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CHALLENGES IN PRE-PROCESSING MULTICHANNEL REMOTE SENSING TERRAIN IMAGES

Abstract: Although remote sensing images have been obtained, processed, interpreted and widely used for various applications in recent 40 years, technology breakthrough and new level of requirements to data quality have jointly led to novel challenges in processing remote sensing (RS) images. It is shown that new challenges mainly arise due to applying multichannel imaging mode in most modern imaging sensors, as well as increasing spatial and spectral resolution. The main challenges are reviewed and explained with demonstrating possible solutions.

1. INTRODUCTION

Since getting first aerial grayscale photos it has become clear that remote sensing from airborne and, later, spaceborne platforms has great potential. In recent years, characteristics of RS systems intended for Earth terrain observation has greatly improved and their facilities have considerably widened [1]. First, spatial resolution of systems operating in different bands (optical, infrared, radio) has become sufficiently better due to technology breakthrough and it has reached few meters and even less. Second, practically all RS systems operating nowadays have become multichannel. By this term we mean that several (component) images of the same terrain are either acquired simultaneously (like this happens, e. g., in multi- and hyperspectral imaging) or formed sequentially (as this takes place, for instance, in multi-temporal observation). Radar systems also widely exploit dual and multi-polarisation as well as multi-frequency modes with providing few channel images [2]. These tendencies have jointly resulted in radical increase of data (3D or multichannel image) volume for a sensed terrain of certain area.

On one hand, better resolution and availability of a larger number of component co-registered and geo-referenced images offer several obvious benefits. The

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most important of them are the following. First, a set of practical tasks that can be solved using multichannel RS data is commonly wider than for single-channel images. Second, accuracy and reliability of information retrieved from multichannel images are sufficiently better. Just these obstacles served as the main motivations for design and exploiting multichannel observation systems.

On the other hand, it has become considerably more difficult to manage and process multichannel images. By managing and processing we mean a wide set of operations that include storage, compression, transferring, calibration, geo-referencing, distortion removal and filtering (enhancement), interpreting, object detection, classification, visualization, etc. [2, 3].

Here it is worth also noting that RS data are now obtained with higher periodicity, often under user's request. They are frequently needed in a form ready for use operatively as, e. g., in such applications as flood and fire control, in emergency situations as earthquakes and so on. This means that the corresponding images are to be acquired, transferred and processed as quickly as possible. This essentially restricts possibility to use outcomes of data processing in interactive mode by highly qualified experts with shifting main stress to automatic or, at least, semi-automatic processing [4].

Keeping this in mind, our goal is to review basic challenges in processing multichannel RS images of terrains. Not all stages of processing are paid equal attention. We suppose that images are already co-registered and geo-referenced (these operations are provided for many types of multichannel images offered to customers). Below we pay main attention to such common operations as data compression, filtering and classification. Besides, we partly consider challenges from customer's point of view, assuming that a customer might have a limited skill in processing of multichannel RS images. In this sense, some focus is also done on social aspects of data dissemination and use. We also take into account that data processing can be carried out in „three places": on-board a carrier of RS system, in a specialized center of RS data processing responsible for data collection, processing and distribution, and a customer's side. At each place, there are different facilities available as well as different priorities of requirements.

2. UNDERSTANDING MULTICHANNEL IMAGE PROPERTIES AND POTENTIAL OF THEIR USE

Entering the field of modern remote sensing, a newcomer or an inexperienced customer is usually shocked by amount of literature on the topic, a number of advertising information and propositions from companies, and diversity of applications for which remote sensing has been already tried. To avoid initial difficulties, one has to understand the following:

- RS images are estimates of a sensed terrain irradiation or reflection characteristics for a given sub-band of electromagnetic waves (where sub-band central wavelength can span from nanometers to meters);

– These estimates can be better or worse depending upon characteristics of a carrier (speed, altitude), imaging system (provided ground resolution, signal-to-noise ratio at its input, principle of its operation, sensing signal bandwidth, etc.), terrain itself (its roughness, presence of vegetation and urban objects, state and properties of the upper layer), and atmosphere (presence of clouds and turbulence, absorption effects);
– Many obtained images do not look like as optical ones we are got used to; infrared images reflect other effects than those observed for optical data, radar images also differ a lot by information content (they can, in particular, contain information on subsurface objects), main factors distorting these images as, e. g., intensive speckle, bounce effects, defocusing of moving objects, etc.), practical invisibility of clouds in these images, etc.

Thus, to get initial understanding what is imaged by a given RS system, especially infrared and radar ones, people need to be trained in order to be able, at least, to recognize such objects as rivers, lakes, bridges, urban areas, etc. It is a similar situation when a patient in a hospital wonders how a doctor can understand ultrasound or tomographic images.

The second aspect is the essence of multichannel remote sensing. It has developed as a result of trying to get more information due to the fact that different channels contain different information being supplementary to each other. In this sense, the situation is similar to considering grayscale and color photos where color surely provides benefits in object recognition although RGB components are highly correlated (cross-correlation factor (CCF) is about 0.8). For multichannel imaging, the main properties are the same. Dual-polarisation radar images have cross-correlation factor about 0.6 if they are not pre-processed (filtered) and about 0.8 after denoising. Component (sub-band) images in multispectral and, especially hyperspectral data are highly correlated too. For some „neighbor" sub-bands, the values of CCF can be practically equal to unity. This means that it is almost no additional information in one sub-band image with respect to information in neighbor channel images. Therefore, in multichannel imaging, one often deals with considerable redundancy of data that, in fact, has resulted from desire to have more information.

Recent studies show that for hyperspectral data (hundreds of sub-bands) it is usually enough to process (analyze) a subset of 8…20 most informative sub-band images [5] for solving a particular application task. Note that the term „informative" here jointly accounts for resolution, signal-to-noise ratio, and image entropy. This means that a user might not need and, thus, request for entire cube of hyperspectral data for solving a given task. In this sense, amount of data to be offered to customer diminishes resulting in specific dimensionality reduction and „compression". Meanwhile, such optimal sets of sub-band images usually depend on a task to be solved.

One more specific property of multichannel RS images is that they are always noisy and can be degraded by other factors as well (blur, geometrical distortions, etc.). Although for some types of multichannel RS terrain images noise cannot be noticed visually, it is anyway present. Such a situation takes place for hyperspectral data where noise is „seen" for only about 10…20% of sub-band images [6]. One existing approach to deal with such sub-bands is to remove the corresponding images from further consideration [5]. However, it does not seem to be an absolutely correct decision. There are also patrticular types of multichannel images for which noise is well seen and is the main distorting factor for all component images. This holds for multichannel radar images. It is worth emphasizing here that noise can be of different type and intensity in different channels (component images). Although considerable efforts have been spent on analysis of basic characteristics of noise for different sensors, the corresponding studies still continue and, actually, noise characteristics are to be investigated for each new RS sensor put into operation [7].

One more problem is visual analysis of multichannel RS images. While it is easily possible to visualize images with the number of channels less than four, it becomes difficult to deal with multichannel data with a larger number of channels. Certainly, it is possible to look images by sequential visualization of each component with observing smaller or sharper changes in image content and properties (for instance, noise level). However, such „scanning" provides limited opportunities to compose and analyze multichannel images as aggregate. There exist other methods for representing multichannel images to visual inspection [8] by specific fusion, but currently it is difficult to recommend a best way of doing this. Besides, for each existing method an observer should be preliminarily trained to manage understanding of the outcomes.

The aforementioned difficulties lead to a situation when a customer is pressed by variability of existing approaches, offered data and recommendations. Then a challenge is to come to a particular good solution of how to behave and what are the steps to be done. To assist, let us list questions that are to be put and answered:

1) Is a given type of RS appropriate for solving Your task? For getting the answer, consider has somebody solved Your task before? If yes, how good were the results? Do such results satisfy You? Has the method been intensively tested and how stable results it has provided?
2) Assuming that positive answers are got, continue with the following set of questions: is there an airborne or spaceborne RS system providing a desired type of RS data? How high is their quality? Is resolution appropriate? Are the data geo-referenced, corrected and calibrated?
3) How often the data are provided? Is it possible to get them for a certain date or a period of interest? How to request for these data?
4) Supposing that You have selected a proper data provider, consider what are the formats and forms the data are offered? Do You have computer programs or software packages for data handling?
5) Analyze and set distribution of responsibilities by answering who will take care over data preprocessing (filtering, classification, object detection, etc.)? What is the price of data offered in different forms?

A large part of these questions is inter-connected. For example, price depends upon data quality, resolution, and stages of data processing carried out by provider, etc. Note that data can be offered as raw data (possibly subjected only to calibration, preliminary correction, and geo-referencing). If so, a customer has to be able to further handling them with performing filtering (if needed) and solving the final tasks as classification, object detection, sensed terrain parameter estimation, etc. This requires high skill of customer expert team and availability of the corresponding facilities. Data can be also archived (compressed in a lossless manner) to decrease their size, to reduce price for traffic (if needed) and to accelerate their getting (this can be crucial in emergency situations). These forms of data are possible if no lossy compression is done on-board, a provider agrees and is able to offer RS data in these forms and a customer has a will to get just such data.

However, there are also other forms (types) of data. Multichannel images can be lossy compressed where such compression can be carried out either on-board or, later, in on-land center of data processing. Images can be also filtered (enhanced) where noise removal can be also performed either on-board or on-land. Filtering and compression can be done both with different order of these operations. For example, pre-filtering leads to better lossless compression [9] and, under condition of careful lossy compression with not large compression ratio, denoising can be applied to decompressed images [10].

Finally, multichannel RS data can be offered in the form of classification maps or other outcomes (indicated regions of heavy pollutions, edge maps, segmented data, etc.). Certainly, this is done under customer's request and the customer needs to pay more if more intelligent pre-processing has been performed by provider. In each particular situation and application, the customer and provider have to agree all questions concerning the most appropriate way of data offering with taking into account many aspects as price, time needed for pre-processing, compatible formats of data, their presentation (if data are offered as maps) and so on.

3. DATA COMPRESSION AND REDUNDANCY REDUCTION

For some period of time, it was considered that the only way to reduce multichannel RS image size is to apply lossless compression. Because of this, the area of lossless compression with application to multi- and hyperspectral data has been under intensive interest and research [3, 11]. Spatial and spectral redundancy as well as complex (3D) prediction models have been exploited to reach larger compression ratio (CR). Although new results in the area of lossless compression are still reported [11], it seems that obtained improvements become smaller and smaller. CR values even for hyperspectral data (for which possibilities to exploit data redundancy in coding are wider than for multispectral images) reach 4 and, sometimes, slightly more depending upon terrain image complexity.

However, such values of CR are often unsatisfactory due to limited bandwidth of downlink communication channel, storage capacity (especially on-board), limited time of data transferring (e. g., from spaceborne platforms to on-land centers). Then, one comes to necessity to apply lossy compression.

It is worth emphasizing that limits of CR for lossless compression are partly explained by the presence of noise in the RS images. Compressing data without losses, any coder spends bits on preserving noise. This leads to reduction of CR. Recently, the advanced lossless coder CALIC [12] has been applied to compress single-look synthetic aperture (SAR) images that are extremely noisy [13]. The provided CR is only slightly larger than unity confirming negative influence of noise on image lossless compression.

In turn, the effect of noise filtering by lossy compression was discovered more than 10 years ago [14]. Moreover, later it has been observed that, under certain conditions, the use of lossy compression can lead to better classification of multichannel RS images [15]. Because of this, research in the area of multichannel image compression nowadays basically concerns design of the so-called near-lossy methods that take into account noise presence and possibility to introduce distortions in compressed images comparable to the noise level.

There are many unsolved problems in this area till the moment. Let us list a set of basic requirements to lossy compression:

1) providing a required CR or a CR not less than some minimal CR_{min};
2) preservation of useful information or providing distortions not larger than some predetermined level;
3) simplicity of control over CR and introduced losses;
4) appropriate computational efficiency;
5) possibility of automatic compression on-board.

The list of requirements can be continued, their priority depends upon application. Anyway, the first and the second requirements are, in general, contradictory. This is well known from the theory of lossy compression that for any lossy coder a larger compression ratio is attained due to introducing larger distortions compared to original image subject to compression [16]. However, in the case of lossy compression of noisy images the situation changes. If compression parameters (for example, quantization step for coders based on orthogonal transforms) are adjusted in such a manner that introduced distortions manly relate to removal of noise and useful information remains practically undistorted, then twofold benefit is provided. First, a CR considerably larger than for lossless coders is provided. Second, noise filtering is carried out and this can be favorable for classification of images compressed in this manner.

An example of filtering effect due to lossy compression is presented in Fig. 1. The original RGB image (left) is corrupted by additive white Gaussian noise with variance about 100, noise is independent in image components. The CR for the compressed image (right) is about 11 and filtering effect is especially well seen in image homogeneous regions of the image (pay attention to water surface (blue) of the Helsinki region image). In textural (in particular, urban) areas of this image the used lossy compression [17] does not introduce visible distortions. This allows expecting that classification of these areas using compressed data will be as well as classification of original data.

There is a trade-off between filtering effect of lossy compression of noisy images and distortions introduced into information content of data. The corresponding parameters of the coder (quantization step, CR or bpp) are treated as optimal operati-

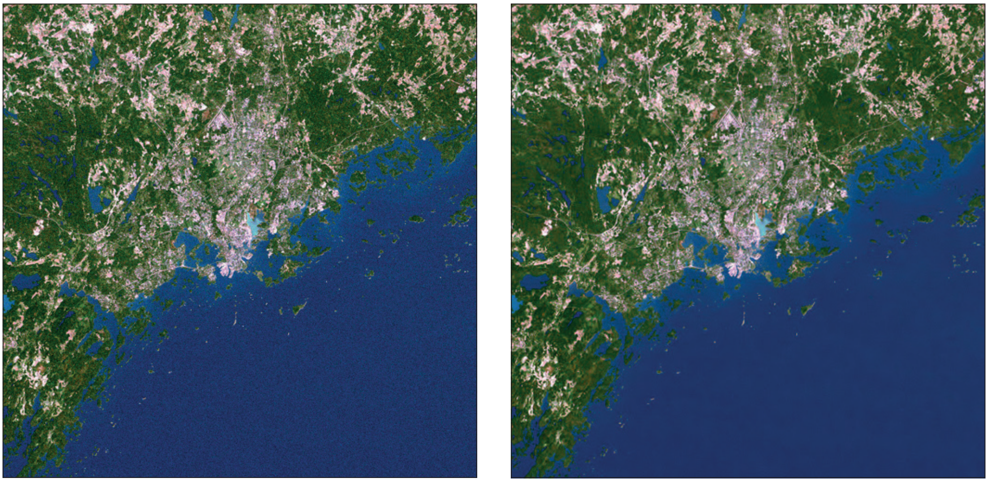

Fig. 1. Original noisy image (left) and compressed image with CR=11 (right)

on point (OOP). If OOP is attained for CR (CR_{OOP}) larger than CR_{min}, then it is reasonable to carry out lossy compression in the neighborhood of OOP. If CR_{OOP} occurs to be smaller than CR_{min}, then it becomes necessary to provide lossy compression with CR_{min}. Note that CR_{OOP} is larger for higher level of noise, images with simpler structure and more advanced compression methods (for example, AGU and its modifications [17] used instead for JPEG or JPEG 2000). It is also necessary to keep in mind that 3D compression of multichannel RS images usually produces few times larger CR than component-wise compression for the same level of introduced distortions [6]. However, 3D compression is more complex and difficult to implement. One can run into necessity to carry out specific operations as image normalization, sub-band grouping, etc. [18].

Control of introduced losses and automation of compression with a desired quality are still problems, too. One reason is that there is no direct correspondence between compression parameters as quantization step (or bpp) and introduced losses. Another reason is that conventional metrics as MSE or PSNR do not adequately characterize quality of compressed images. This is true for both typical classes of images as grayscale or color photos and multichannel RS images [19]. Because of this, current research is focused on establishing an agreed set of compressed image quality criteria (metrics) or, better, one optimal metric. However, there is doubt that such one (optimal) metric will be finally agreed and accepted by community. The reason is not in problems within community but in the problem of straightforward correspondence between metrics used in compression and quantitative criteria characterizing efficiency of solving final tasks. For example, metrics that characterized noise suppression (local MSE) are in good agreement with probability of correct classification of terrain types that are rather homogeneous as grasslands, water surface, etc. Meanwhile, for such kinds of terrains as urban areas probability of correct classification better correlates with metrics characterizing visual quality of compressed or filtered images. Therefore, design and practical selection of metrics for RS data compression is still challenging.

Recent research in lossy compression using other than MSE and PSNR metrics [20] shows that it is possible to reach quite large values of CR with providing visually absent distortions. In this case, quantization step for discrete cosine transform (DCT) based coders is to be set of the order D_k/(25…40) where D_k denotes dynamic range of a component image in a k-th channel. Applicability of such an approach presuming visually lossless compression has been tested for hyperspectral Hyperion data. It has been demonstrated [6] that for CR about 10 the classification of compressed images is practically the same as for original ones. Novel methods specially adapted to provide higher visual quality for a given CR (or, equivalently, larger CR for a given visual quality) have been designed. Compared to the standard JPEG and JPEG 2000, they produce by about 20…40% larger CR, However, the current problem is to design modifications of these coders able to incorporate inter-channel correlation of data. Then, it is expected that CR can be increased by 2…3 times compared to component-wise compression. In general, the tendency to increase of CR in the case of applying 3D compression instead of component-wise holds for different approaches to lossy compression of multichannel RS data. However, we would like to stress that one should be careful with direct (without special pre-processing) application of 3D compression to multichannel images because of considerable differences in dynamic range and SNRs in component images of multichannel RS data [21]. One more warning is that noise type is to be taken into account. If noise is signal-dependent, then there are two ways to follow. The first is to use the corresponding homomorphic transform for converting signal-dependent noise to additive [22]. The second way is to take into account noise type and characteristics just in local setting of quantization step in blocks of DCT-based coders [13]. An example of such compression is presented below in Fig. 2. Quantization step in each nm-th block is set individually for each spatial frequency and proportionally to local mean and multiplicative noise standard deviation ($QS(n,m,k,l)=\beta\bar{I}(n,m)\sigma_{\mu}\sqrt{W_{norm}(k,l)}$ where β is proportionality factor, $W_{norm}(k,l)$ is normalized DCT spectrum of speckle). If $\beta\approx 1$, one deals with visually lossless compression as it is demonstrated in Fig. 2 where CR is about 3.1, i. e. about three times larger than for lossless compression. For $\beta\approx 4$, the neighborhood of OOP is observed and CR is about 20. Then filtering effect is observed. Note that for $\approx$ the method preserves spatial and statistical characteristics of speckle allowing to effectively remove it after decompression.

The example presented in Fig. 2 shows that intensive noise can be present in RS images (the horizontal-horizontal polarization image of TerraSAR-X taken from `http://www.infoterra.de/free-sample-data` is presented although currently dual or multi-polarisation SAR images are typical).

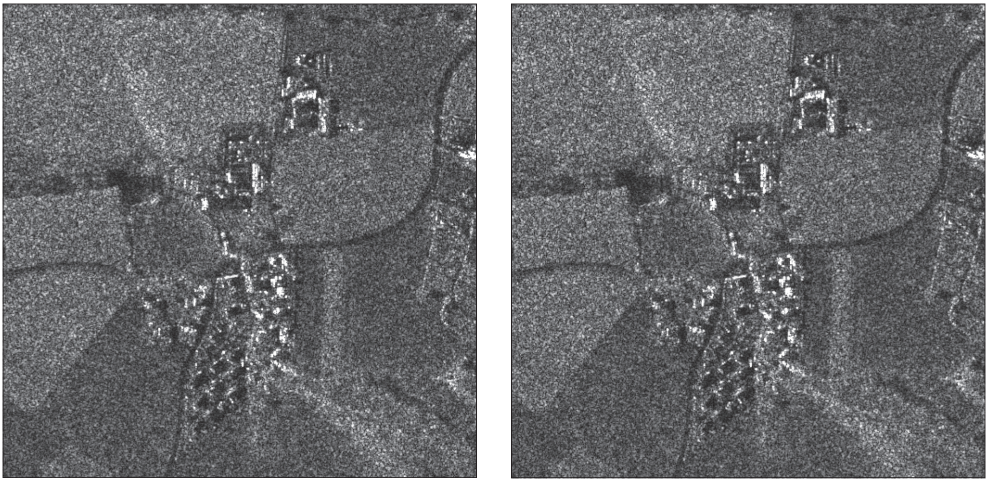

Fig. 2. Visually lossless compression of real life SAR image:
original image (left) and compressed image (right)

4. EFFICIENT FILTERING OF MULTICHANNEL RS TERRAIN IMAGES

The example shown in Fig. 2 shows that there exist certain types of RS images for which noise is very intensive. For other than radar images noise is typically less intensive but it is anyway worth suppressing it.

Although lossy compression is able to carry out noise filtering, it is not the best way of doing this [23]. Not going deeply into details, noise suppression efficiency of the state-of-the-art denoising methods is considerably better than that one for lossy compression in the neighborhood of OOP. The difference is about 3 dB in terms of PSNR. The same difference is observed in terms of the metric PSNR-HVS-M characterizing visual quality. This means that image filtering is to be applied at least for component images of multichannel RS data that are characterized by low SNR. Filtering can be carried out in combination with lossy compression where parameters of lossy compression in this case are to be set properly [10].

Optimal combination of lossy compression and filtering is an interesting topic that still requires intensive studies. However, below we will concentrate on denoising of multichannel RS images itself. There are numerous papers dealing with different aspects of image filtering. Filtering of grayscale images is investigated most and this experience can be useful for the case of component-wise processing of multichannel data. Meanwhile, multichannel images can be processed both in component-wise and 3D (vector) manner.

Component-wise filtering is simpler and can be carried out in parallel. 3D filtering is potentially more efficient [24], but it is more complex. Besides, methods of 3D filtering are mostly studied for the case of a limited number of channels (e. g. for color images [25]) under assumption that noise has the same properties in all component images. However, this does not hold for multichannel RS images and this makes problematic the use of known methods designed for color image filtering to processing of data with considerably larger number of channels. Therefore, a lot of work is awaiting for researchers in this direction. It is clear that inter-channel correlation should be taken into account for more efficient filtering of multichannel RS images.

Similarly, different noise types are considered in literature dealing with filtering. Additive white Gaussian noise is studied most. However, this model is too simple for adequate description of the noise in multichannel images. Signal-dependent noise seems to be more typical for new generation of sensors [7]. This case is more complex since many known denoising methods as wavelet based techniques and modern non-local filtering ones are unable to easily take into account invariance of noise statistics [26].

There are, at least, two ways to follow. The first is to adapt denoising techniques to an observed dependence of noise statistic on local mean. This can be quite easily done for DCT-based methods since processing is carried out in blocks of finite size [27]. But this is problematic for other groups of modern methods. The second way is to carry out the corresponding homomorphic variance stabilizing transforms. Then, the situation partly simplifies and a larger number of denoising techniquies can be applied. The problem is that one has to know in advance or to pre-estimate dependence of noise variance on local mean for setting parameters of filters or homomorphic transforms. The accuracy of methods for blind (automatic) estimation of signal-dependent noise characteristics is also worth improving [28].

One more problem is that in many types of multichannel RS images the noise is, in fact, spatially correlated in contrast to traditional assumptions on uncorrelatedness of noise. This property typical for, e. g., SAR images additionally complicates the task of noise removal. Filtering becomes less efficient than in the case of i. i. d. noise. Moreover, for increasing the filtering efficiency it becomes necessary to know in advance or to pre-estimate noise spatial spectrum in a blind manner.

For image filtering, a similar problem is actual as for lossy compression. This is the problem of dependence between efficiency of filtering commonly analyzed in terms of traditional criteria as output MSE and/or PSNR and accuracy of solving final tasks of RS data exploitation as, e. g. classification. Obviously, more efficient filtering usually results in better accuracy of the final task solving. In particular, probability of misclassifications can be reduced by 2…3 times due to efficient filtering and this is an excellent result.

Meanwhile, a lot of work is to be done in multichannel image filtering field. First, potential limits of image denoising have been determined only for component-wise processing in terms of output MSE only for the case of additive i. i. d. noise [29]. The results have demonstrated that even for this well-studied case there is still a considerable room for further improvement if an image structure is not very complex and the noise is not very intensive. It is worth trying to achieve such limits for the cases of signal-dependent and spatially correlated noise. Second, image filtering efficiency is to be studied in combination with further classification and object recognition. In particular, it is worth getting understanding what are input SNRs in component images for which it is possible to skip denoising. If this goal will be reached, it will allow to group components of multichannel data for which it is desirable to carry out 3D (joint) filtering and to make possible parallel processing of these groups with accelerating processing.

5. SOCIALIZING MULTICHANNEL RS IMAGES

It might seem that RS images can be of interest and use for scientific community in the field and direct customers of data that can be retrieved as governmental and regional boards, ecological and meteorological services, nature protection and emergency control organizations, etc. However, recent advances demonstrate that there is a tendency to socializing RS data. Google maps are the first and, probably, the most known example when multispectral Landsat data have been used for creating multilayer facilities intensively exploited by millions of ordinary people. There quite many ordinary customers of Internet who wish to see their house, garden, school, university, enterprise how they look from up. Such maps can be also used not only for curiosity but for other purposes of everyday life as to choose some picturesque place (resort) to vacations or travel, to select an interesting route to go by car, to look for a proper place for building a country-side house, etc. Also note that Landsat and other remote sensing data have been used for creation of maps by other service providers as Yahoo, Yandex, Bing, Google Earth Planet, etc.

Natural landscapes and relief can be also exploited for other purposes. They are already widely used in computer games. It is possible to predict that new computer and Internet facilities can appear in future as look from airplane illuminator for carrying out virtual travels and to see places where You have never been and, probably, will never attend in life. In all aforementioned cases there is a need in wide set of image processing operations as color conversion, scale transformation, reconstruction, enhancement since users would like to have pleasant looking images.

Here we come again to visual quality of images. This topic is important for many applications and a great number of publications deal with it [30]. A specific feature of research in this area is that a large number of experiments with volunteers is required to analyze correspondence between objective visual quality metrics (indices) and subjective perception of image quality by humans [31]. Moreover, it is important that such judgments are to be performed by mostly ordinary users rather than by specialists and experts in image processing. A desired number of volunteers is hundreds. This requirement has been satisfied by creators of modern databases of distorted images as LIVE [31] and TID 2008 [32]. In spite of efforts and time spent on creation of these databases, the creators have made them available for entire scientific community. This has allowed using the results of image ordering and scoring (with getting mean opinion score) for design and testing new metrics as well as for comparisons.

The authors in [33] have gone further. They propose to organize Internet accessible site with providing an opportunity to participate in image quality assessment experiments to any user, i. e. to exploit social databases. This takes off problems with attracting volunteers which were mainly students of universities for experiments carried out earlier.

Another step forward has been done recently. The site `http://www.infoterra.de/free-sample-data` provides a wide variability of SAR images for all continents. These images are presented in different forms allowing various groups of users to download and to analyze this specific type of RS data. Astrium GEO-Information Services offers training for understanding radar images. Interest to radar images can also stem from short comments for many images that describe specific effects appearing in a given image as the 49 th Paris Air Show on 24 of June, 2011, the extent of the severe flooding of Fitzroy River near the town of Rockhampton, Queensland, an imaged moving train in agricultural region of Ukraine, digital elevation models for different regions, volcanoes, Panama channel with change detection. Such examples attract people to remote sensing field and clearly indicate that facilities offered by remote sensing are not theoretical but mainly practical nowadays. To our mind, it is worth expecting similar sites to appear and develop for other types of remote sensing data. Certainly, some of them already exist like examples of AVIRIS data (`http://aviris.jpl.nasa.gov/html/data.html`).

There is one more problem in remote sensing that requires socializing of data. In optical image processing community, there is a commonly accepted set of test images for which efficiency analysis for many image processing algorithms is usually performed with possible comparisons. It is extremely desirable to have such commonly accepted test data for multichannel RS imaging including SAR, multi- and hyperspectral data [34].

6. CONCLUSIONS

It is shown that there are still many challenges in multichannel RS data processing. The basic challenges result from huge amount of data (for high spatial and spectral resolution sensors), a limited knowledge on image and noise characteristics, and necessity to provide reliable outcomes within limited terms.

There are several strategies of multichannel data processing that consist of several stages. These stages are interconnected, some of them can be skipped, but all operations performed at used stages influence the outcomes together in a complex (aggregate) manner.

However, research for methods and algorithms applicable at different stages is usually separated. There are also limited facilities for verification of the designed methods since on-land measurements are labor-consuming and should be planned in advance. Exchange of data by different teams active in the field can considerably accelerate research. Different forms of socializing the obtained data can efficiently improve the studies' outcomes and intensify the application of RS, too.

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