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Fusion of the Multi-sensor Data of the COSMO-SkyMed Mission

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Summary - The COSMO-SkyMed mission will provide remotely-sensed data of the Earth that are very interesting for two main reasons. First, the short revisit time over ground areas, made possible by the constellation of satellites involved, will allow to extract information about the territory or the sea surface on a daily basis. Second, this mission will provide data acquired by sensors of different and complementary nature: SAR, multispectral camera with high-spatial resolution (HRC), and hyperspectral camera (HYC). An appropriate signal processing, based on a synergistic use of the data that will be acquired and transmitted to ground stations, will represent a powerful and flexible tool for the investigation of the state of the soil and its changes, and for object detection. Data fusion techniques will be of primary importance in order to exploit the complementary nature of the sensors involved. The purposes may be different, such as a composite display of the information derived from different sensors, target detection, classification, change detection, etc. In this paper, after recalling some basic information about the COSMO-SkyMed mission, a brief survey of the most widespread techniques for the fusion of remote sensing data will be provided. Experimental results obtained with real data will also be presented.

INTRODUCTION

The COSMO-SkyMed mission will be based on a constellation of small satellites for Earth observation acquiring remote sensing data in such a way to cover a broad range of applications like risks management, in particular, but also resource management, land use and coastal monitoring. The ambitious objective assigned to the COSMO-SkyMed mission are allowed thanks to the intrinsic characteristics of the system. The seven satellites constellation aims at providing remote sensing data of higher quality from the spectral, temporal and spatial points of view. Three satellites of the

constellation carry optical instruments such as: a panchromatic camera, a multispectral camera and a hyperspectral camera, providing imagery with a valuable information content. The four other satellites are equipped with a Synthetic Aperture Radar (SAR) to give an insight in the microwave range and, consequently, to provide all weather and day/night acquisition capability unreachable by optical sensors, but at the price of a more limited spectral information content. A more detailed description of the COSMO-SkyMed mission instruments is given in the next section.

Because of its valuable panel of heterogeneous and complementary sensors, the COSMO-SkyMed mission belongs to the next generation of Earth observation systems for which adapted processing methodologies must be considered. The synergistic use of the numerous available sensors, which can be achieved by data fusion, allows to merge their advantages in order to obtain a richer information by enlarging the spectral view, improving the spatial resolution and/or getting a better revisit time of a given study area. Moreover, it reduces the uncertainty associated with the data from individual sensors. Data fusion can be defined as a formal framework in which are expressed means and tools for the alliance of data originating from different sources [1]. It opens a way to reach a better analysis and understanding of the remote sensing data, and consequently, to obtain information of greater quality. Aware of the limitations of analysing single sensor data whatever the processing complexity, the remote sensing community, like other scientific communities, has shown in the last few years a particular interest and motivation for data fusion. The important number of papers, conferences, workshops and special issues on data fusion are convincing indicators about its importance and usefulness. Among the current major processing targets of data fusion in remote sensing, we recall improved geometric correction, substitution of missing data, image sharpening, multisource classification for improved accuracy and change detection.

THE COSMO-SKYMED CONSTELLATION

The COSMO-SkyMed primary mission objective includes the monitoring, surveillance and intelligence applications for defence users, the management of exogenous, endogenous and anthropogenic risks. However, a broad range of other important applications, in the field of the resource management, land use and commercial products and services may be also satisfied once the primary objective is fulfilled. In particular, the fulfilment of the risk management user needs calls for the following general characteristics:

- fast response time (up to the final users)
- very good image quality, to allow a robust image interpretability at the requested scale of analysis
- all weather and day/night acquisition capability
- collection of large areas during a single pass capability
- along-track stereo during a single pass capability
- global coverage
- acquisition of a sufficiently large and interpretable image in a single pass
- acquisition of homogeneous and comparable multi-temporal data set, characterised by adequate spatial and spectral resolution suitable to perform analyses at different scales of detail

Most of the mission user needs have to be carried out through a correct mix of optical and SAR sensor observations. The most required spectral characteristics are multispectral (VIS), hyperspectral (NIR, SWIR, TIR, VIS), panchromatic (VIS) and microwave.

The sensors should be based on multi-satellite Earth observation systems combined with a fast data reception capability. Such a provision of data on an operational basis with the associated implications of continuity and quality is an essential characteristic of the system. Required resolution and revisit time imply a constellation of satellites, small in size and mass for economical reasons. Therefore, the best promising constellation has been identified and the relevant characteristics are here below summarised.

SAR Satellites Selected Orbit
Orbit: Dawn-dusk SSO
Total satellite Number: 4
Altitude: $\cong$ 600 km
Revisit Time: 12 hours

Optical Satellites Selected Orbit
Orbit : Near-noon SSO
Total satellite Number: 3
Altitude: $\cong$ 600 km
Revisit Time: 24 hours

The utilisation of X-band is suitable for flood risk management, oil-spill and small scale weather forecast on the sea, to study the content of water in the snow (for avalanches monitoring) and for on ground pollution monitoring (oil), etc... An X-band SAR instrument can be designed to meet the above needs together with the capability of measuring sub-centimetres swelling by means of differential interferometry using corner reflectors. The fundamental characteristics of the Synthetic Aperture Radar instrument operative modes (Fig. 1) are summarised as follows:

Modes with one polarisation selectable among HH, VV, HV or VH:

- HIMAGE
 - resolution: few m
 - swath width: $\approx$ several tens of km
- WIDERECTION
 - resolution: few tens of m
 - swath width: $\approx$ hundreds of km
- HUGEREGION
 - resolution: several tens of m
 - swath width: $\approx$ few hundreds of km
- FRAME
 - resolution: order of the m
 - spot width: several tens of km²

Modes with two polarisation selectable among HH, VV, HV or VH:

- PING PONG
 - resolution: few m
 - swath width: $\approx$ several tens of km

The need of a high resolution panchromatic sensor is due to different user needs. During the warning and crisis phases, the users requirements are to be in possession of images "as prompt as possible", "as accurate as possible" and "as synoptic as possible". In particular during the warning and crisis phase of earthquakes or floods, the availability of high resolution images, acquired just after and if possible just before the crisis, is of great advantage to understand where the most damaged areas are localised in order to organise the rescue operations. High resolution images with very high swath, is of great value also for off-line services requested by user needs: topography

updating, urban areas maps, land use maps at big scale. Moreover, if the sensors will have the best characteristics, interesting products could be also offered on the market for commercial purposes.

The multispectral sensor should mainly be oriented to the production of images useful during the knowledge and prevention phase of risk management. The applications are oriented to the land use determination (e.g. flood risk, seismic risk, forest fire risk), vegetation and habitat map (e.g. forest fire risk) and damage evaluation of forest fires. The TIR camera will be devoted to monitor surface, sea temperature, forest fires and volcanic activities.

The Hyperspectral camera should be mainly devoted to the water pollution management, vegetation mapping, drought evaluation, geological applications. They are of great importance to assess the vulnerability of the environment during the Knowledge and Prevention phase of natural and anthropic risks.

The fundamental characteristics of the optical instrument operative modes (Fig. 2) are summarised as follows:

High-Resolution Camera:

- Type:
push broom imager operating in 6 different and simultaneous spectral channels
- Multispectral bands and resolutions:
 - 1: 0.5-0.90 μm (PAN) order of the m at nadir
 - 2: 0.45-0.52 μm (blue) few m at nadir
 - 3: 0.52-0.60 μm (green) few m at nadir
 - 4: 0.63-0.69 μm (red) few m at nadir
 - 5: 0.76-0.90 μm (NIR) few m at nadir
 - 6: 1.55-1.75 μm (SWIR) few m at nadir
- Swath : tens of Km
- Access region : $\pm 35^\circ$ (across-track)

Hyperspectral Camera:

- Operational modes:
 - Wide mode - Low resol.
 - Narrow mode - High resol.
- Resolutions: 20 m to 300 m (VIS, NIR)
50 m to 300 m (IR)
- Swaths: 20 Km to 300 Km
- Access region: $\pm 35^\circ$ (across-track)

COSMO-SKYMED AND RISK MANAGEMENT

In the field of Risk Management, one basic consideration is that all natural hazards are of multidisciplinary nature and can be typified by origin:

- exogenous (floods, drought, landslides)
- endogenous (volcanism, earthquakes)
- anthropogenic (industrial accident, water pollution & coastal management).

Risk management is evolving from pure post-accident activities to prevention, preparedness and mitigation of crisis, so increasing the role of pre-crisis activities in order to avoid or to mitigate the consequences of a disaster. In this perspective, risk management can be seen as subdivided into three major phases, each one having its own information and timeline needs. These phases can be stated as follows:

- Knowledge and Prevention Phase (K&P), which gathers all activities performed to reduce vulnerability and to perform monitoring at various levels in order to be ready in case of an emergency situation. Such a phase is characterised by the production of thematic and base maps which can be carried out with the contribution of remote sensing techniques contribution, by the conventional photo-interpretation and/or visual computer assisted techniques. The K&P phase includes the monitoring routines also effected to predict the crisis, and therefore also performed with prohibitive weather/sun illumination conditions.
- Warning and Crisis Phase (W&C), mostly pertaining to the alarm and first operation activities to mitigate and provide first aids to population. The contribution of space remote sensing techniques should be particularly valuable in such a phase. The "vision" of what is going on, during the emergency, should be assured with every weather/sun illumination conditions too.
- Post Crisis Phase (PC), to perform restoration, evaluation of the damages and lesson learning to improve the overall management of the risk. Remote Sensing techniques are also important for this phase.

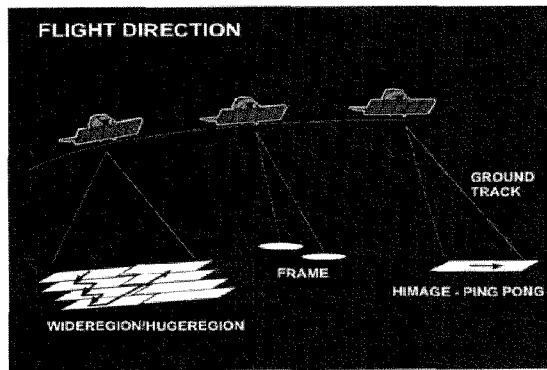


Fig. 1. Fundamental characteristics of the X-band Synthetic Aperture Radar instrument operative modes

All these phases contribute to create and exploit a knowledge base of the risk which represent the key element for the mitigation of damages and to reduce the consequences on population.

DATA FUSION TECHNIQUES

Depending on the nature of the data, several kinds of fusion can be distinguished. In our case, we will consider only the fusion aspects related to the COSMO-SkyMed mission. As mentioned above, the first kind is the fusion of multi-sensor data which plays a key role in data fusion due to the importance of the synergistic use of different sensors. The concept of satellites constellation, adopted in the COSMO-SkyMed mission, aims at opening the way to provide data with a very good revisit time (12 hours for the SAR sensors and 24 hours for the optical sensors). The exploitation of the temporal information is fundamental for risk management and change detection purposes but can be also valuable in image classification to improve the classification accuracy. This can be reached by the fusion of multi-temporal data. A third kind of fusion is the combination of multi-resolution data for which an important example of advantage is to overcome the difficulty to get high spatial and spectral resolution at the same time. In the case of the COSMO-SkyMed mission, the merging of data provided by the panchromatic and hyperspectral cameras will allow to provide imagery with both characteristics and so of higher quality.

The combination (fusion) of data can take place at three different processing levels, namely: pixel, feature and decision levels. In the pixel (low) level

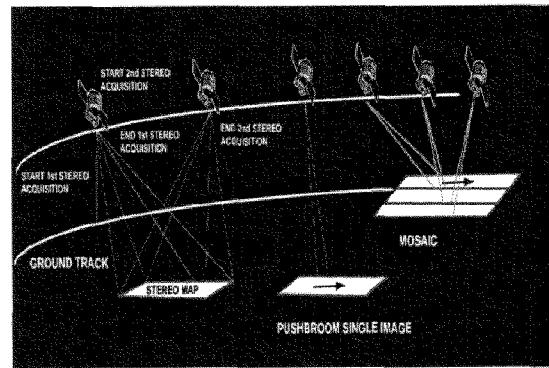


Fig. 2. Fundamental characteristics of the optical instrument operative modes

fusion, images coming from different sources are registered and then combined, pixel by pixel. In the case of feature (intermediate) level fusion, images are first processed to extract features of interest such as geometric, structural or spectral features; then the merging process is applied to such features. Finally, in the decision (high) level fusion, the data from each sensor are processed independently and the outcomes from all the sources are combined after giving them different weights of significance or reliability.

Numerous methodologies, like the probabilistic methods, the Dempster-Shafer evidence theory, neural networks and fuzzy logic, propose a solution to the problem of data fusion. The probabilistic methods include the stacked-vector method [2] characterised by a concatenation of the data from different sources in the same measurement vector. The stratification methods [3]-[4] and relaxation labeling technique [5] are generally used for the integration of ancillary data (other than remotely sensed images). The extended statistical fusion method [6] develops an original idea by introducing the concept of "reliability factors" aiming at weighing the different information sources according to their reliability. To provide a global model of probability density function for multi-sensor data, some statistical methods can be suitable such as: the dependence trees [7], based on the idea to approximate any multidimensional probability density function by a product of second order probability density functions; the Parzen approach, based on the principle of superposition of kernel functions; the expansion by basis functions or the projection pursuit density estimation [8]. Markov Random Fields [9]-[10] represents another

powerful probabilistic mathematical tool because of its remarkable ability to integrate any source of information (multi-sensor, multi-temporal, spatial contextual and/or ancillary information) in the scene model by the concept of energy functions. For the multi-temporal fusion problem, the Expectation-Maximisation algorithm was proved to be interesting to estimate the temporal information linking images separated in time [11].

The Dempster-Shafer theory of evidence [12]-[13] represent another approach to deal with the data fusion problem. In such a scheme, a conclusion (decision) is drawn according to the use of two confidence levels called respectively "belief" and "plausibility" reflecting the uncertainties related to the data sources.

Because they do not need any prior knowledge about the information sources, neural networks allow a straightforward but also efficient merging of different information sources. Among them, the MultiLayer Perceptron (MLP) trained with the error backpropagation learning algorithm is the most widely used and proved to be an effective multi-sensor fusion tool as shown by the results obtained in [14], [15]-[16]. The MLP popularity is explained by its ability to generate arbitrary decision boundaries in the feature space, provided that its two or more hidden layer architecture supports enough neurons. The Radial Basis Function (RBF) neural networks represent also an interesting alternative to the MLP due to their intrinsic simplicity and their low training cost [17]. Another neural network model is the Probabilistic Neural Network (PNN) in which statistically derived activation functions are used instead of the classical sigmoid activation function of the MLP. It can produce non-linear decision boundaries approaching the Bayes optimal ones, which can be modified in real-time due to the quasi-zero training phase it requires [18].

Fuzzy Sets theory, known as a simple and efficient mathematical tool aiming at imitating the human reasoning mechanisms, can represent a simple alternative approach for data fusion [19]-[20]. Depending on their behaviour, fuzzy operators belong to one of the three basic categories, namely: conjunctive-type (severe), disjunctive-type (indulgent) and compromise operators (cautious) like respectively the MIN, MAX and MEAN fuzzy operators. In dealing with the multi-temporal fusion aspect, the approach described in [21] starts by defining the spectral class distributions by exploiting rules based on an expert knowledge and applies a fusion of the multi-temporal data sets by carrying out a concatenation of the different bands

assuming no class change over time. Then a conjunctive operator is used for the class membership decision. In [22], two fuzzy-based fusion strategies of different temporal data sets aiming at obtaining a fusion that is neither purely conjunctive nor purely disjunctive are applied for linear feature detection with application to road network extraction. The first strategy is carried out by an implementation of compromise operators, while the second one consist to fuse the extreme operators.

Other mathematical tools were investigated such as the Fourier Series for the analysis of the vegetation phenology [23] and land cover classification [24]. It was observed that the Fourier Series can be useful to define some frequency characteristics from the class temporal signatures of a temporal sequence of remotely-sensed data.

The wavelet decomposition is another mathematical tool to which interest has been devoted, in particular to enhance the poor spatial resolution of multispectral data by means of a combination with images of higher resolution. Better performances (i.e. visual quality and spectral fidelity) compared to classical methods are reported in [25],[26] and [27].

TWO DATA FUSION EXPERIMENTS

Due to the unavailability of real data from the COSMO-SkyMed mission at the moment, we will present two experiments carried out with real data acquired from other remote sensors. The selection of the data sets was made in order to deal with the peculiarities of the COSMO-SkyMed missions and, in particular, on the one side the optical/radar data duality aspect and, on the other side, the multi-temporal data aspect. In the first experiment, we will show the benefit of merging both optical and SAR data together in a classification scheme. Whereas the second experiment will highlight the advantage of fusing multi-temporal data to improve significantly the classification accuracy with respect to single dates.

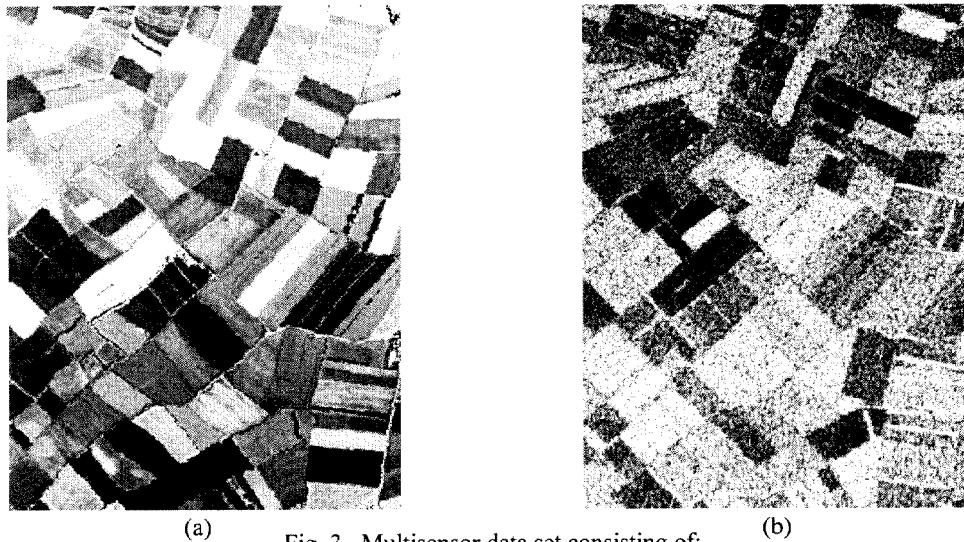


Fig. 3. Multisensor data set consisting of:
(a) optical image (ATM sensor); (b) SAR image

Multi-sensor Data Fusion

The fusion of heterogeneous data, such as optical and radar data, gives rise to the difficulty of finding a common statistical model to estimate the class conditional probability density functions (pdf). Adopting a parametric approach, by assuming a specific functional form of the distribution, may be a straightforward solution, but may be also far to provide a model which fits the real distribution of data. An effective alternative to the parametric approach is the non-parametric approach which includes methods like the K-nearest neighbours, the kernel estimators and neural networks. In this experiment, we will use the K-nearest neighbours (K-nn) to fuse the multi-sensor data set described later. From a classification viewpoint, the K-nearest neighbours decision rule represents a simple way to associate to any pixel in the feature space a label corresponding to an information class. The principle is to search, for any unlabeled pixels, the K nearest labeled neighbours available from the training set and, then, the decision can be made on the basis of the majority label in the set of the K nearest neighbours for which weights can be assigned according to the distance pixel-neighbour. The main weakness of the K-nn method is the computational load involved by the distance computations which can be overcome by adapting sophisticated search algorithms (like the Kd-Trees) to speed up the search process. The K parameter depends on the training set size but is in general set empirically.

The multi-sensor data set, on which the experiment was carried out, is made of two images referencing the same ground area. The first image was taken in July 1989 by a Daedalus 1268

Airborne Thematic Mapper (ATM) scanner from which six channels were considered in this experiment (all the TM channels apart from the thermal infrared channel). The second data set is a SAR image acquired in August 1989 by a PLC-band, fully polarimetric, NASA/JPL SAR airborne sensor, yielding nine different channels corresponding to all possible combinations of bands (P, L or C) and polarisation (HH, HV or VV). The ATM and SAR images (Fig. 3), separated in time by only few days, were registered by taking the SAR image as reference. They illustrate a part of 250x350 pixel size of a scene representing an agricultural area near Feltwell, U.K, in which five land cover types are dominant, namely: sugar beets, stubble, bare soil, potatoes and carrots. Both the multi-sensor and single-sensor data sets were classified using different K values, from K=3 up to K=50. The best results on the test set with and without multi-sensor fusion are summarised in terms of Overall Accuracy (O.A.) in the following table:

SENSOR	O.A. [%]
SAR	74.0
ATM	80.5
SAR+ATM	89.8

The obtained results show well that exploiting the information from only one sensor may give poor performances (74.0[%] for SAR data only), while taking advantage from the complementarity between SAR and ATM data improves considerably the results with +15.8[%] and +9.3[%] with regard, respectively, to the single SAR and ATM images.

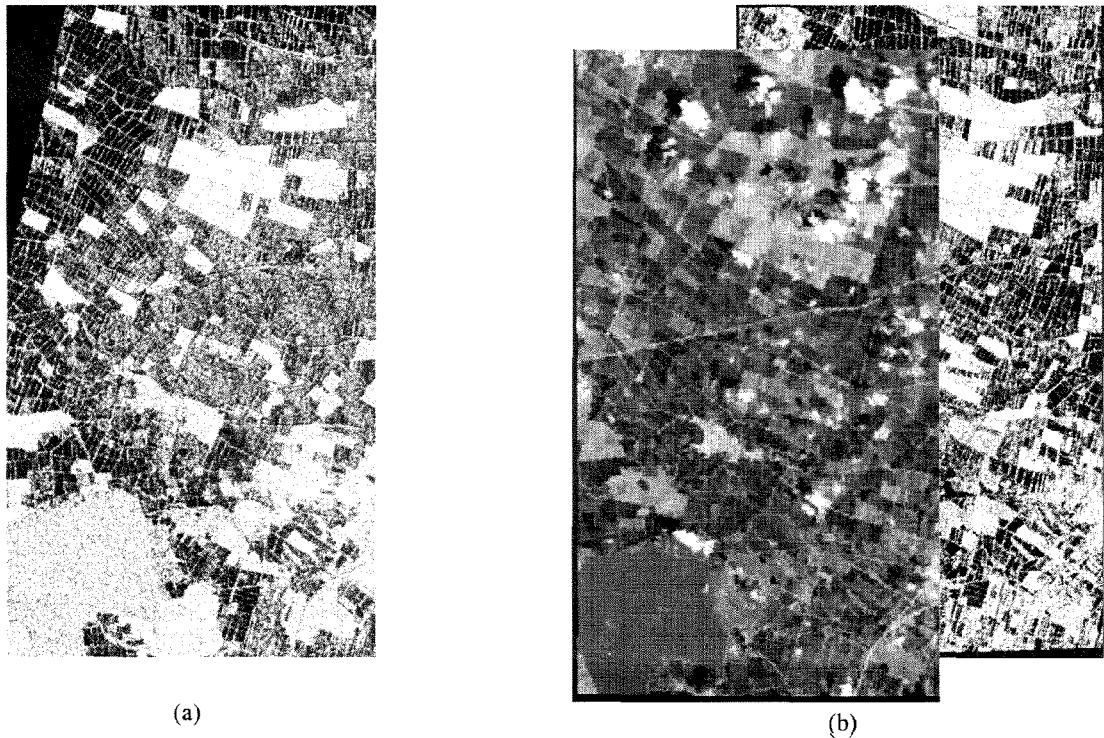


Fig. 4. Multitemporal and multisensor data set consisting of:
 (a) SAR image (April 1994); (b) optical and SAR images (May 1994)

Multi-temporal and multi-sensor Data Fusion

As we mentioned above, in addition to the multi-sensor data fusion, the integration of the temporal information carried by a multi-temporal data set may represent an effective way to improve the classification accuracy. The experiment, which will be described briefly in this section, was presented in [11] to which the reader is referred for further information. The multi-sensor fusion aspect is dealt with by using a Multi-Layer Perceptron (MLP) neural network, trained with the error back-propagation algorithm according to the Minimum Square Error (MSE) criterion, for a non-parametric estimation of posterior class probabilities. The temporal correlation between the multi-sensor images acquired at two dates is captured by using the joint class probabilities related to possible land cover changes. A technique based on a specific formulation of the iterative Expectation-Maximisation (EM) algorithm is applied to compute such estimates. Then, the posterior class probabilities and joint class probabilities are exploited by the multi-temporal classification approach which is based on the application of the Bayes Rule for minimum error to the "compound classification" of pairs of multi-sensor images acquired at different dates.

For different reasons, in real applications, the available sensors at two dates may be different. For example, at one date, both optical and SAR images may be available, whereas at the other date, the optical image may convey no or few information because of cloud covering. Because of its daily revisit time, this situation will undoubtedly appear frequently for the COSMO-SkyMed mission when, for a given period of time characterised by bad weather conditions, only SAR data will be utilisable. The multi-temporal multi-sensor data set considered for this experiments (Fig. 4) refers to an agricultural area in the Basin of the Po River, in northern Italy, and is represented by two registered images acquired in April and May 1994 by, respectively, the ERS-1 SAR sensor and the Landsat TM and ERS-1 SAR sensors. The dominant land cover types in April for the study area are four, namely: wet rice fields, bare soil, cereals and wood. In May, an additional cover type (corn areas) is to be included increasing the size of the set of possible classes to five. For the May data set, 11 features were extracted: 6 intensity features from the Landsat TM image, 1 intensity feature from ERS-1 SAR (C band, VV polarisation) image and 4 texture features (entropy, difference entropy, correlation and sum variance) computed from the ERS-1 SAR image using the gray-level co-

occurrence matrix. Whereas for the April image, only 5 features were utilised (1 intensity and 4 texture features as described above). For each date, a feed-forward MLP neural network, with one hidden layer of eight neurons, is trained. The number of input and output neurons correspond, respectively, to the number of features and of classes considered for each date. The EM algorithm was applied and reached the convergence after six iterations to provide the estimate of the joint class probabilities. The classification results of the two temporal images independently (without temporal fusion) and with temporal fusion obtained by the proposed approach are illustrated in the following table. In this case, they will be expressed in terms of Average Accuracy (AA) in [%] (i.e. the mean value of the accuracy over the different classes).

	WITHOUT FUSION	WITH FUSION
April	75.16	92.16
May	89.58	89.43

A significant improvement is obtained for April image with a value of +17[%], while, for the May image, the results are almost identical. The use of the Average Accuracy to appreciate the results was adopted to show that classes which are poorly discriminated in a given date can be recovered by the use of the temporal information. In this case, the improvement is mainly due to the class "cereals" in April with an increase of accuracy from 16.67[%] (without temporal fusion) to 75[%] (with temporal fusion). The early growth of this plant in April makes difficult its discrimination and, in particular, with only one sensor (SAR). The temporal information, extracted from the May image in which the discrimination of the class "cereals" is better (+84.26[%] without temporal fusion), played a valuable role to recover the class.

CONCLUSIONS

The COSMO-SkyMed mission with its valuable panel of sensors belongs undoubtedly to the next generation of Earth observation systems, whose main objective is to contribute in increasing the weigh of remote sensing in numerous real-world applications. For the COSMO-SkyMed mission, an emphasis is given to the risk management application whose interest is not to show with the increasing number of natural hazards that characterise the Earth in these last years. The

qualitative and quantitative aspects of the data acquired by the new generation of remote sensors make the data fusion a strategic way by which a better exploitation of the data can be reached. The importance of data fusion methods has been illustrated by the two experiments presented in this paper. In particular, the synergistic use of both optical and radar data and/or the integration of the temporal information can considerably improve the performances of a classification scheme. This pushes the remote sensing community to go further in the development of new data fusion methods dealing with the multi-sensor, multi-temporal and multi-resolution aspects in order to obtain optimised processing performances.

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