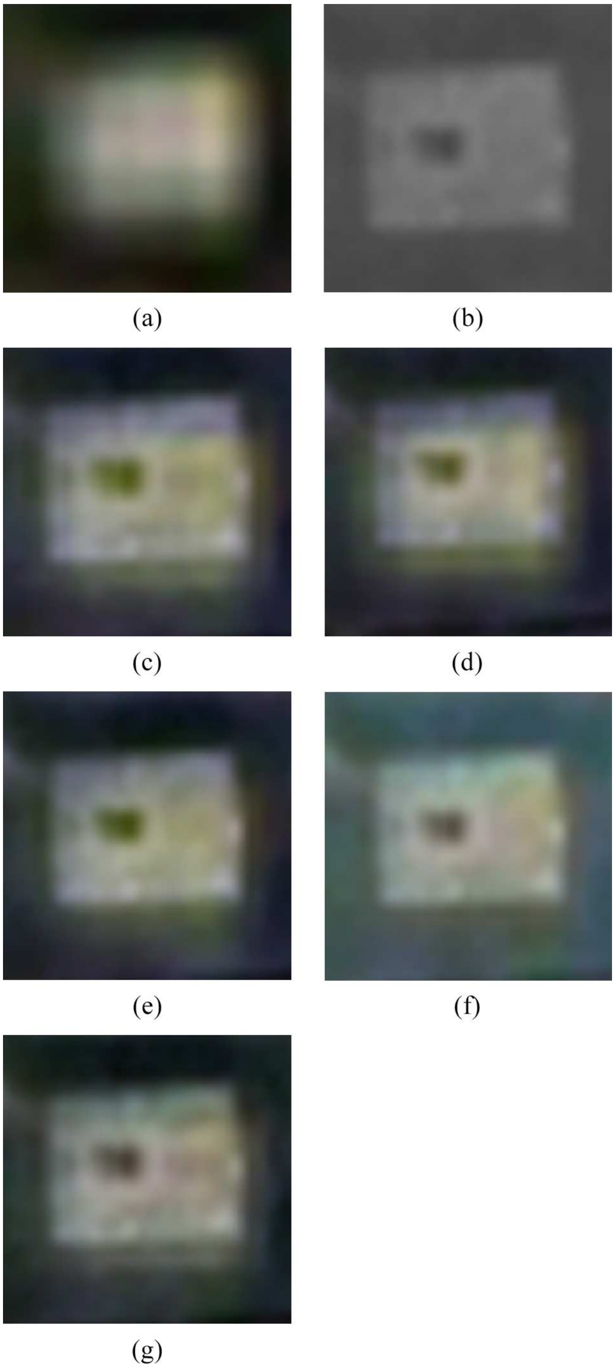

Fig. 3. Detail of peri-urban area image. (a) Original multispectral Quickbird image. (b) Original panchromatic Quickbird image. (c) DWT. (d) SIDWT. (e) DT-CWT. (f) IHS. (g) WIHS transform.

As far as the numerical evaluation of the fusion process is concerned, three types of indexes were used: The 2-D correlation index (r) [4], the peak-signal-to-noise ratio (PSNR) [8], and the similarity-based quality index (SSIM) have been used [7]. The 2-D correlation index is a statistical index showing correlation of the values of the pixels between two images compared. The entire image is taken into consideration during calculations. The PSNR is a physical-statistical index showing the ratio between signal and noise in an image. The SSIM index is a similarity-based structure studying the combination of image contrast and luminance.

TABLE I
PSNR INDEX BETWEEN FUSED AND ORIGINAL MULTISPECTRAL BANDS, IMPLEMENTING VARIOUS IMAGE-FUSION METHODS

PSNR index (multispectral bands)						
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img. 1	blue	30,3416	31,4903	**31,4995**	29,6339	24,0650
	green	31,4538	**32,3941**	31,8656	27,9065	24,0740
	red	31,3060	**32,2095**	31,7761	29,2831	24,0658
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img. 2	blue	31,7805	**32,7908**	32,7625	24,8583	27,0950
	green	32,8300	**33,5278**	33,1197	24,5767	25,8100
	red	32,6579	**33,3570**	33,0285	25,9805	25,1352

TABLE II
CORRELATION INDEX BETWEEN FUSED AND ORIGINAL MULTISPECTRAL BANDS, IMPLEMENTING VARIOUS IMAGE-FUSION METHODS

Two dimensional correlation index (multispectral bands)						
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img.1	blue	0,7686	0,7952	**0,8620**	0,7331	0,8303
	green	0,9150	**0,9342**	0,9159	0,8087	0,8759
	red	0,8992	**0,9196**	0,9001	0,8684	0,9051
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img.2	blue	0,8096	0,8397	0,8218	**0,8914**	0,8903
	green	0,9425	**0,9539**	0,9442	0,9151	0,9153
	red	0,9374	**0,9494**	0,9407	0,9350	0,9436

Of the above indexes, the 2-D correlation is insufficient because it does not fully describe all statistical dimensions of an image, whereas the PSNR and SSIM indexes provide a more complete understanding. Any significant differences between index values start from the second decimal place. For all indexes, high index values imply high quality of fused images in terms of spectral information. Spatial criteria are not introduced in these indexes. They can be indirectly implied only on the basis of the spectral consistency between the initial and the fused image.

Among the three indexes, the PSNR index presents a steady behavior (Table I), pointing the SIDWT (31.49–32.21) as the most effective fusion algorithm for all bands and datasets followed closely by the DT-CWT. The method that comes third is the DWT.

Regarding the 2-D correlation indexes (Table II), the same conclusions are produced for the green and red bands: SIDWT (first) and DT-CWT (second) are the most effective fusion algorithms.

The SSIM (Table III) is the index with the highest range of values (0.34–0.79) because of the inclusion of both contrast and luminance criteria. According to the evaluation, for the red and green bands, the SIDWT appears to provide the best fusion results (0.75 for the green and 0.70 for the red band) followed by the DWT (0.73 for the green and 0.68 for the red band). Given the obviously degraded spatial results of this algorithm (Fig. 3), the weakness of the index in evaluating spatial characteristics is substantiated. The DT-CWT takes the third place (0.73 for the green and 0.64 for the red band).

TABLE III
SSIM INDEX BETWEEN FUSED AND ORIGINAL MULTISPECTRAL BANDS, IMPLEMENTING VARIOUS IMAGE-FUSION METHODS

SSIM index (multispectral bands)						
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img. 1	blue	0,53230	0,79050	0,55600	0,67240	**0,73540**
	green	0,68400	**0,73140**	0,67220	0,60020	0,56560
	red	0,65890	**0,70560**	0,64950	0,59250	0,34940
	Band	Method				
		DWT	SIDWT	DTCWT	IHS	WIHS
Img. 2	blue	0,65150	0,69070	0,66440	0,45700	**0,73880**
	green	0,75110	**0,78040**	0,73960	0,41950	0,69740
	red	0,73000	**0,75900**	0,72060	0,48780	0,35170

The spectrum of the panchromatic band includes part of the near infrared region and does not fully overlap with the blue region, causing problematic spectrum matching. Each fusion algorithm covers this defect in a different way, which becomes obvious in the evaluation results of the blue band. The three indexes present the highest differences in their evaluation. According to the SSIM, the best results are produced by the SIDWT and the WIHS. The 2-D correlation index shows that the first place is shared by the DT-CWT (first dataset) and the IHS (second dataset), and the WIHS holds the second place. The PSNR presents the DT-CWT and the SIDWT as the best fusion algorithms. Thus, objective conclusions based on the indexes cannot be drawn for this band.

Based on the evaluation of all indexes, the spectral distortions of IHS fused results, clearly observed through the photointerpretation procedure, are successfully quantified. Moreover, based on the same evaluation, we note essential improvements in terms of spectral attribution produced by the WIHS algorithm.

VII. CONCLUSION

In the current survey, the DT-CWT-based fusion algorithm was developed and applied for the first time on Quickbird imagery. For evaluation purposes, the DT-CWT fusion results were compared to the results from other wavelet-based and color-related techniques, such as the DWT, the SIDWT, the IHS transform, and the WIHS.

As far as the evaluation is concerned, a photointerpretation procedure as well as a numerical evaluation took place. Through the former, emphasis was given on the clearness of the fused image (e.g., unambiguous edges, revealing of details, etc.), whereas the latter focuses on the quantified evaluation of the preservation of the spectral information of the initial data on the fused results. Three types of numerical indexes were used: the 2-D correlation, the PSNR, and the SSIM index.

Based on the interpretation results, it was proved that the DT-CWT algorithm produces images with excellent spatial characteristics similar to those produced by IHS. Compared to other wavelet fusion algorithms, it most eliminates spatial distortions followed by the SIDWT and WIHS algorithms. In the spectral domain, evaluation indexes and photointerpretation converge on the evaluation of the SIDWT as the algorithm with the highest preservation of the spectral information. DT-CWT closely follows as well as the DWT fusion algorithm. The IHS transform presents the worst results. Regarding computational cost between SIDWT and DT-CWT, complexity of the SIDWT is much higher than the respective of the DT-CWT.

Based on the overall evaluation criteria, the DT-CWT appears to be an effective tool for Quickbird image fusion. The weakness of Quickbird panchromatic image to fully cover the blue spectral region becomes obvious through the numerical evaluation of the blue fused band. Similar evaluation results are expected in case that the infrared band, instead of the blue, participates in the fusion procedure. However, this will be subject of future work.

REFERENCES

[1] N. Kingsbury, "The dual-tree complex wavelet transform: A new technique for shift-invariance and directional filters," presented at the IEEE Transactions Digital Signal Processing Workshop, DSP, Bryce Canyon, UT, Aug. 1998, Paper no. 86.

[2] ——, "Image processing with complex wavelets," *Philos. Trans. R. Soc. London, A Discuss. Meeting on Wavelets: The Key to Intermittent Inf.*, London, U.K., Feb. 24–25, 1999, vol. 350, no. 760, pp. 2543–2560. Paper 1471-2962.

[3] S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 11, no. 7, pp. 674–693, Jul. 1989.

[4] M. Misiti, Y. Misiti, G. Oppenheim, and J. M. Poggi, *Wavelet Toolbox for Use with Matlab*. Natick, MA: The Mathworks Inc., 2004.

[5] O. Rockinger, "Image sequence fusion using a shift-invariant wavelet transform," in *Proc. ICIP*, 1997, vol. 3, pp. 288–291.

[6] M. Unser, "Texture classification and segmentation using wavelet frames," *IEEE Trans. Image Process.*, vol. 4, no. 11, pp. 1549–1560, Nov. 1995.

[7] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

[8] Z. Wang, H. R. Sheikh, and A. C. Bovik, "Objective video quality assessment," in *The Handbook of Video Databases: Design and Applications*, B. Furht and O. Marqure, Eds. Boca Raton, FL: CRC, 2003, ch. 41, pp. 1041–1078.