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Discrimination of land cover from a multiparameter SAR data set(*)

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Summary. — The identification of the most valuable radar observation parameters (*e.g.*, frequency, polarisation, incidence angle) is important both for designing non-redundant high-performance sensors (*i.e.* selection of frequency bands and polarisations) and for specifying mission operation requirements (*i.e.* temporal sampling, incidence angle). Moreover, the task of classifying multiparameter SAR images may require to adopt a strategy that implies the selection of a number of features among those available from this kind of sensors. In this paper we have performed this kind of analysis in a specific area of interest to account for the particular conditions in which remotely sensed data are going to be used. The paper summarises the results of the analysis of the radar data acquired during the MAC Europe '91 and X-SAR/SIR-C campaigns over the Montespertoli test site in Italy. The analysis is based mainly on a statistical approach aiming at demonstrating what is the contribution of different measurements performed by the polarimetric SAR for discriminating the surface coverage. The work is intended to furnish a guideline to develop an optimal strategy for acquiring and processing polarimetric data to be used for land classification.

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1. – Introduction

Data acquired by a radar polarimeter supplies many independent pieces of information that are correlated to the scattering of the electromagnetic energy by the Earth surface and can be used to discriminate the class cover on the ground and to estimate quantitatively geophysical parameters of the surface (*e.g.*, soil moisture). These measurements are characterised by their own statistics that are related to the scattering processes themselves, to the ground processing (*e.g.*, number of looks) and to the intrinsic variability of the targets belonging to a certain class [1, 2].

The analysis of the most valuable radar observation parameters (*e.g.*, frequency, polarisation, temporal sampling, and incidence angle) is important both for designing non-redundant high-performance sensors (*i.e.* selection of frequency bands and polarisation's) and for specifying mission operation requirements (*i.e.* temporal sampling, incidence angle). Moreover, the task of classifying multiparameter SAR images may require to adopt a strategy that implies the selection of a number of features among those available from this kind of sensors. Many authors have analysed the polarimetric signature of different land covers and particularly of different vegetation types. Studies have regarded the frequency and temporal behaviour and are based both on modelling and experimental frameworks [3-5]. The subsequent task of classifying the SAR images has also been undertaken in the literature by using different techniques. They consist in using different possible features extracted by the polarimetric measurements that may include multi-temporal [6] and textural features as well as different normalisation strategies [7]. Some approaches are based on *a priori* knowledge of the scattering mechanisms that determine the radar response [3, 8, 9]. The average radar response of each identified field is sometimes used, implying previous segmentation by visual interpretation or automatic methods. The statistical behaviour of the fluctuation of the SAR measurements, that depends on the number of looks, is taken into consideration by authors attempting to develop per-pixel classifications [10] or to apply, before the final classification task, a speckle reduction algorithm [11, 12]. Finally, the classification algorithm may be based on statistical decision rules or other approaches like neural network [13, 14] or fuzzy logic. Besides the abundant literature on these topics, it is helpful to perform this kind of analysis in a specific area of interest, to account for the particular conditions of the environment.

This work makes use of data acquired during the MAC Europe '91 campaign by the JPL AIRSAR polarimeter and during the X-SAR/SIR-C experiment over the Montespertoli test site [15]. MAC Europe '91 provided us with a multifrequency (P, L and C bands), multipolarisation (fully polarimetric), multiangle (20, 35 and 50 degrees incidence angles) and multitemporal data set. The X-SAR/SIR-C flew on two different Space Shuttle missions (6 days each). It provided us with polarimetric data at C and L bands and copolarised (vertical) data at X-band with incidence angle ranging from 25 to 57 degrees.

The data set is very valuable and here is analysed using different statistical techniques [16]. The work aims to single out what measurements most contribute to discriminate land cover types in a typical agricultural area in Italy. The role of different features that can be extracted from polarimetric data, when they are used in a classification scheme, is investigated. This includes the analysis of the contribution of different frequency bands and polarisations. In particular, since the information on phase differences between the returns at different polarisations is distinctive of polarimetric radar, the role of these pieces of information is analysed. Moreover, the paper compares quantitatively the classification accuracy obtained for the different acquisition events and evaluates the improvements due to multifrequency and multitemporal observations.

2. – The radar data: theoretical background and the experiments

2·1. *Background.* – The radar polarimeter is able to measure the scattering matrix $\mathbf{S}$ that relates the received (backscattered) electromagnetic wave $\mathbf{E}^{\mathrm{s}}$ to the incidence wave $\mathbf{E}^{\mathrm{i}}$ [1]:

$$\mathbf{E}^{\mathrm{s}} = \begin{bmatrix} E_{\mathrm{H}}^{\mathrm{s}} \\ E_{\mathrm{V}}^{\mathrm{s}} \end{bmatrix} = \frac{e^{jk_0 r}}{r} \begin{bmatrix} s_{\mathrm{HH}} & s_{\mathrm{HV}} \\ s_{\mathrm{VH}} & s_{\mathrm{VV}} \end{bmatrix} \begin{bmatrix} E_{\mathrm{H}}^{\mathrm{i}} \\ E_{\mathrm{V}}^{\mathrm{i}} \end{bmatrix} = \frac{e^{jk_0 r}}{r} \mathbf{S}\mathbf{E}^{\mathrm{i}}, \tag{1}$$

where subscript h and v indicate horizontal and vertical components, k_0 is the wave number, r is the distance of the radar from the target. It is common to arrange the independent elements of the scattering matrix in a complex vector $\mathbf{U}$ with 3 elements (considering that $s_{\mathrm{HV}} = s_{\mathrm{VH}}$ when reciprocity holds) and to refer to the covariance matrix $\mathbf{\Sigma}$ of $\mathbf{U}$, whose elements may also be arranged in a complex vector $\mathbf{X}_{\mathrm{c}}$ (6 elements) or in a real vector $\mathbf{X}$ (9 elements), as done in the following equations:

$$\mathbf{U} = \begin{bmatrix} s_{\mathrm{HH}} \\ s_{\mathrm{VV}} \\ s_{\mathrm{HV}} \end{bmatrix} \Rightarrow \mathbf{\Sigma} = \mathbf{U}\left(\mathbf{U}^T\right)^* = \begin{bmatrix} \langle s_{\mathrm{HH}} s_{\mathrm{HH}}^* \rangle & \langle s_{\mathrm{HH}} s_{\mathrm{VV}}^* \rangle & \langle s_{\mathrm{HH}} s_{\mathrm{HV}}^* \rangle \\ \langle s_{\mathrm{VV}} s_{\mathrm{HH}}^* \rangle & \langle s_{\mathrm{VV}} s_{\mathrm{VV}}^* \rangle & \langle s_{\mathrm{VV}} s_{\mathrm{HV}}^* \rangle \\ \langle s_{\mathrm{HV}} s_{\mathrm{HH}}^* \rangle & \langle s_{\mathrm{HV}} s_{\mathrm{VV}}^* \rangle & \langle s_{\mathrm{HV}} s_{\mathrm{HV}}^* \rangle \end{bmatrix} \tag{2}$$

$$\Rightarrow \mathbf{X}_{\mathrm{c}} = \begin{bmatrix} \langle s_{\mathrm{HH}} s_{\mathrm{HH}}^* \rangle \\ \langle s_{\mathrm{VV}} s_{\mathrm{VV}}^* \rangle \\ \langle s_{\mathrm{HV}} s_{\mathrm{HV}}^* \rangle \\ \langle s_{\mathrm{HH}} s_{\mathrm{VV}}^* \rangle \\ \langle s_{\mathrm{HH}} s_{\mathrm{HV}}^* \rangle \\ \langle s_{\mathrm{HV}} s_{\mathrm{VV}}^* \rangle \end{bmatrix} \Rightarrow \mathbf{X} = \begin{bmatrix} \langle s_{\mathrm{HH}} s_{\mathrm{HH}}^* \rangle \\ \langle s_{\mathrm{VV}} s_{\mathrm{VV}}^* \rangle \\ \langle s_{\mathrm{HV}} s_{\mathrm{HV}}^* \rangle \\ \Re\langle s_{\mathrm{HH}} s_{\mathrm{VV}}^* \rangle \\ \Im\langle s_{\mathrm{HH}} s_{\mathrm{VV}}^* \rangle \\ \Re\langle s_{\mathrm{HH}} s_{\mathrm{HV}}^* \rangle \\ \Im\langle s_{\mathrm{HH}} s_{\mathrm{HV}}^* \rangle \\ \Re\langle s_{\mathrm{HV}} s_{\mathrm{VV}}^* \rangle \\ \Im\langle s_{\mathrm{HV}} s_{\mathrm{VV}}^* \rangle \end{bmatrix},$$

where $\langle ... \rangle$ represents expectation value. $\mathbf{\Sigma}$ and $\mathbf{X}$ (or $\mathbf{X}_{\mathrm{c}}$) are specific characteristics of the observed object referred as the matrix/vector representing the *scene*. They are sensed by the instrument by averaging a number of independent measurements of the target (look summation), thus providing the matrix/vector of *observation* that will be indicated as matrix $\mathbf{Z}$ and vector $\mathbf{Y}$ (or $\mathbf{Y}_{\mathrm{c}}$). It can be demonstrated that the observations $\mathbf{Z}$ and $\mathbf{Y}$ (or $\mathbf{Y}_{\mathrm{c}}$) are random matrix/vector and in particular $\mathbf{Z}$ has a Wishart statistical distribution [17]. The first three elements of $\mathbf{Y}_{\mathrm{c}}$ ($y_{\mathrm{c}}(i)$, $i = 1,3$, elsewhere indicated as HH, VV and HV) are intensity measurements, while the other terms ($y_{\mathrm{c}}(i)$, $i = 4,6$, elsewhere indicated as HH-VV, HH-HV and HV-VV) are cross products containing information about the mean phase difference between the co-polarised and cross-polarised components of the radar echo.

2·2. *MAC Europe '91 and X-SAR/SIR-C experiments.* – This work is based on the polarimetric radar images collected on the Montespertoli test site (close to Florence, Italy) during the MAC Europe '91 campaign [15] and the X-SAR/SIR-C experiment [18].

TABLE I. – *Main characteristics of the radar data from the MAC Europe experiment.*

Date	Frequency (band)	Polarisation	Coverage (km)	Resolution (m)	Number of look (#)	Incidence angle (°)
	$P/L/C$	4-pol	12×8	12	16/16/12	20(*)
June 22	”	”	”	”	”	35
	”	”	”	”	”	50
	”	”	”	”	”	20(*)
June 29	”	”	”	”	”	35
	”	”	”	”	”	50
	”	”	”	”	”	20(*)
July 14	”	”	”	”	”	35
	”	”	”	”	”	50

(*) Not used in the statistical analysis.

As far as MAC Europe is concerned, the data were collected by the DC-8/AIRSAR sensor [19] of the Jet Propulsion Laboratory (JPL) during three different days on June 22, June 29, and July 14, 1991. Each day three parallel flights have been performed providing images at three different incidence angles, namely 20°, 35°, and 50°. The radar image products consist of the complete polarisation information at P, L and C bands. Each 16-look image (12-look at C-band) is about 12 by 8 km wide and the ground resolution is about 12 meters. The analyzed AIRSAR images are those acquired during the flights at 50° and 35° of incidence angle. The complete multifrequency data set has been used, apart from the data taken at 50° of incidence during the third overpass when only P and L bands are considered, since some problems in data co-registration and in the phase behaviour of C-band were identified.

The X-SAR/SIR-C experiment was performed during the flights of the Shuttle Radar Lab SRL-1 in April and SRL-2 in October of 1994. In this paper we only consider the April spaceborne mission when the test site conditions were more comparable to those during the airborne experiment. The Shuttle Imaging Radar C (SIR-C) instrument, developed by JPL, collected polarimetric data at L and C bands, while the X-SAR, built by Deutschen Zentrum fr Luft- und Raumfahrt (DLR) and the Agenzia Spaziale Italiana (ASI), acquired X-band images at VV polarisation [20]. The multifrequency data set covered a 20 to 60 km wide swath (depending on the incidence angle and polarisation mode) on the Montespertoli test site. The site was observed at different incidence angles at each of the 7 overpasses during the entire Shuttle mission from 12 to 18 of April. The incidence angle ranged from about 25° to 57°. The image resolution is 25 meters for all the frequency channels with 4 looks. The SIR-C collected the complete polarimetric information (*i.e.*, the covariance matrix $\mathbf{\Sigma}$) during the first five overflights, while only the dual polarisation mode was set during the last two passes (only two elements of the vector scattering matrix, specifically s_{HH} and s_{HV}, were measured). Table I and II summarise the main characteristics of the radar data.

3. – The ground truth data

The statistical analysis presented in this paper concerns a flat agricultural area surrounding the Pesa river, characterised by the following prevalent crops: wheat, colza,

TABLE II. – *Main characteristics of the radar data set from the X-SAR/SIR-C experiment.*

Date	Frequency (band)	polarisation	Coverage (km)	Resolution (m)	Number of look (#)	Incidence angle (°)
April 12	$L/C/X$	4-pol/4-pol/VV	26/26/27×100	25 × 25	≈ 4	27
April 13	”	”	33/33/30×100	”	”	35
April 14	”	”	30/30/31×100	”	”	44
April 15	”	”	20/20/30×100	”	”	48
April 16(*)	”	2-pol/2-pol/VV	55/55/34×100	”	”	52
April 17	”	”	57/57/36×100	”	”	55
April 18	”	”	54/54/35×100	”	”	57

(*) Not used in the statistical analysis.

alfalfa, sunflower and sorghum. Some areas of bare soil and urban covers are also considered, as well as woodland, vineyard and pasture areas that mainly extend in the hilly portion of the test site.

The maps of the Pesa basin produced for each AIRSAR overflight during MAC Europe '91 and each Shuttle mission allowed us to identify about eighty known fields belonging to the above-mentioned classes. Some differences were present between the two experiments in terms of terrain cover. They mainly regard the agricultural fields and their growing stage, since the Shuttle passes have been performed earlier in the growing season with respect to the airborne ones and many fields were therefore bare. Since the discrepancies concern mainly individual agricultural fields and the agricultural practice did not change very much in the relevant years, most of the findings of the data analysis can be directly compared and the differences attributed either to the growing stage or to the different properties of the measurement systems. Approximately the same area was mapped during the two experiments. The ground truth has been recorded on a regional map at a 1:10000 scale. The polygons representing the fields have been digitised to be automatically superimposed to the SAR image after geocoding. In fig. 1 we present the ground truth map in UTM projection acquired during the X-SAR/SIR-C spring mission. Note that the reported statistical analysis has, however, been performed using visually selected polygons to avoid any possible error of a purely automatic procedure.

As far as the multitemporal analysis of MAC Europe '91 data is concerned, the training set has been screened to select those fields common to all the radar acquisitions. We selected 57 polygons belonging to 10 different classes for a total of 6400 image pixels. As for X-SAR/SIR-C data, the analysed training fields that have been imaged at each Shuttle overflight were 45, amounting to about 1200 pixels grouped into 12 classes.

4. – Statistical analysis: methods and results

The different combinations of features that are extracted from the polarimetric data are usually organised in a vector (the *feature vector*) to which we will generically refer as vector $\mathbf{z}$ (of dimension p). The classification performances using different sets of frequencies and polarisations have been compared. In this respect, decreasing the number of features is important for reducing computer load but also to allow a more accurate estimation of the covariance matrix. In particular this happens when the amount of training data is limited with respect to the number of used features, as in the case of multitemporal and multifrequency data.

Fig. 1. – Map of the ground truth acquired during the April X-SAR/SIR-C mission in the area of the Montespertoli test site surrounding the Pesa river.

As far as multitemporal analysis is concerned, we have co-registered the MAC Europe data taken at the same incidence angle by using a standard polynomial transformation technique trained by image-to-image Ground Control Points. The X-SAR/SIR-C data taken at different time differ also for the incidence angle so that the method could be questionable. However, it should be considered that for such a spaceborne system the local incidence angle does not change very much within the area covered by the ground truth and therefore the image distortion is less important. Despite of the mentioned difficulties, such a very simple registration method gives acceptable results. The maximum mis-registration in the flat portion of the test site is in the order of one pixel.

4˙1. *The statistical methods*. – The discriminant analysis is based on the maximum-likelihood criterion that maximises the probability of an observed feature vector $\mathbf{z}$ being a member of class i, where $i = 1, N_{\mathrm{c}}$ and N_{c} is the number of classes. The classification rule places each observation in the class from which it has the smallest distance; such distance is given by different formulas, depending on the specific feature vector that is selected and the assumptions about its statistical distribution.

Assuming $\mathbf{z}$ is a real vector with Gaussian distribution the following applies:

$$d_i(\mathbf{z}, i) = (\mathbf{z} - \mathbf{m}_i)^T \left[\mathbf{C}_i\right]^{-1} (\mathbf{z} - \mathbf{m}_i) + \log \mid \mathbf{C}_i \mid , \tag{3}$$

where $\mathbf{m}_i$ is a vector containing the means of the features within class i and $\mathbf{C}_i$ is the corresponding covariance matrix. Vectors $\mathbf{m}_i$ and matrices $\mathbf{C}_i$ can be estimated from a set of observations selected from pixels whose class is known (training data). In the case of a multifrequency and/or multitemporal data set the feature vector $\mathbf{z}$ is obtained by stacking the vectors coming from the individual channels/dates.

Alternatively, the procedure proposed by Lee *et al.* [10] is based on a rigorous approach that assumes the Wishart distribution for the covariance matrix $\mathbf{Z}$ measured by the radar. The following formula is derived for the distance:

$$d_i(\mathbf{Z}, i) = \ln \mid \mathbf{\Sigma}_i \mid + \mathrm{Tr}\left[\mathbf{\Sigma}_i^{-1} \cdot \mathbf{Z}\right] , \tag{4}$$

where $\mathbf{\Sigma}_i$ is the covariance matrix of the class i that can be also estimated from the training set. For multifrequency data it is also assumed that the different frequency channels are uncorrelated so that the distance can be obtained by adding the ones defined for each channel. Note that in both cases the prior probabilities of the classes have been considered all equal.

To reduce the number of variables to be retained in subsequent processing, the *Canonical Discriminant analysis* has been used [21]. From a real vector $\mathbf{z}$ in the feature space, it computes a new vector $\mathbf{y}$ whose elements (the *Canonical Components*) are linear combinations of the original ones that summarise between-class variation in much the same way that principal components summarise the total variation:

$$\mathbf{y} = \mathbf{T} \cdot (\mathbf{z} - \mathbf{m}) , \tag{5}$$

where $\mathbf{m}$ is the vector containing means of the variables, vector $\mathbf{y}$ has dimension n that is equal to p or $N_c - 1$, whichever is smaller. A possible point of view to look at the canonical components is based on the fundamental partition theorem of multivariate analysis of variance. The sum of squares and cross-products (SSCP) of the total set of observations is called the *total sample* SSCP and is indicated by $\mathbf{A}$. The SSCP computed for the observations belonging to a certain class can be averaged together to give the *pooled within group* matrix $\mathbf{W}$. Finally we can compute a SSCP from the mean values of each class and call it the *between groups* matrix $\mathbf{B}$. The discriminating power of the feature vector $\mathbf{z}$ can be measured by the ratio of the determinants of the two matrices $\mathbf{W}$ and $\mathbf{A}$ that is usually denoted as Wilks' lambda (Λ). It represents the ratio between the mean variability within the classes and the total variability of the data set and decreases as the discriminating power increases. Matrix $\mathbf{T}$ of the canonical component transformation (5) can be computed by solving an eigenvalue problem for the matrix $\mathbf{W}^{-1}\mathbf{B}$ and the eigenvalues λ_j are related to the Wilks' lambda as shown by the following formula:

$$\Lambda = \frac{\mid \mathbf{W} \mid}{\mid \mathbf{A} \mid} = \prod_{j=1}^{n} \frac{1}{1 + \lambda_j} . \tag{6}$$

The capability of each single polarimetric feature (the elements of $\mathbf{z}$) to discriminate the surface cover has been determined by a *stepwise selection technique* that selects a subset of variables through an iterative process [22]. At each step of the selection process, the algorithm retains a variable or removes it depending on its contribution to the discriminatory power of the subset considered at that moment. The process stops when any variable does not meet the criterion to exit or the criterion to enter in the subset. The discriminatory power is measured by Wilks' lambda, which is defined in eq. (6). Once a variable is definitively entered, its relative relevance is measured by the partial canonical correlation with the discrete variable $i = 1, ...N_c$ representing the class.

4·2. *Determination of the relevant radar features.* – The stepwise selection analysis applied to each multifrequency data set allows one to identify the most effective frequency bands and polarisations and to understand if the elements of $\mathbf{z}$ related to the phase information can contribute to the discrimination power. In this analysis we have normalised the scene vector $\mathbf{X}$ defined in eq. (2) in order to manage quantities of comparable magnitude and to put in evidence the contribution of the phase information by dividing all the complex terms by their absolute values. The following normalised $\mathbf{X}_N$ (thus its measurement $\mathbf{Y}_N$) has been considered for a single-frequency band:

$$
\mathbf{X}_N = \begin{bmatrix} -10\log\sigma^0_{\mathrm{HH}} \\ -10\log\sigma^0_{\mathrm{VV}} \\ -10\log\sigma^0_{\mathrm{HV}} \\ 30\,\Re\langle s_{\mathrm{HH}}s^*_{\mathrm{VV}}\rangle/\sqrt{\sigma^0_{\mathrm{HH}}\sigma^0_{\mathrm{VV}}} \\ 30\,\Im\langle s_{\mathrm{HH}}s^*_{\mathrm{VV}}\rangle/\sqrt{\sigma^0_{\mathrm{HH}}\sigma^0_{\mathrm{VV}}} \\ 30\,\Re\langle s_{\mathrm{HH}}s^*_{\mathrm{HV}}\rangle/\sqrt{\sigma^0_{\mathrm{HH}}\sigma^0_{\mathrm{HV}}} \\ 30\,\Im\langle s_{\mathrm{HH}}s^*_{\mathrm{HV}}\rangle/\sqrt{\sigma^0_{\mathrm{HH}}\sigma^0_{\mathrm{HV}}} \\ 30\,\Re\langle s_{\mathrm{HV}}s^*_{\mathrm{VV}}\rangle/\sqrt{\sigma^0_{\mathrm{HV}}\sigma^0_{\mathrm{VV}}} \\ 30\,\Im\langle s_{\mathrm{HV}}s^*_{\mathrm{VV}}\rangle/\sqrt{\sigma^0_{\mathrm{HV}}\sigma^0_{\mathrm{VV}}} \end{bmatrix}, \tag{7}
$$

where σ^0_{pq} is the backscattering coefficient for vertical (VV), horizontal (HH) and cross (HV) polarisation. When analysing a multifrequency (or a multitemporal) data set the feature vector $\mathbf{z}$ is obtained by stacking the vectors coming from the individual channels.

In figs. 2 and 3 we show the results of this analysis for each considered pass of the airborne and spaceborne sensors, respectively. The partial canonical correlation of the selected elements of the multifrequency feature vector with the class identifier is indicated in the figures by a horizontal bar representation. The vertical axis represents the elements of the polarimetric feature vector of eq. (7) with the two terms of $\mathbf{z}$ representing a phase difference (the real and imaginary parts) coupled as a single piece of information. The bar length represents the partial correlation of each selected variable. The bars corresponding to different passages are stacked so that the longer is the entire stack the more recurrent is the selection of that particular feature and/or the higher is the partial correlation. It can be seen that the results for the two experiments are comparable. Note that the C-band is seldom selected in the MAC Europe data set [23]. This is manly due to the fact that we are comparing data which are affected by a different statistics since only 12 looks are added for deriving MAC Europe images at C-band compared to the 16 looks of the other frequency bands. The L and P cross-polarised returns seem to be the most useful quantities that have been selected for any incidence angle and acquisition day as can be expected considering that the discrimination concerns

Fig. 2. – The partial canonical correlation of the MAC Europe polarimetric features selected by the stepwise selection technique within each multifrequency dataset taken at different acquisition days and incidence angles.

mainly agricultural crops. As far as the polarisation property is concerned, this could be explained by the presence of elements like branches, twigs, stems and leafs ribs which produce much more depolarised backscattering from vegetation than that of the soil, so that cross-polarised return gives the maximum contrast between bare and vegetated soil. With reference to the frequency behaviour, this reflects what has been found in the literature using modelling approaches [24]. Those results indicate that P and L bands are effective to separate agricultural fields from other targets, the P-band being more useful for monitoring forests and olive groves, the L-band for crops with low plant density and both C and L bands for crop with high plant density. This is strictly related to the need for a greater penetration into the more dense vegetation which can be achieved by the lower frequency bands and to the single-scattering properties of elements of different size and shapes.

A more detailed analysis of our results, in particular the analysis of the confusion matrix, seems to confirm that lower classification errors are achieved at C-band for classes such as oat, alfalfa and barley. The phase difference between co-polarised returns is also particularly relevant at the L-band. Even at the C-band it plays an important role

Fig. 3. – The partial canonical correlation of the X-SAR/SIR-C features selected by the stepwise selection technique within each multifrequency dataset taken at different acquisition days and corresponding incidence angles.

compared to other features and taking into consideration the greater random variation from which it is affected. It is presumable that, being equal the radiometric resolutions, the role of the phase difference will be comparable for the two frequency bands as found in [5]. A possible interpretation of this remarkable behaviour of the phase difference is the double bounce scattering effect which may be appreciable in the case of forest trunks, urban environment and sometimes for large stalks, like those of corn and sunflower. Finally, the phase difference between co-polarised and cross-polarised returns is never selected, as expected when the target does not present azimuthal asymmetry, such as most of the cover classes presents on our test site [7]. A remarkable departure from the azimuthal asymmetry is present in the case of vineyards or vegetated fields with an important contribution of the double bounce effect in the presence of sloping terrain (such as forests). Both cases may produce specific polarimetric signatures, as for example discussed in [25], but these effects have not been analysed in this paper since they are beyond a more conventional land classification problem.

As far as the X-SAR/SIR-C data are concerned, the cross-polarised return at L-band still appears the best feature for discrimination. The co-polarised HH return at L-band is, in this case, more important, probably because the information at P-band is not available. The phase difference between co-polarised returns is still relevant. Also in this case the phase difference between co- and cross-polarised returns has never been selected and they are not shown in the figure. The X-band exhibits low canonical correlation (the bars are shorter when compared for example to the L-band); nevertheless it is selected most of the time. We will see in a following paragraph that the X-band has very low discrimination capability when used alone, while it can give independent information when merged to

Fig. 4. – Total error rate, averaged over the complete set of MAC Europe acquisitions, obtained by using different normalisation's (non-normalised and normalised covariance elements) and statistical assumptions on the considered feature vector (Wishart or Gaussian distribution).

the other frequency channels. Apparently, the incidence angle and acquisition date do not influence in a systematic way the relative relevance of the different features.

4˙3. *Comparing the performances of different set of features.* – We have applied the classification rules described in subsect. **4**˙1 to the images acquired by AIRSAR and X-SAR/SIR-C considering either single-frequency or multifrequency data. The resulting accuracy of the classification is measured by the total error rate (the average percentage of error of all classes) obtained when classifying the training set. In this way the accuracy is overestimated but the comparison between different cases is still significant.

First of all we have compared different choices regarding the feature vector and the classification rule. In fig. 4 we show the total error rate, averaged on all the MAC Europe passes, obtained by classifying the single-frequency and the multifrequency data. The figure shows the results obtained using different discrimination rules, that is by assuming the observed covariance matrix $\mathbf{Z}$ with Wishart distribution as in eq. (4), the feature vector $\mathbf{Y}$ with Gaussian distribution as in eq. (3) and the normalised feature vector $\mathbf{Y}_N$ of eq. (7), again with Gaussian statistics. It can be remarked from the figure that classifying the single band images using the rule in eq. (4) is always better than considering a Gaussian distribution for the element of $\mathbf{Y}$, as expected from the theory [10]. Nevertheless, the vector normalised as in eq. (7) produces the lowest error rate. When considering all channels, it probably takes advantage from the use of a stacked multifrequency feature vector in alternative to adding the distances of each frequency band. Moreover, the normalisation might compensate for differences in the training fields due to various unpredictable effects (including, for example, slight differences in surface slope).

Fig. 5. – Total error rate of the classification obtained for a 10-class problem at the three frequency bands (P, L and C) for each AIRSAR acquisition at 35° and 50° compared to the multifrequency ($P/L/C$) and multitemporal data set (at 50° only).

Figure 5 summarises the results obtained for the complete set of data (three days, two incidence angles) of MAC Europe '91 using the feature vector defined, for each frequency, by eq. (7) and a Gaussian statistics. We present the total error rate obtained by using the polarimetric information coming from each single-frequency band and from the entire multifrequency data set. The results are comparable for the aircraft passes at 35° and 50° of incidence angle and they do not address any systematic effect of the angle. There are not specific reasons for explaining the differences among dates apart from the different crop phenological stage. Instead, the relative classification performances of the different frequency bands are retained at each date, as well as the rate of improvement coming from a multifrequency data set. It can be noted that no single-frequency classification may produce acceptable classification maps for the case study considered here, characterised by 9 land cover classes (namely, woodland, colza, 2 classes of alfalfa, sunflower, wheat, sorghum, vineyard and urban areas) aggregated in small fields (maximum extent is 4-5 ha).

Figure 6 presents the same analysis performed on the X-SAR/SIR-C spaceborne data still considering all the crop classes observed during ground truth collection, that is 12 classes of land cover (namely, bare soil, untilled, sown fields, oats, wood, colza, alfalfa, favino, wheat, barley, vineyard, urban). In this case different data takes are separated by one day, but they differ also for the incidence angle. The results using one-frequency band are always very poor, particularly at X-band where only a single polarisation is available. The multifrequncy data set strongly improves the results, even if the total error rate is still unacceptably high. Note that the last two data takes are poorer since SIR-C operated in the dual polarisation mode, so that the comparison to the first data take can makes the contribution of the fully polarimetric measurements appreciable.

Fig. 6. – Total error rate of the classification obtained for a 12-class problem at the three frequency bands (L, C and X) for each X-SAR/SIR-C acquisition compared to the multifrequency ($X/L/C$) and multitemporal/multiangle data set.

The poor accuracy suggested us to assess a classification assuming a lower number of classes, namely a 5-class problem. In particular we considered a unique class grouping the herbaceous crops, the class of vineyard (which are always well discriminated), a class grouping all the high vegetation (wood), in addition to urban areas and bare soil fields. The same analysis of fig. 6 has been repeated for this 5-class problem leading to the results shown in fig. 7. It can be noted that a general decrease of the total error rate is found, but it is substantial only for those data takes that do not take advantage from the fully polarimetric information.

The accuracy obtained with a single data take acquired at different times and incidence angles has been compared to a multitemporal data set and shown in the last group of bars of fig. 5, and figs. 6, 7 for MAC Europe and X-SAR/SIR-C, respectively. In order to do this, a precise coregistration of the image pixels was necessary. It is important to mention again that the X-SAR/SIR-C multitemporal data set is also a multiangle data set, while this does not happen for the MAC Europe data. When dealing with multitemporal data it becomes extremely important to use a proper method to decrease the number of features since the dimension of the feature vector becomes impractical. After some comparison work considering also the Principal Component technique and the stepwise selection technique, the Canonical Components have been preferred since they better preserve the between class variability without exaggerating the within class variability that is largely due to the speckle noise. As for MAC Europe the analysis is limited to the 50° incidence angle because of some problems in image-to-image registration at 35° incidence angle.

The multitemporal results for the multifrequency data set is relative to the classification of the first five canonical components obtained from each multifrequency image and has produced a final total error rate of 5%. The analysis of X-SAR/SIRC-C multitemporal/multiangle data set leads to a total error rate of 4.43% for the 12-class problem

Fig. 7. – The same as fig. 6 but for a 5-class problem.

and 4.15% for the 5-class problem. Note that the reduction of the number of classes does not contribute significantly to reduce the error when a proper multiparameter data set is available. The best total error rate obtained from satellite data is even better than the one obtained from aircraft. This result does not necessarily indicate that spaceborne data would produce better classification maps, since the analysis is performed using training data manually selected inside large agricultural fields, so that the effects of the worse geometric resolution are left out. However, they mean that the amount of information coming from the spaceborne mission in terms of number of passes and multiangle measurements compensate for the reduced radiometric resolution of the 4 look X-SAR/SIR-C images compared to the 16/12 looks of AIRSAR.

5. – Conclusions

The capability of discriminating between different classes in the Montespertoli test site is strongly influenced by the inherent variability of the land coverage due to different agricultural practices, land use fragmentation, slopes, etc. The best results were achieved by a classification criterion making use of a feature vector obtained from the terms of the measured covariance matrix normalised and scaled in a non-linear way. The classification rule is developed assuming a Gaussian probability density function of this vector. The pixel-by-pixel classification takes an enormous advantage from the use of the fully polarimetric, multitemporal and multiangle information. The canonical discriminant analysis can be successfully used to reduce the dimension of the polarimetric measurements. A quantitative comparison of the polarimetric signatures shows that the cross-polarised power returns (at P and L bands) contribute the most to terrain cover discrimination. The phase difference between co-polarised returns plays a role, which is not negligible at the L and C bands. A multitemporal data set allows one to further improve the accuracy by decreasing the error rate up to about 4%.

The performance of the spaceborne X-SAR/SIR-C system is worse than the airborne

AIRSAR when considering single-frequency and/or single-acquisition data set. Both systems take advantage from exploiting multitemporal data and particularly the spaceborne one when all passes at different incidence angles are merged.

The results of this statistical analysis are being used as guidelines to perform an end-to-end classification experiment aiming to produce a final thematic map of the test site in a standard cartographic projection and to estimate the classification accuracy on an independent set of test data.

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