Methods and Algorithms for Pre-processing and Classification of Multichannel Radar Remote Sensing Images

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Abstract. Multichannel methods of radar remote sensing from airborne and/or spaceborne carriers provide a large amount of information that can be of great value for different applications. However, it is a problem to retrieve this information from multichannel remote sensing data (images) due to several reasons. Thus, in practice one deals with a complex of problems to be solved. The basic attention in this report is paid to the following items: a) consideration of the methods for multichannel image registration, their accuracy analysis; b) design and performance study of the methods for component image filtering; c) vector and locally adaptive methods for joint processing of multichannel radar images; d) some aspects of data classification; e) application of the considered and designed methods to the particular task of remote evaluation of bare soil parameters; f) automatic procedures that can be exploited at some stages of multichannel radar remote sensing data processing. The applicability of the proposed methods, algorithms and designed software to solving a particular practical task of bare soil erosion state determination is demonstrated using real data including the comparison of remote sensing interpretation results to in situ measurements for agricultural field in Ukraine. Besides, the efficiency of the designed techniques applied at different stages is also confirmed by several examples of real life radar image processing.

1. INTRODUCTION

Airborne and spaceborne remote sensing of Earth surface is of ever-growing interest since the corresponding imaging systems are efficient tools for providing numerous users and customers by valuable information, often almost in continuos mode [1,2]. Many countries are involved in international joint projects and/or are developing their own remote systems to satisfy the needs of nature protection, industry, agriculture and forestry, ice type determination, ecological monitoring, etc. Few examples of existing satellite imaging systems are the LandSat, Radarsat, SIR-C/X-SAR [3,4], etc. At the same time, many states are also successfully exploiting airborne remote sensing systems and complexes serving different particular goals. One of such complexes called MARS [5] was designed in Ukraine by the Institute of Radiophysics and Electronics (IRE) and A.I. Kalmykov Center of Earth Radiophysical Sensing (CERS), National Academy of Science and National Space Agency of Ukraine.

MARS includes several on-board radar imaging subsystems: two side-look radars (SLARs) with the operation wavelengths 8 mm (HH and VV polarizations) and 3 cm, and two synthetic aperture radars (SARs) with the wavelengths 23 cm and 1.8 m. Commonly the spatial resolution provided by all radars was about 25x25 square meters although both SAR subsystems are able to ensure better resolution in fully focused mode. This complex has been used and tested for solving different practical tasks during almost twenty years (the subsystems have been gradually modified). Note that the considered remote sensing complex is multichannel. Here by the term multichannel we mean that it offers an opportunity to obtain the images of the same terrain using the radars with different operation frequencies and, for some bands, polarization. More generally, by multichannel image one can mean a set of several component images of the same terrain that can be obtained, for example, during consequent sessions. This mode is more often referred as to multitemporal imaging [2]. For optical remote sensing a set of images can be got using many spectral bands, then they are called multispectral.

However, irrespectively to the term used and the electromagnetic wave band considered, the reasons and motivations for applying just multichannel remote sensing are practically identical. Really, more reliable interpretation of remote sensing data and the improved accuracy of the sensed object parameter estimation can be usually ensured in cases of optical and infrared multispectral or radar multichannel (multifrequency and/or multipolarization) imaging due to exploiting the redundancy of the obtained data. Moreover, on the contrary to one-channel images, the multichannel data give additional dimensionality and this permits to solve the inverse and interpretation tasks that can not be principally solved by exploiting one-channel data. This holds for multispectral optical images and mutichannel radar ones. In the latter case the basic measured (recovered) characteristic of the sensed terrain is the radar cross-section (RCS) and commonly it depends not upon one but upon several chemical and physical characteristics of cover (sensed terrain) types. One example is the simultaneous dependence of RCS on surface roughness and upper layer moisture [6,7] for bare soils. For this case only the use of multichannel radar remote sensing allows discriminating these effects and performing evaluation of both characteristics [7,8,9].

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Therefore, below the basic attention is paid to considering the methods for multichannel image (remote sensing data) processing. Obviously, in comparison to the case of one-channel image processing for which the studies and method design have been intensively performed for decades (see, for example, the fundamental books [10-12] and references therein), new problems stemming from three-dimensionality of images arise. Let us mention only few of them. Taking into account that even one-component (one-channel) remote sensing images contain thousands or even millions of pixels for areas of hundreds square kilometers, there is an urgent need in computationally efficient algorithms of image processing. This is important if some stages of data pre-processing are performed directly on board of the carrier. This also concerns image analysis stage. If remote sensing data compression is carried out, then for multichannel images this is, certainly, a more complicated task than for one-channel images.

Another aspect is that multichannel radar images as well as multispectral optical ones possess quite high degree of inter-component correlation (similarity). In fact, the retrieval of useful information from multichannel remote sensing data is just based on correct exploiting both similarities and differences in component images. Then, two problems become of prime importance. The first one is how to register (warp) the multichannel remote sensing data to provide pixel-to-pixel correspondence (matching). The second problem is how to perform filtering of multichannel images - either separately for each component image or jointly, i.e. by using vector representation and vector processing of data. Concerning the latter problem, it is worth mentioning that the design of vector filters was started only 12-14 years ago (see, for example, [13]) and, thus, the experience in this area is considerably smaller than in the area of one-channel image filtering. The vector methods of multichannel image filtering have already demonstrated their advantages gained, in the first order, due to taking into account the inter-component correlation [14,15]. However, the main attention has been paid to vector filter application for color image processing [13-16]. The number of publications dealing with vector processing of multichannel radar images is much smaller. To name a few, let us mention [17] and our papers [18-20]. There are several reasons for this, but one factor should be specially stressed. In opposite to multispectral or color images for which the dominant noise is commonly additive, Gaussian and has practically the same variance for all component images, the dominant noise in multichannel radar images is multiplicative and its probability density function (pdf) as well as relative variance can be considerably different for component images. For example, for SLAR images the multiplicative noise obeys Gaussian distribution and is not very intensive while for SAR images the multiplicative noise (speckle) can have essentially non-Gaussian pdf and be very intensive [21]. These obstacles lead to additional difficulties in designing the filters for processing the radar images, both one- and multichannel, either separate (component) or vector ones.

One more problem is the desired automation of remote sensing data processing for all stages: image preliminary analysis and noise characteristic evaluation, multichannel image registration, data filtering and classification, interpreting and information retrieval [1,2]. Since the amount of data to be processed drastically increases due to three-dimensionality (for the considered case), the rapid development of remote sensing systems and the need to retrieve the useful information in more limited terms, the automation combined with the use of rather simple and computationally efficient algorithms and software seem to be the approaches able to satisfy the practical needs.

This paper describes the results of investigations that have been performed by the group of researchers headed by the author during the period of 12 years. This group was organized at Department of Transmitters, Receivers and Signal Processing, National Aerospace University, Kharkov, Ukraine in order to design methods and to create the corresponding algorithms and software for processing the multichannel radar images obtained by the complex MARS. The cooperation with IRE (the group headed by Prof. G.P. Kulemin responsible for radiophysical background of multichannel remote sensing) and with CERS (headed by Dr V.N. Tsymbal) which provided the real data, modified the MARS hardware and created their software in parallel was prolific and still continues within several Projects. The obtaining of the results presented in this paper in the next Sections could not be possible without many year assistance of Prof. A.A. Zelensky as well as without cooperation of the author and his Ph.D. Students with the scientists of the Institute of Signal Processing, Tampere University of Technology, Finland, namely, Professors J. Astola, P. Kuosmanen, K. Egiazarian, Doctors P. Koivisto, S. Peltonen, K. Saarinen.

2. MULTICHANNEL REMOTE SENSING: STAGES OF DATA PROCESSING, IMAGE/NOISE CHARACTERISTICS, REQUIREMENTS TO DATA PROCESSING METHODS AND ALGORITHMS

Multichannel image processing and interpreting (classification) commonly consist of several basic stages. Some of them are necessary, another ones are optional or unnecessary, this depends upon image and noise characteristics, the availability of a priori information about the remote sensing data one has to process and its extent, the particular application. Our belief is that the resulting reliability and accuracy of solving the final task for each particular case depend upon the performance of methods used at each stage, and the requirements to the properties of these methods and the accuracy provided by the method applied at each stage are interconnected. Thus, let us first name and briefly review these stages:

1) Image forming. In some cases the User gets already formed images. Then, it is impossible to enhance the image at image forming stage. At the same time, if one gets, for example, raw SAR data, then it is possible to try to form the original image with acceptably high quality. For SARs nobody is able to avoid the presence of speckle noise in the formed images, although it is possible to decrease the SAR response side lobes (for example, due to the use of weighted processing of raw data for the row images [22]) and to take into account the carrier trajectory fluctuations [23]. And this is worth doing, since for the further stages of image procesing it will be much more difficult to cope with these phenomena and they will influence the final task of remote sensing data interpreting in a negative way.

2) Obtained image preliminary analysis and/or visual inspection. In general, this stage is optional. If one deals with a set of one-channel or multichannel images formed by the same remote sensing system or complex, if the User is confident that the statistical characteristics of noise in images do not change from one session to another and these characteristics are already known (evaluated), if there are no some specific artifacts or distortions that can from time to time occur in the formed images, then this stage can be skipped. However, in other cases the obtained image preliminary analysis and/or visual inspection are worth performing. One example of such a case is the presence of a phenomenon that we have called impulse bursts. This type of image degradation (see Fig.1,a) can occur if an image is formed on-board of a satellite or aircraft and then transferred to on-land center of remote sensing data processing via communication lines which are not well protected against interference (for example, in APT mode [24]). Visual inspection allows deciding whether the impulse bursts are present and, thus, has one to apply the special methods [24,25] to remove them (see Fig. 1,b demonstrating the application of the method proposed by us). Visual inspection can be also useful for detect other specific types of distortions like image row (column) mutual shifting, presence of impulse noise, etc. This is important, since, i.e., such effect as image row (column) mutual shifting should be eliminated at initial stages of image processing (before filtering) [26], and the selection of a proper (the most efficient) filter depends upon noise type and properties [12,21]. Preliminary analysis of noise characteristics can take considerable efforts and in this sense its automation is of urgent need. Many very good papers dealing with this problem have appeared recently [27,28]. We also performed our own research [29,30]. Although appropriately accurate estimations of additive or multiplicative noise variance can be provided [28-30] and the multiple factor influence situations can be identified with rather high probability [27], the automatic methods for estimation of statistical characteristics of noise components in mixed noise environment are still to be designed in future.

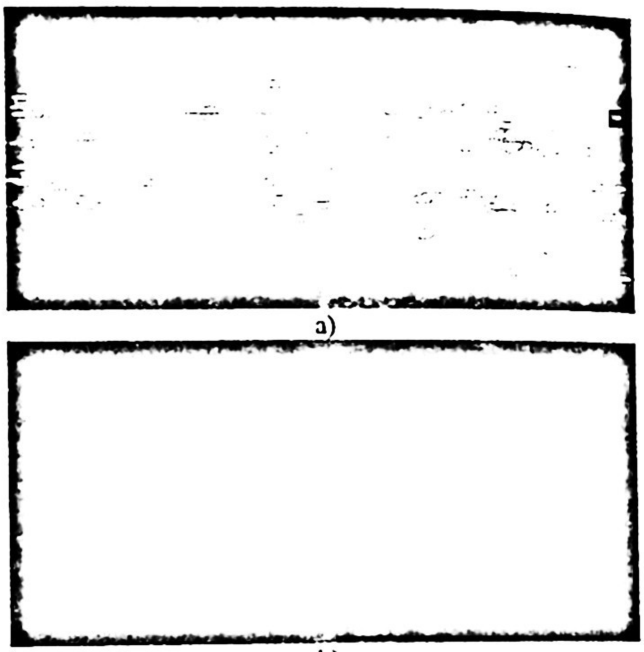


Fig. 1. The original satellite radar image transmitted in APT mode and containing impulse bursts (a) and the result of its pre-processing using the proposed method (b)

3) Image geometric and radiometric correction, calibration. These are typical operations used in remote sensing data processing. Conventional methods can be found in fundamental books [1,2]. However, there are still quite many problems. For example, for image geometric and radiometric correction it is desirable to take into account the relief of the sensed terrain, and this relief should be somehow obtained with appropriate accuracy. But this is not an easy task [31,32]. Perfect calibration of imaging subsystems is an especially important task for multichannel radar complexes since the useful information retrieval can be based on estimation of intensity (RCS) ratios for component images [7,8,20]. In this case the calibration errors of about 0.5...1 dB can result in considerable misclassifications. At the same

time, the preliminary quantitative estimations have shown that the troposphere, clouds, precipitation, carrier trajectory fluctuations, etc. can in aggregate lead to such level of calibration errors, especially for imaging radar subsystems operating in K_a-band [33,34].

4) **Multichannel image registration, warping, interpolation.** Clearly, multichannel images can be useful from their further interpreting point of view if they are represented in a common spatial grid (coordinate system) and, if possible, superimposed to topology map of the sensed region. However, this is not true for many cases of original multichannel remote sensing images. For example, as it was said above, the spatial resolution and the pixel size for MARS subsystems [5] is approximately the same, but not exactly the same. Because of this, the spatial locations of the pixels with the same indices for different images do not coincide (note, that the spatial sampling rate at image forming stage is selected such that one resolution element for each direction is slightly larger than the pixel linear size). Additional errors and distortions are caused by trajectory fluctuations of the carrier, especially if component images have been obtained during different flights (remote sensing sessions).

Certainly, there exist quite many methods and procedures for image registration [2,8,35]. One advantage of the image registration method based on (ground) control points is that its accuracy can be partly controlled and evaluated [8], and this can be useful for further stages of multichannel image processing. However, it is often desirable to improve the accuracy of conventional image registration methods. Another task is to minimize the efforts spent by the User to perform this operation since it is very time consuming. And it could be very nice to make it fully automatic [35,36]. Besides, one of the operations applied at this stage is image interpolation and the performance of the corresponding methods is also worth improving.

5) Multichannel radar image filtering. The question we were frequently asked at the beginning of 90-th was whether or not it is necessary to filter radar images before their interpreting. This question deals with the known fact that any kind of filtering being aimed on noise suppression inevitably distorts in less or larger degree some useful information contained in images. Now it is possible to state that, at least, for radar images it is strongly desirable to apply filtering before interpreting. And there are, at least, two reasons for this. First, for radar images, in opposite to some case optical ones, the noise is an inherent factor degrading original image quality, and this noise is rather intensive, especially for SAR images. Because of this, noise is one of the basic factors preventing reliable interpreting of radar remote sensing data [8,9]. Second, it was demonstrated both quantitatively and qualitatively for test and real scene multichannel radar images that the application of image filtering gives considerable impact on data interpreting improving [9].

However, this statement is true if and only if one applies such filters that preserve well (or, at least, do not distort a lot) the information useful for further image interpreting. The basic classes of such useful information are the following: a) the mean level in image homogeneous regions that corresponds to RCS of the corresponding objects (taking into account image calibration data), this mean level should not be distorted while filtering; b) the object edges, details (small sized and prolonged objects), their locations, shapes and contrasts; all this has to be preserved; c) the texture features (characteristics) that are quite often used in image segmentation, classification and interpreting [37,38]; d) the ratios of component image values for all pixels that, in some sense, correspond to color information in RGB images [15,18], this requirement is specific for multichannel remote sensing data and it can be satisfied if the requirements mentioned above in items a), b), and c) are satisfied.

For multichannel images it is possible to use different approaches to filtering: to perform it separately for all component images, to use vector filters, and to carry out some combined processing. The advantages, drawbacks and problems of the corresponding methods will be discussed in Section 4. But it is necessary to note some peculiarities of noise typical for radar images. First, the dominating noise is multiplicative. Besides, the multiplicative noise typical for radar images can be spatially correlated for neighbor pixels. This can be observed for original images [21,39] and the spatial correlation properties of noise can change at the stage of image registration due to scaling and interpolation. Besides, multiplicative noise pdf and relative variance σ_μ^2 are commonly different for different channel images. For example, for MARS complex the relative variance is about 0.006 for the Ka-band images and 0.012 for X-band image [21,29]. The images formed by SAR subsystems are characterized by approximately Rayleigh pdf of speckle with $\sigma_\mu^2 \approx 0.17$ [21,39,40,41].

The probability of spike occurrence is usually not large but for some obtained images they have been observed. These spikes mainly originated from encoding/decoding errors.

Different channel images of the same terrain are characterized by non-equal contrasts of the edges and objects corresponding to each other in the obtained images. Moreover, some objects can be present in some images while in other images they are absent. Respectively, the images can be highly cross-correlated or have low cross-correlation. A general tendency is that the larger the relative difference in sensing signal wavelength, the lower the cross-correlation. For example, the Ka and X-band (filtered and registered) radar images formed by MARS complex commonly have cross-correlation factor R approximately equal to 0.7. The Ka-band SLAR and L-band SAR images are less correlated (R is about 0.4).

6) <u>Multichannel radar image classification</u>. The majority of multichannel image classification methods are based on joint analysis of intensities and/or their ratios for a set of the registered component (one-channel) images [3,6,8,42,43]. Some other features, i.e. textural ones, can be also exploited [37].

The noise presence leads to errors of intensity or intensity ratio evaluation, noise also masks the textural features. Therefore, the performance of any classifier becomes worse as the noise variance increases. Image pre-filtering allows to partly alleviate this problem. However, the classification reliability also depends upon the type of classifier used.

Neural networks (NNs) [44] have become a type of classifiers mostly often applied for solving the considered problem (see [42,43] and references therein). The advantages of NN exploited here are the following: a) the ability to learn for rather small size data sets (for the object types to be classified) and then to be applied to classification of large size (entire) images; b) the ability to incorporate into consideration different types of features; c) the capability to discriminate the classes if feature space pdf is not Gaussian (i.e., to outperform conventional Bayesian classifiers in the corresponding situations), etc.

Besides conventional classification, another approach to multichannel data processing called primary local recognition (PLR) was proposed and considered by us [45,46]. Initially this approach that presumes detailed classification of data in 5x5 scanning window was intended for improving the performance of locally adaptive filtering [45,46]. However, later it has been understood that it can be also useful at remote data classification stage since it allows taking into account the information whether or not a given pixel of vector data belongs to common homogeneous region, edge neighborhood or small sized object [47]. Moreover, graph-based method of PLR misclassification correction has been proposed and tested for a set of images and a set of slightly different classifiers performing image PLR [47-49].

The use of NNs, PLR and misclassification correction methods allows improving data classification in semi-automatic mode. After classification of object type, the retrieval of required information about characteristics of the sensed surface (terrain parameter evaluation) is generally performed using the corresponding (adequate) radiophysical models of backscattering for the terrain type. And this is the final stage of multichannel remote sensing data processing, just their interpreting.

In this Section the main requirements to multichannel image processing methods and algorithms are stated. The additional requirement could be the providing of an appropriate computational efficiency. Let us now consider some of these stages more in details.

3. IMAGE REGISTRATION METHODS AND THEIR ACCURACY

There are two basic approaches to image registration used in practice: one is based on determination of cross-correlation between component images [11] and the other presumes selection (or finding) of a set of (ground) control points (GCP) and their further use for derivation of transform parameters [8,11,35,36]. The first approach does not suit well the case of multichannel radar image registration [35] and basically the second approach is used.

The main problems for GCP-based approach are the following: 1) how to select an appropriate model of deterministic and stochastic components of distortions, 2) how to provide an appropriate accuracy of GCP coordinate estimation and to optimize the number and spatial configuration of control point set; 3) how to perform the image interpolation while carrying out their registration (coordinate system transformation); 4) is it possible to perform image registration or, at least, some operations in automatic mode.

One simple method is to apply linear (affine transform) methods [11]. According to our own experience and conclusions of another researchers, the linear spatial transformations can be used only for small size images or their fragments formed by mainly spaceborne radar subsystems.

For example, the bare soil agricultural field we dealt with in [8,9] was of the size of about 1000x1000 m^2, and it corresponded to approximately a 50x50 pixel fragment. The entire images were of the size 256x256 pixels (see these images in Fig. 2).

When the linear (affine) registration was applied after selection of control points shown in Fig. 2, the root mean square error (RMSE) for the considered fragment was about 1.5 pixel linear size, i.e., about one resolution element. But for the 200x200 pixel fragment, the use of the same linear transform resulted in RMSE up to 2-3 pixel linear size.

This means that for larger size images (or their fragments) one has to apply nonlinear transforms that are able to provide more appropriate results [9]. The question concerns the type of nonlinear transform to be applied and how to improve the registration accuracy.

Fig. 2. Radar images of the a) HH Ka-band, b) VV Ka-band; c) HH X-band

The relation between the object coordinates (G_x, G_y), (F_x, F_y) of the reference and the transformed images, respectively, can be represented as

$$\begin{aligned} G_x &= W_x(\mathbf{Z}_x, F_x, F_y), \\ G_y &= W_y(\mathbf{Z}_y, F_x, F_y), \end{aligned} \tag{1}$$

where $\mathbf{Z}_x$, $\mathbf{Z}_y$ are the transform parameters, $W_x(\cdot)$, $W_y(\cdot)$ define the nonlinear functions that determine the transforms to be performed. The transform is to be executed after correction of the random geometric distortions resulting from the carrier trajectory fluctuations and relief roughness, the polynomial transformation is a good choice [9]. The orthogonalized combinations of pair functions of one variable ($f_k(F_x, F_y) = F_x^l \cdot F_y^m, l,m = \overline{0,M}$) as the basis functions were used. The orthogonalization have been done by means of classical Gram-Schmidt method [9].

The influence of the number and locations of the control points (in images to be registered) on registration accuracy has been analyzed. The conclusion was that for images with approximately equal number of pixels *Xm* and *Ym* for both axes it is not worth using more than 7-12 control points. They have to be placed as sparsely as possible.

It is possible to estimate the mean accuracy of the control point registration using the selected control points. Its analysis allows deciding is the provided accuracy appropriate for further processing of multichannel data or one has to try to improve it. The improvement can be performed by selection of another set of the control points (those control points looking "suspicious" can be eliminated from the set and/or new ones can be included).

The nonlinear procedure of image-to-image registration for multichannel data fragment of 200x200 pixels provided the reduction of residual errors by two times in comparison to linear (affine) transformation. As a reference image, the image in Figure 2,a was used. As seen, 10 control points were selected. The resulting three-channel image in monochrome representation is represented in Fig. 3. For interpolation of the transformed image after registration, the nearest neighbour interpolation was used since it produced less dynamic errors in the neighbourhood of edges and fine details in comparison to bilinear and bicubic techniques [11]. Besides, nearest neighbor interpolation is simple and requires less computations.

It is also worth noting here that the nonlinear methods of image registration have been tested for the images of size 3000x3000 pixels and for these images they produced only slightly larger RMSE of residual registration errors. The methods of GCP selection described in papers [35,36] allow simplifying and making more robust the procedure of control point selection and matching, thus reducing the User efforts spent for image registration stage.

Fig. 3. The obtained multichannel image in monochrome representation

Therefore, it is possible to conclude that the provided accuracy is rather good and it is quite difficult to further improve it. However, even in this case the edges and small sized objects (details) in the obtained multichannel image (Fig. 3) are a little bit smeared. Because of this, it is still worth reducing the residual errors of image registration at the next stages of data processing. Besides, the noise in the obtained multichannel image is well seen.

4. COMPONENT VERSUS VECTOR FILTERING OF MULTICHANNEL RADAR IMAGES

The analysis of one and three-channel images presented in Figures 2 and 3 shows that it is necessary to remove noise. One more requirement is that if there are residual errors of image-to-image registration then it is also worth trying to reduce their influence, i.e. to make the object edges sharper.

As said, the multichannel image filtering can be performed in three different ways. One way is to separately process each component image. The second way is to apply vector filtering. Finally, some combined techniques can be designed and used. So, let us consider the advantages and drawbacks of these approached more in details.

During recent years we paid much attention to performance analysis and design of filters for one-channel image processing. Three basic approaches have been considered and developed. They are the locally adaptive filtering, the iterative (multistage) filtering, and the transform based denoising.

The basic principle of locally adaptive filtering can be explained by the block-diagram presented in Fig. 4. The main idea of this approach is that the image for each scanning window position should be processed by such (nonlinear) filter that provides the best efficiency depending upon "local behavior" of an image and noise. By local behavior we mean that, for instance, the given position of the scanning window can correspond to image homogeneous region, edge neighborhood, small sized object, texture, etc. Besides, for given position the impulses can be present or absent. Then, the task of local activity indicator (LAI) analysis performed in block 4 is to discriminate these situations as reliably as possible. The available information from blocks 1 and 2 should be taken into account while calculating LAIs in block 3, undertaking decision in block 4, forming the filter sub-bank in block 5 and calculating their outputs in block 6.

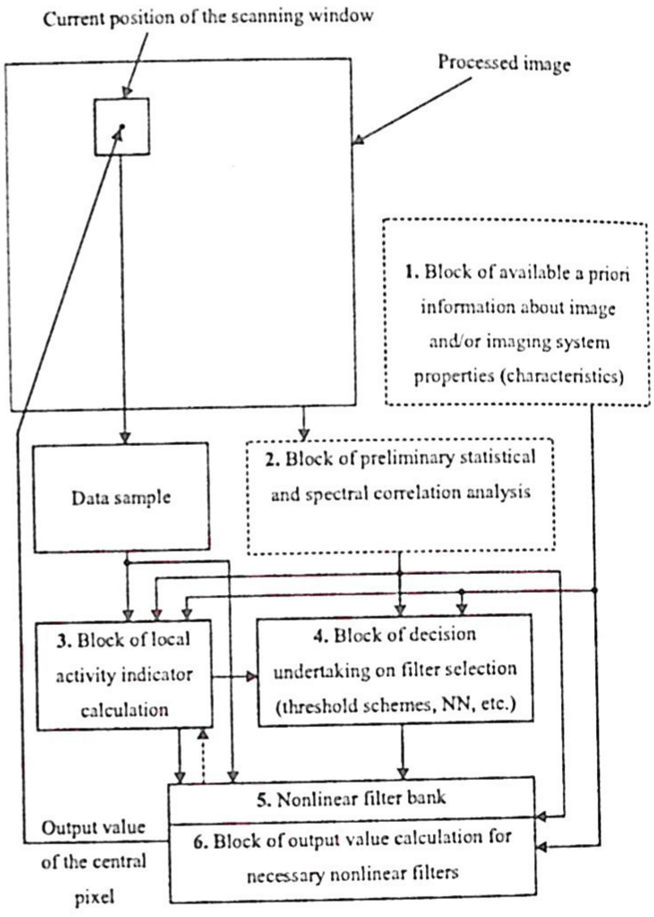
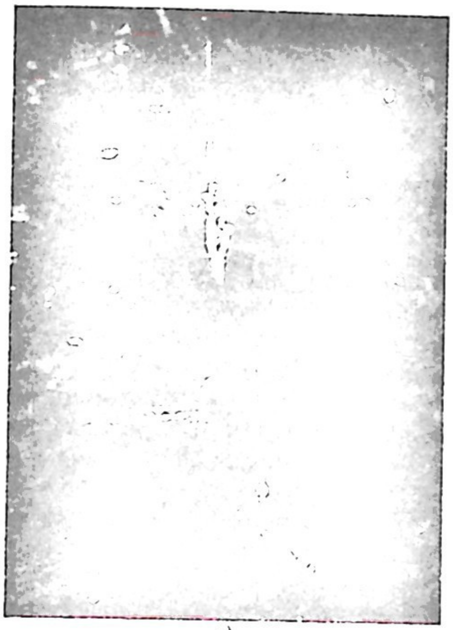


Fig. 4.

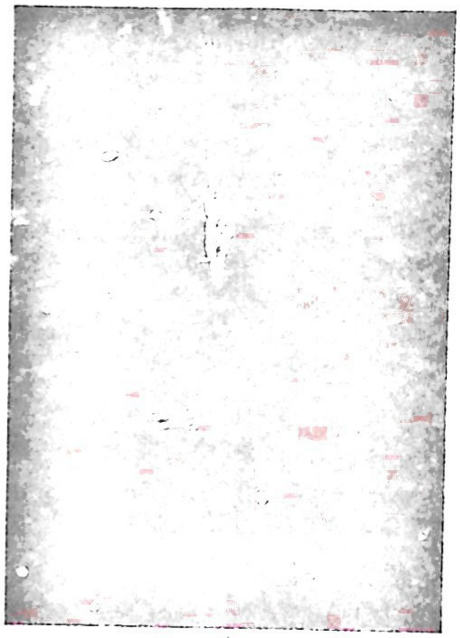
The situations of Gaussian and non-Gaussian pdf of multiplicative noise as well as different percentage of impulsive noise have been considered. The priority of requirements to filter properties has been taken into account.

For SLAR images without spikes we have recently designed the three-state (three-component) locally adaptive filter with good texture preserving capability [50]. The special attention was paid to texture feature preservation since for soil erosion determination the RCS is commonly a slowly spatially varying function that appears itself as texture in radar images. Fig. 5 gives examples of original noisy Ka-band radar image (a), the obtained pre-classification map (gray color corresponds to texture, by white color the edge and detail neighborhoods are indicated while black dots correspond to the pixels belonging to image homogeneous regions) (b) and the output image (c). As seen, noise is suppressed and the useful information is preserved well.



a)

b)



c)

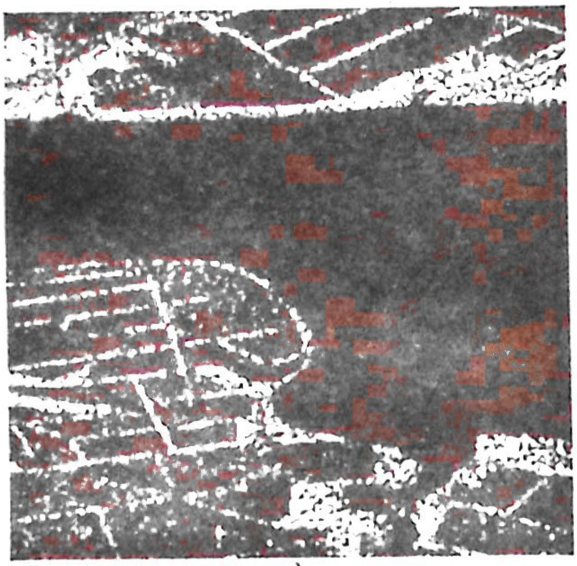
Fig. 5. The original (a) and filtered (c) Ka-band radar image, the obtaine pre-classification map (b)

If the percentage of impulsive noise is small, the modified sigma filter is a good choice since it provides an appropriate trade-off between noise suppression in homogeneous regions of images and edge/detail preservation [51]. A better noise suppression can be provided by the introduced sigma filter with adaptive scanning window size [52]. If the occurrence of impulsive noise in SLAR images is of about 3-5% then a locally-adaptive filter described in our paper [53] can be used. Several two-state locally adaptive filters are also presented in our papers [54-56]. Some designed versions are able to perform in the case of non-Gaussian pdf of speckle typical for SAR images and possible presence of impulsive noise [54,55]. The expedience of using homomorphic transforms is considered in details in paper [56].

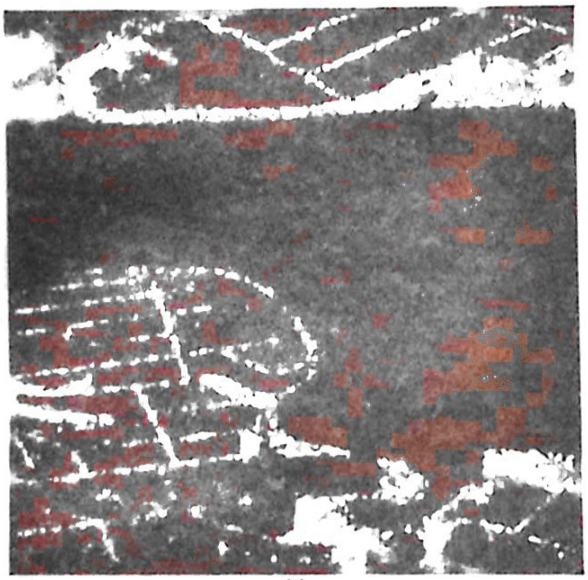
Iterative approaches to component image processing have the following idea behind them. At each stage one or few particular goals are attained due to application of the filter well suited for the considered purpose. For example, if the considered component image is formed by an SAR with a small number of looks and spikes are present, one possible solution is to apply the iterative procedures [40] based on the use of the local statistic Lee filter [57] at the first stage and the FIR median hybrid filter [58] at the second stage. As known, the latter filter is robust with respect to spikes and it provides their removal (the spikes are remained by the local statistic Lee filter at the first stage of image processing). If the impulse noise is absent, at the second stage it is more reasonable to apply transform-based denoising methods [41, 59].

In general, wavelet or DCT-based denoising ›chniques have been originally designed for additive oise suppression in images. But with quite simple odifications based on homomorphic transforms or reshold setting in dependence to the local mean, ey can be also applied to images corrupted by mul-plicative noise [60].

The example of one-look real scene SAR im-ge processing using the iterative procedure [40] are presented in Fig. 6.



a)



b)

Fig. 6. The original (a) and the output (b) real scene SAR image

However, if the multichannel image is proc-essed using component filtering, the edges and fine details being well preserved in the component images can be still smeared in the multichannel image be-cause of the influence of residual errors of image-to-mage registration. To prove this, Fig. 7 presents the result of component separate filtering applied to the image in Fig. 3.

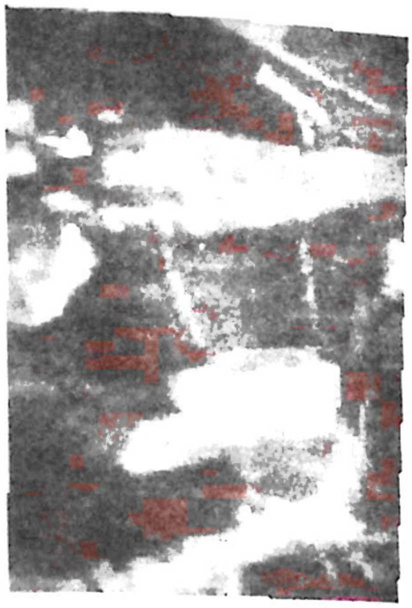


Fig. 7. The three-channel radar image (in monochrome representation) after application of component filtering to the image in Fig. 3.

If the component images are registered with residual errors smaller than one pixel linear size, it is reasonable to apply the modified vector sigma filter for their processing [20]. Due to exploiting correlation between component images, this filter is able to pre-serve low contrast edges and details considerably better than if component separate image processing is used. One drawback of the modified vector sigma filter is that it can be applied only in the case all com-ponent images are corrupted by noise having Gaus-sian pdf.

The proposed way out consists in preliminary processing of the component images that possess non-Gaussian pdf of multiplicative noise (speckle) by the local statistic Lee filter [57] that normalizes resid-ual multiplicative noise [41]. So, in fact, the process-ing procedure becomes hybrid, i.e. it combines com-ponent filtering (applied only to SAR component im-ages) with vector processing of multichannel remote sensing data. But keep in mind, that the modified vec-tor sigma filter is unable to cope with residual image-to-image registration errors.

One method that is helpful in the case the aforementioned errors influence is large enough is to apply the adaptive vector filter proposed in our paper [19]. This method also combines filtering of compo-nent images using properly selected algorithm at the first stage with further detection of edges in vector space and applying vector processing of multichannel data for only the detected pixels. Due to application of vector operations, it becomes possible to enhance edges that have been smeared at registration stage and component image pre-filtering. This is well seen from comparison of the multichannel images pre-sented in Figures 8 and 7. The edge/detail sharpening provides favorable pre-conditions for further image classification and interpreting.

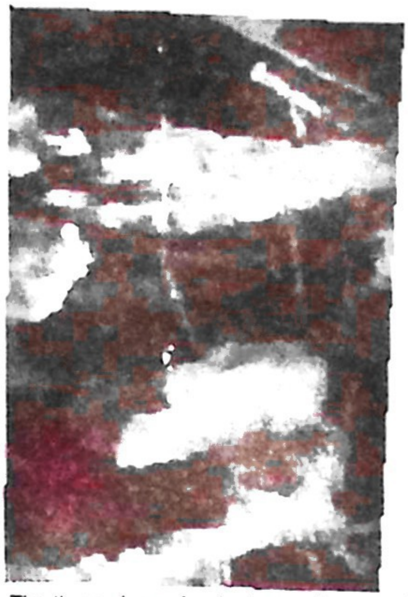


Fig. 8. The three-channel radar image (in monochrome representation) after application of adaptive vector filtering to the image in Fig. 3.

5. MULTICHANNEL IMAGE INTERPRETATING

One goal can of multichannel radar image classification is to determine the types of objects present in the considered remote sensing data. This task is rather complicated because the objects can have different number of pixels and considerably different features to be used for their classification.

A simple approach presumes direct application of some conventional classifiers to multichannel remote sensing data. But it is worth noting that for the considered application, the classes are rather wide in the sense that the characteristics used for classification can vary in very wide limits for a given class. In particular, for a class "bare soil", the RCSs in Ka-band images (two polarizations) vary by up to 8 dB depending upon the erosion (surface roughness). Even larger variations take place because of moisture content influence [6,7].

Because of this, conventional Bayesian classification techniques suffer from sufficient level of misclassification errors. To perform this classification task, it is better to use neural networks [42,43]. Two types of the NNs, the three layer perceptrons and the radial basis function networks (RBFN), have been applied for supervised classification of multichannel radar images [9,43]. The NN outputs Z_k have represented the degree of image pixel belonging to the k-th object class, k=1...3 for the considered test case and the real scene images. A hard classification mode was used although it is not the obviously best decision.

The classification methods have been applied to the initial (noisy) data, to the images after component filtering and to the vector processing output data. The three layer perceptron and the RBFN, both with the corresponding optimal number of hidden layer neurons, have been analyzed. For different classes, equal sizes of training sets have been used (several hundreds of vector samples).

The probability of correct classification P_c has been analyzed as the parameter characterizing the classification reliability. For simulated test images it was easy to determine it. For real scene images the sensed region topographic map was available and, thus, it was also possible to evaluate P_c.

The results of multichannel image classification have demonstrated that P_c depends on many factors: the type of classifier, its parameters, the methodology of data processing, etc. The basic conclusions were the following:

1) the NNs provide considerably better classification than the standard Bayesian technique, the percentage of wrong decisions was decreased by several times; the values of P_c for both types of the considered NNs for optimal numbers of neurons in the hidden layer are practically the same;
2) The use of the component and, especially, the vector filters provides better classification results, especially in the cases the NN classifiers are used; the percentage of wrong decisions (P_w=1-P_c) in cases of vector filtering is approximately two times smaller than in the corresponding cases of component image filtering.
3) In comparison to classification of original noisy images, the vector pre-filtering leads to reduction of P_w by several times (depending upon multiplicative noise pdf and intensity in different component images).
4) For the case of separate component filtering, the misclassifications are most often observed in edge/detail neighborhoods, i.e. in places where residual image registration errors are have great impact,

This confirms that the it is reasonable to perform filtering before multichannel data classification and demonstrates that vector data processing is preferable. The real three-channel radar image classification results are presented in Fig. 9 (original images are given in Fig. 2, registered and processed image is presented in Fig. 8). The bare soil regions are shown by white, the forests and the sunflower field - by black color. The classification has been performed with P_c over 0.93.

All the pixels belonging to the considered agricultural field without vegetation (bare soil) placed in the central part of the radar images in Figures 2,3,7,8 have been classified correctly.

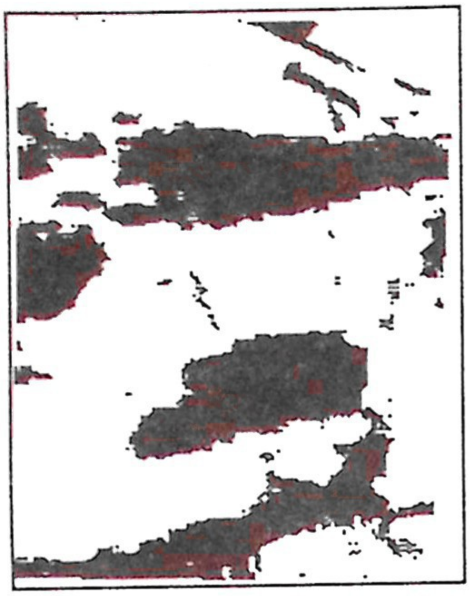


Fig. 9. The three-channel radar image classification after pre-filtering by learned NN classifier.

For this agricultural field, the remote sensing determination of soil erosion state has been performed using the methodology proposed by Prof. G.P. Kulemin [7,8]. The obtained enlarged erosion map with four states (degrees of erosion) is represented in Fig.10. The higher erosion degree is indicated by darker color.

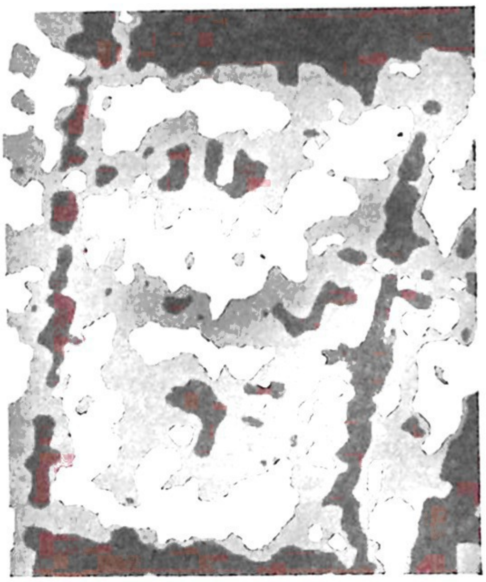


Fig. 10. The enlarged erosion state map.

Besides, the comparison of remote sensing estimation (interpreting) to *in situ* measurements has been carried out. Erosion has been estimated using the methods used in agriculture for several small lots (comparable to the pixel linear size). An appropriate coincidence of the remote sensing data and *in situ* measurements has been observed [9], all lots have been referred to the same class according to both *in situ* and remote sensing measurements.

While carrying out our investigations during several years, we considered different image processing methods for solving the final task of information retrieval from multichannel radar images. At the beginning stage, the soil erosion was determined after filtering the "image" obtained as the ratio of intensities for Ka-band polarization images [8]. Later we applied separate component filtering before calculation of this ratio; finally, the soil determination using ratio data has been performed after vector filtering [9]. The classification accuracy was improving step by step. Our plan now is to consider the application of texture preserving filtering techniques [50] and to analyze their performance for both test and real scene radar images.

7. CONCLUSIONS

It is shown that multichannel remote sensing can be a useful tool for solving many practical tasks. But for radar complexes the properties of noise considerably differ from the situations one deals in multispectral imaging. This motivates the design of special methods and algorithms to be suited just for radar remote sensing data processing.

As demonstrated, the obtained data processing should be performed in several stages. The noise and distortions degrading original images are to be removed step by step with perfect "distribution" of functions between the methods and algorithms applied at different stages. Automation of operations is desirable and some ways to provide it have been already proposed or are under study.

The design of powerful means for recognition and classification of remote sensing data are still of great need. The application of NNs and other modern methods is able to ensure considerable gain in this sense. Besides, it is shown that effective "information-preserving filtering of radar data before interpreting can be strongly recommended.

One example of multichannel radar remote sensing application to the particular task of information retrieval is presented. To our opinion, the designed methods and algorithms are well suited for other applications but ground control measurements are required and the carrying out such complex experiments needs the collaboration of researchers who are experts in different areas like forestry, agriculture, ecology, etc.

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