PROCESSING MULTICHANNEL RADAR IMAGES BY MODIFIED VECTOR SIGMA FILTER FOR EDGE DETECTION ENHANCEMENT

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ABSTRACT

Some peculiarities of modified vector sigma filter are studied. In particular, its edge preservation ability is considered in case of processing multichannel remote sensing (RS) images. Such a problem is of high importance for many scene recognition and segmentation tasks. It is demonstrated through comparative quantitative and visual processing data that the proposed filter simultaneously provides efficient noise suppression and excellent edge preservation. Edge detection results that prove this fact are also depicted.

1. INTRODUCTION

It is well known that many existing RS systems operate in multichannel mode [1,2]. The term “multichannel” is used for feature description of multispectral optical, fully polarimetric radar, multitemporal observation systems, etc. The appearance of multichannel RS systems was conditioned by growing needs for informational capacity and reliability of RS data interpretation. For example, various combinations of radio frequencies and polarizations of radiated and received signals are required to provide more informative vision for exploring of soils, vegetation, and agricultural crops in different stages of their development. This is because physical phenomena associated with sensed object features appear themselves differently for different wavelengths and polarizations [1,2,3].

The obtained multichannel RS images (MRSIs) should be represented in a common coordinate grid. Their precise registration is an important prerequisite. The residual image registration errors can be relatively small like for multipolarization radar systems operating in synchronized manner or for multispectral imaging. Otherwise, these errors can be partly removed by applying nonlinear geometric transforms and specific nonlinear filters [3,4]. In this paper we concentrate on the former case.

Another requirement to MRSI preprocessing algorithms after prior registration is efficient suppression of noise and appropriate edge/detail preservation. Below we suppose that the noise in component images is the major factor degrading reliability of MRSI interpretation.

MRSI can include optical components where additive noise is the dominant degrading factor as well as images formed by radars for which prevailing impact of multiplicative noise is typical. Note that multiplicative noise can also be non-Gaussian. This takes place in case of using synthetic aperture radar (SAR) with a small number of looks for which images are corrupted by intensive multiplicative noise (speckle). Moreover, impulse noise can be present in few or all component images. All these cases are studied in [5] where the specialized pre- and post-processing techniques are proposed. This allows obtaining common type of noise for all component images but noise variance in them could be not the same. Therefore, let us concentrate below on analyzing multichannel radar images as a more complex noise situation in comparison to color images (CIs) [6] for which noise is commonly assumed to be of the same type and to have identical characteristics in all components.

The approach considering an MRSI as a vector data array [4,7] has good prospects a priori. It has shown promising results in RGB CI processing [6]. The advantage of vector filtering of CIs is stipulated by a pronounced inter-component correlation [6]. Such correlation is also inherent for MRSI components but to a less extent [4]. However, not all vector filtering algorithms efficient for CIs are applicable (directly) for MRSI processing [5]. Among

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those that are applicable, even less vector filters are able to preserve edges and details well enough. And note that good preservation of edges and details is highly required for solving many tasks of MRSI interpretation [8].

In our earlier papers, several effective component-wise [5,9] filters, the adaptive vector filter [10] and the combined version [4] have been proposed. The component-wise modified sigma filter (MSF) [9] has shown itself as an efficient algorithm for processing component images. For images containing many details, MSF (applied component-wise) outperformed even one of the best vector filters - a vector double window modified trimmed mean filter [11]. However, the modified vector sigma filter (MVSF) [7,12] produced either approximately the same or better results in terms of MSE, PSNR and other quantitative measures than aforementioned filters, especially for images containing a lot of details and texture.

These properties of MVSF have been shown very useful for solving particular MRSI interpretation tasks [12]. Thus, in this paper we focus on considering another advantage of MVSF, namely, its excellent edge preservation ability and its exploiting for edge detection.

2. MODIFIED VECTOR SIGMA FILTER

The standard (scalar, or 2-D) sigma filter [13] is known to be among the best edge/detail preserving algorithms [5,14]. For obtaining the filter output, one has to average the pixel values within the ασ-neighborhood formed in respect to the value of the scanning window (SW) central pixel. This approach can be easily extended to the vector case with prevailing influence of multiplicative noise. The detailed description of MVSF algorithm can be found in [10]. Shortly, the algorithm can be described as following.

The ασ-neighborhood (α commonly equals to 2) can be formed in multidimensional space in different ways. The simplest is to form the neighborhood (from minimal to maximal values) separately for each k-th component as

$$\begin{cases} I_k^{\min} = I_k^c(1-2\sigma_{\mu k}) \\ I_k^{\max} = I_k^c(1+2\sigma_{\mu k}) \end{cases}, \qquad (1)$$

where k=1,...,K is the channel index, K is the number of channels, multiplicative noise is supposed to have mean equal to unity and relative variance $\sigma_{\mu k}^2$, I_k^c is the window SW central pixel value for the k-th component image.

One disadvantage of the standard scalar sigma filter and, respectively, its vector analog is that they both are unable to remove spikes. Yet another problem is rather poor noise suppression ability of the standard and vector sigma filters [7,11,12].

Two main modifications have been introduced in [9] for improving the noise suppression and providing spike removal ability of the standard sigma filter. The first modification serves the goal of spike detection. One has to count the number of samples belonging to the initial neighborhood and if it is less than some predetermined value then it is considered as a spike. In this case it is proposed to apply some robust filtering algorithm for obtaining the output, e.g., the FIR median hybrid filter [15].

The second modification is intended for improving noise suppression efficiency of the MSF. It presumes shifting of the initial neighborhood towards the probable center of noise distribution (see [9] for details). No sample from initial neighborhood is dropped out from averaging but some new ones could be added. Then, noise suppression efficiency of scalar MSF filter has been considerably improved in comparison to the standard versions [9] – for image homogeneous regions residual noise MSE decreased approximately twice. However, the edge/detail preservation remains practically unchanged.

In [11] these principles were successfully extended to the vector case. This resulted in improving the noise suppression and detail preservation properties of the MVSF.

3. MVSF PERFORMANCE IN EDGE/DETAIL NEIGHBORHOODS

The edge/detail preservation of the MVSF has been analyzed both quantitatively and visually. The simplest and the most efficient way to do this is to examine the MVSF using artificial test images.

Taking into account the peculiarities of real multichannel radar images [2,5] we have simulated three-channel artificial radar images with a large number of details with different shapes and orientation (see Fig.1,a,b). These images have been corrupted by multiplicative noise in the way close to reality. In particular, we assumed that two one-channel radar images have been formed by two-polarization side-look aperture radar and they have identical values of relative variance ($\sigma_{\mu 1}^2 = \sigma_{\mu 2}^2 = 0.008$ throughout the tests in Fig 1,b-k). The third component image has been simulated as that one formed by one-look SAR and corrupted by Rayleigh speckle noise ($\sigma_{\mu 3}^2 = 0.273$). According to the multistage procedure [5], this component has been preprocessed by the local statistic Lee filter before vector/component-wise filtering.

Images presented in Fig.1,b-k illustrate edge preservation efficiency visually. For edge detection, a robust edge detector (normalized quasirange (NQ) [14]) has been applied. Comparative edge detection results are presented for original noisy image components and for detector applied to the outputs of several good edge preserving filters like scalar MSF and local statistic Lee filter. As can be seen, image pre-filtering considerably improves edge detector performance. Application of NQ to the results of MVSF processing provides the most precise contour map as well as good detection of small sized objects (Fig.1,f,k). This fact one more time emphasizes originally better visual edge preservation provided by MVSF [12].

The advantage of MVSF in edge/small detail preservation can be also demonstrated quantitatively. For this purpose, the peak signal to noise ratio (PSNR) provided by different vector and scalar filters (including the filter based on discrete cosine transform (DCT) [14] and vector LQ filter [10]) was analyzed for different classes of fragments for the test three-channel image. The PSNR values, both aggregate, obtained for entire image ($PSNR_a$), and local ones calculated for image homogeneous regions ($PSNR_h$), edge-detail neighborhoods ($PSNR_{edn}$) and texture regions ($PSNR_{tex}$) for processing component image corrupted by Gaussian multiplicative noise (σ_μ^2=0.005, its noise-free version in is shown in Fig. 1,a) are presented in Table 1. Noise variances in other components of the test MRSI are additionally given for vector filtering cases.

As seen, quantitative results also prove the MVSF superiority in the sense of edge/detail preservation. The MVSF provides the best $PSNR_{edn}$ among all considered vector and scalar filters. The $PSNR_{edn}$ values for the scalar MSF are slightly worse. Note that the other considered vector filters produce much smaller $PSNR_{edn}$, i.e., in fact, they introduce sufficient distortions in edge-detail neighborhoods. At the same time, MVSF produces appropriate noise suppression in image homogeneous regions. $PSNR_h$ in case of using MVSF is approximately the same as for the scalar MSF and considerably better than in case of applying other vector filters. Texture processing results for MVSF are the best among vector filters. Only texture preserving scalar DCT-filter [14] outperforms MVSF in this sense. Also note that the use of 7x7 SW for MVSF ensures the best results for entire image processing.

CONCLUSIONS

Edge/detail preserving properties of the modified vector sigma filter are studied for the case of processing multichannel radar RS images. Using visual and quantitative results, it is shown that MVSF possesses appropriate compromise of noise suppression and edge/detail/texture preservation. In future we plan to quantitatively compare edge detection efficiency for different considered approaches in terms typical for edge detection applications. Real life images processing examples are given in [5,11].

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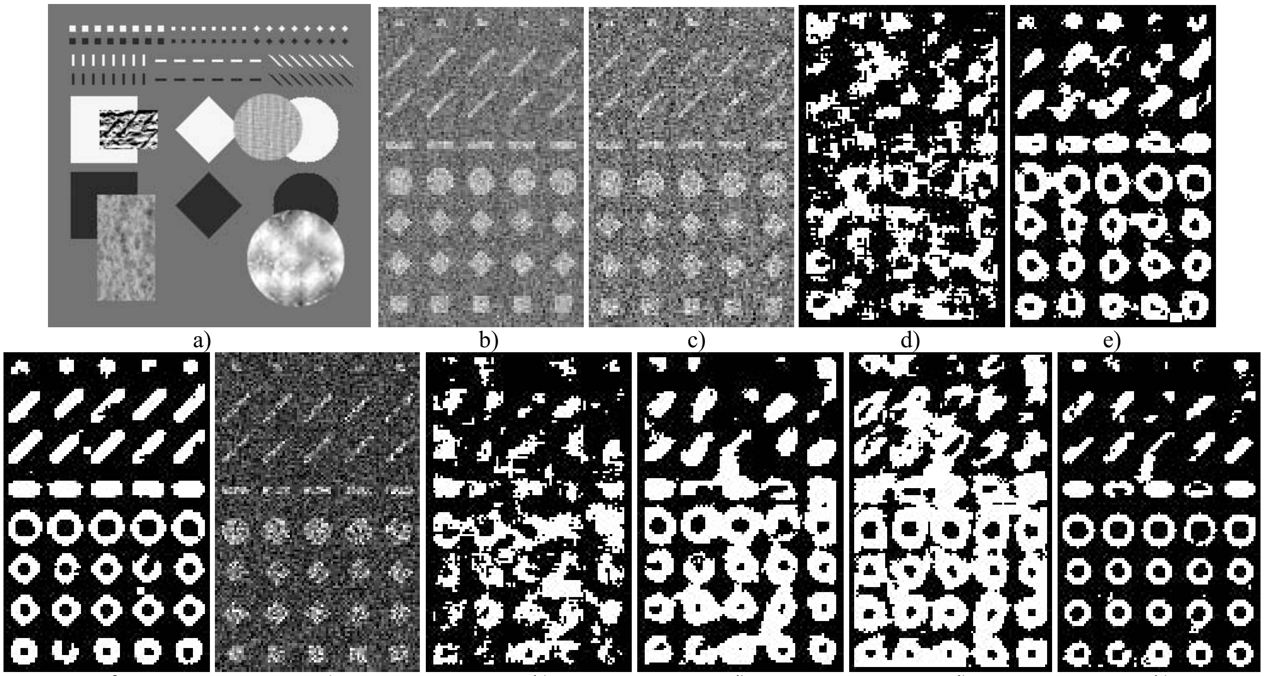

Fig. 1. The edge detection results for component images: a) noise-free test image; b) joint RGB representation of a fragment of the test three-channel radar image (*R* and *G*-components correspond to images corrupted by Gaussian multiplicative noise with $\sigma^2_{\mu 1} = \sigma^2_{\mu 2} = 0.008$; *B*-component corresponds to the image corrupted by speckle with $\sigma^2_{\mu 3} = 0.273$); c) noisy *G*-component; d) edge map for noisy *G*-component; e) edge map for *G*-component image pre-processed by the scalar MSF; f) edge map for *G*-component pre-processed by MVSF; g) original image in *B*-component ($\sigma^2_{\mu 3} = 0.273$); h) edge map for *B*-component image; i) edge map for *G*-component image pre-processed by the local statistic Lee filter (residual variance $\sigma^2_{\mu 3 res} = 0.009$); j) edge map for *G*-component image pre-processed by scalar MSF; k) edge map for *G*-component image pre-processed by the MVSF.

Table 1. The aggregate and local PSNRs (dB) for one-component image ($\sigma^2_{\mu 1} = 0.005$) in case of applying different vector and scalar filters. The variances of noise in other components are indicated in brackets (for case of applying vector filtering to the test MRSI).

Filter type and parameters	$PSNR_a$	$PSNR_h$	$PSNR_{edn}$	$PSNR_{tex}$
Noisy image (σ_μ^2=0.005)	29.23	30.05	29.32	27.2
Scalar MSF, SW=5x5	34.74	42.19	35.24	28.86
Local statistic Lee filter, SW=5x5	32.82	37.18	31.12	29.81
Hard threshold DCT filter (8x8 blocks, full overlapping)	34.30	41.59	31.93	**31.16**
MVSF, SW=5x5 ($\sigma^2_{\mu 2} = \sigma^2_{\mu 3} = 0.012$)	34.55	42.64	35.13	28.84
MVSF, SW=5x5 ($\sigma^2_{\mu 2} = 0.012, \sigma^2_{\mu 3} = 0.005$)	34.75	42.62	35.29	29.08
Scalar MSF, SW=7x7	34.83	44.16	35.58	28.62
MVSF, SW=7x7 ($\sigma^2_{\mu 2} = \sigma^2_{\mu 3} = 0.012$)	34.91	**44.8**	35.64	28.9
MVSF, SW=7x7 ($\sigma^2_{\mu 2} = 0.012, \sigma^2_{\mu 3} = 0.005$)	**35.26**	44.75	**35.94**	**29.32**
Adaptive vector LQ ($\sigma^2_{\mu 2} = \sigma^2_{\mu 3} = 0.012$)	26.14	38.64	24.56	23.34
Adaptive vector LQ ($\sigma^2_{\mu 2} = 0.012, \sigma^2_{\mu 3} = 0.005$)	26.18	41.02	24.53	23.45
Vector median filter, SW=3x3 ($\sigma^2_{\mu 2} = \sigma^2_{\mu 3} = 0.012$)	26.31	35.32	24.95	23.35
Vector median filter, SW=3x3 ($\sigma^2_{\mu 2} = 0.012, \sigma^2_{\mu 3} = 0.005$)	26.33	35.36	24.95	23.4
Vector median filter, SW=5x5 ($\sigma^2_{\mu 2} = \sigma^2_{\mu 3} = 0.012$)	23.0	38.45	21.11	20.97
Vector median filter, SW=5x5 ($\sigma^2_{\mu 2} = 0.012, \sigma^2_{\mu 3} = 0.005$)	23.0	38.82	21.14	20.89