Optimized PCA Based Feature Extraction from Multi-look/Multi-resolution TerraSAR-X Data

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***Abstract*—With the launch of the German TerraSAR-X system in June 2007, a new generation of high-resolution spaceborne Synthetic Aperture Radar (SAR) data is available; which facilitates a spatially and thematically detailed SAR scene analysis. In fact, the high resolution of TerraSAR-X enables scene on land cover, such as urban areas, deserts, forests and fields, to be accurately mapped. Among the several feature extraction tools available in the literature, we choose in this paper to use Principal Components Analysis (PCA). In fact, based on covariance analysis, the PCA represents the input data in a linear subspace with minimum information loss. Our first objective in this article is to provide an optimal processing for finer PCA based feature extraction from SAR images.**

Then, since the presence of speckle in SAR images changes the radiometric and textural aspects of the different structures that may exist in the scene, our second objective is to study the sensitivity of the PCA performance, with regards to the amount of speckle that might be included in the SAR image. To control more accurately this amount, a speckle reduction was carried out by means of multi-looking.

***Index Terms*—TerraSAR-X data, PCA, Speckle reduction, Multi-looking.**

I. Introduction

In the last few decades, the constantly intensive global urbanization has made the urban and suburban areas among the most dynamic sites on earth. Therefore, in order to provide a better assessment and a finer description of these areas, the demand on remote sensing techniques is getting heavier and heavier. In particular, Synthetic Aperture Radar (SAR) imagery, has become increasingly popular as some of its properties are favorable to optical imagery. In fact, SAR is a coherent imaging mode in the microwave domain ([1]–[3]) that can operate regardless of weather conditions, and whose resolution is independent of sensor height.

SAR imagery was proved to be able to improve significantly the automatic monitoring of cities in a wide spectrum of applications, e.g. road detection ([4], [5]), 3-D reconstruction of man-made objects ([6], [7]). However, the performances of such automatic monitoring tools are highly dependent on the relevance of the extracted signatures. That's why the feature extraction problem was and is still a field of ongoing research. Indeed, many approaches in the literature were developed in order to propose solutions to this problem. Among them, Principal Components Analysis (PCA) based algorithms were widely used, for the analysis and the compression of different kinds of signals and images ([8], [9]). In general, these algorithms assume that the target images are centered and even sometimes the background is extracted as much as possible. Thus, when dealing with images where the targets are randomly occluded like the case of urban areas, these algorithms would produce higher false alarm rates. The first step of our work consists thus, in proposing an optimal pre-processing for a better PCA based feature extraction, from a four-class database including urban areas, deserts, forests and fields.

Another important issue that might complicate the SAR images interpretation and deteriorate the information extraction performance, is the presence of the speckle noise. This introduces the second step of our work, which consists in studying the sensitivity of the PCA to the amount of speckle, that might be included in the SAR image. To carry out this study, we have used a 15 multi-look/multi-resolution four-class databases extracted from the 15 TerraSAR-X images over Egypt obtained after, a speckle reduction by means of multi-looking, with 15 different levels.

The organization of this paper is as follows: section II is dedicated to the description of the optimal pre-processing for PCA based feature extraction. Then, section III gives a short overview on the multi-looking technique. Section IV describes the databases that we have used. After that, we report some preliminary results in section V, while section VI gives some conclusions.

II. Optimal processing for PCA based feature extraction

PCA is one of the most popular statistical method for feature extraction. It is based on the assumption that high information corresponds to high variance. The PCA transform is defined as follows:

$$Y = H^T X, \qquad (1)$$

where X is $d \times n$ dimensional vector samples, Y is transformed $m \times n$ dimensional vector samples, and H is a $d \times m$ transform matrix.

H is calculated as the m largest eigenvectors of the $d \times d$ covariance matrix C_X of X. It is assumed, in this case, that most of the X information content is stored in the directions of the maximum data variance, under the constraint of orthogonality. Since the m largest eigenvalues equal the maximal variances, the m corresponding eigenvectors are exactly the columns of the matrix H. These eigenvectors are called Principal Components (PCs). It is also worth to note that the transformation defined in (1), gives uncorrelated components.

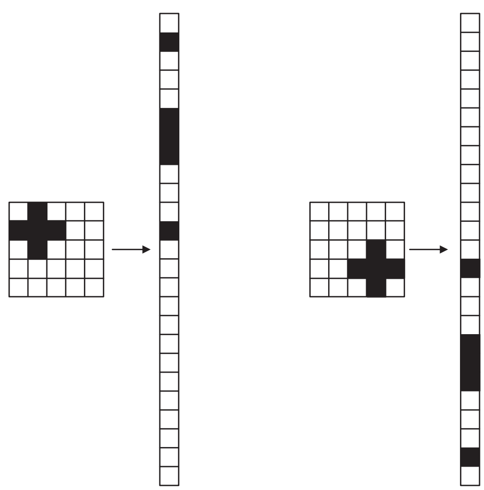
Thus, performing a PCA on a dimensional vector samples X results, from a matrix computation point of view, in solving the following eigenvalues equations:

$$C_X V^i = \lambda^i V^i \quad ; \quad i = 1, 2, \ldots, m, \tag{2}$$

where λ^i and V^i denote respectively the m largest eigenvalues of the covariance matrix C_X, and their corresponding eigenvectors.

To apply this technique on images (2-D signals) databases, a simple matrix to vector conversion is done before performing the PCA.

In general, in the literature, the PCA based feature extraction algorithms ([8], [9]) assume that the target images are centered and even sometimes the background is extracted as much as possible. Nevertheless, these algorithms would produce higher false alarm rates with images where the target parts are randomly occluded. This is actually, the case of images over urban areas. In fact, as shown in [10], the backscattering behavior of man-made targets is much more complicated than conventionally modeled. This results, in the matrix to vector conversion step, into quite ill-structured vectors where the different backscattering magnitudes are distributed in a varying way even for images belonging to the same class, as could be seen in Fig.1.



(1) (2)

Fig. 1. A 3×3 '+' target can seem differently according to its position in a 5×5 sub-image: (1) or (2).

To overcome this problem, a descending sorting of the pixels could be an intuitive optimal pre-processing. Indeed, following this technique, two images containing the same target but in different positions, will be converted into the same sample vector.

When applied on a four-class database (urban area, desert, forest and field), the optimal PCA algorithm flowchart could be described by Fig.2.

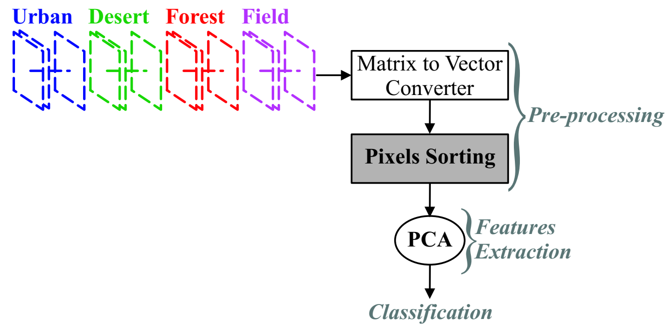


Fig. 2. Optimized PCA based feature extraction algorithm flowchart.

Mathematically speaking, applying pixels sorting on the input dataset, is nothing else than multiplying the $d \times n$ dimensional vector samples X, by a permutation matrix P to get the new vector samples:

$$X_{new} = PX. \tag{3}$$

The covariance matrix of X_{new} is written as:

$$\begin{aligned} C_{X_{new}} &= X_{new} X_{new}^T, \\ &= PX(PX)^T, \\ &= PC_X P^T. \end{aligned} \tag{4}$$

The PCA requires that we solve the following new eigenvalues equations:

$$C_{X_{new}} V_{new}^i = \lambda_{new}^i V_{new}^i \quad ; \quad i = 1, 2, \ldots, m, \tag{5}$$

where λ_{new}^i and V_{new}^i denote respectively the m largest eigenvalues of the covariance matrix $C_{X_{new}}$, and their corresponding eigenvectors.

By taking into account (4), the eigenvalues equations (5) become:

$\forall i, i = 1, 2, \ldots, m$:

$$PC_X P^T V_{new}^i = \lambda_{new}^i V_{new}^i, \tag{6}$$

$$C_X (P^T V_{new}^i) = \lambda_{new}^i (P^T V_{new}^i). \tag{7}$$

Thus, using the eigenvalues equations (2), and since P is a permutation matrix ($PP^T = I$ where I is the identity matrix), the eigenvectors and eigenvalues of the new covariance matrix $C_{X_{new}}$ could be written as:

$$V_{new}^i = PV^i. \tag{8}$$

$$\lambda_{new}^i = \lambda^i. \tag{9}$$

The new transform matrix H_{new} could be computed as follows:

$$H_{new} = PH. \tag{10}$$

Therefore, from a feature extraction point of view, the pixels sorting pre-processing step could be seen as a projection of the data in a new more organized feature space.

III. Multi-looking

The simplest approach to reduce the speckle in SAR images, is to average the intensity over several pixels, within a window centered on a specific pixel. The obtained separate images are referred to as looks, so that this process of averaging in intensity is known as multi-looking, and the resultant images is known as L-look, where L denotes the number of incoherently summed looks or pixels. Such an approach reduces the speckle variance by a factor L, i.e. reduces the uncertainty of the measured data, and as a consequence, the noisy appearance of the SAR image. However, this increase in the radiometric resolution is gained at the expense of the spatial resolution, which is degraded by the same factor resulting in the blurring of small objects.

The L-look average intensity is:

$$I = \frac{1}{L}\sum_{k=1}^{L} I_k, \tag{11}$$

where the I_k are independent variables each exponentially distributed with mean σ, is known ([11]) to obey a gamma distribution with order parameter L and $I_0 \geq 0$ according to:

$$p_I(I = I_0) = \frac{1}{\Gamma(L)}\left(\frac{L}{\sigma}\right)^L I_0^{L-1}\exp(-LI_0/\sigma). \tag{12}$$

The moments of the average intensity are:

$$\langle I^m \rangle = \frac{\Gamma(m+L)}{\Gamma(L)}\left(\frac{\sigma}{L}\right)^m, \tag{13}$$

with special cases $E\{I\} = \sigma$ and $var(I) = \sigma^2/L$. The latter relations motivate the definition of the Equivalent Number of Looks (ENL) as:

$$ENL = \frac{(E\{I\})^2}{var(I)}, \tag{14}$$

where the averages are carried out in intensity, over a uniformly distributed target. The ENL is equivalent to the number of independent intensity values averaged per pixel.

If we make a change of the variables and set $E\{I\} = \sigma = \mu_I$, we obtain the conditional probability density function, also known as the likelihood function of I given its mean value μ_I:

$$p_I(I = I_0|\mu_I) = \frac{1}{\Gamma(L)}\left(\frac{L}{\mu_I}\right)^L I_0^{L-1}\exp(-LI_0/\mu_I). \tag{15}$$

with a conditional mean $E\{I|\mu_I\} = \mu_I$ and a conditional variance $var(I|\mu_I) = (\mu_I)^2/L$.

An interesting property of the probability density function described by (15) around a given mean value μ_I, is its interpretation as a multiplicative noise. It can be seen that the distribution of I with mean μ_I, is identical to the one obtained by multiplying, a fixed cross-section μ_I with a noise process n_I that is distributed according to $p_I(I_0|\mu_I = 1)$:

$$I = \mu_I \times n_I = \mu_I \times I_{\mu_I=1}. \tag{16}$$

Due to this property, speckle is considered to be a multiplicative noise with:

$$p_{n_I}(I = I_0) = p_I(I_0|\mu_I = 1). \tag{17}$$

IV. Multi-look/multi-resolution TerraSAR-X databases Description

For our experiments, we have used a TerraSAR-X High Resolution Spotlight mode (HS), Multi Look Ground Range Detected (MGD) image, over the Pyramids of Gizeh in Egypt, which was multi-looked at 15 different levels. Then, to build our databases, we have selected, from each multi-looked image, four classes (50 samples per class) including urban area, desert, forest and field. The samples were chosen so that, at each multi-looking level, they frame almost the same structures. Details about the different databases are listed in Tab.I and samples from each class are shown in Fig.3.

TABLE I
ENL, Azimuth resolution and sample size for the 15 multi-look/multi-resolution TerraSAR-X databases.

TerraSAR-X Database	ENL	Azimuth Resolution	Sample Size
1	1	1.2	161×161
2	1.2	1.4	137×137
3	1.6	1.6	119×119
4	2	1.8	107×107
5	2.5	2.0	97×97
6	3	2.2	87×87
7	3.5	2.4	81×81
8	4.1	2.6	73×73
9	4.8	2.8	69×69
10	5.5	3.0	65×65
11	6.1	3.2	59×59
12	7	3.4	57×57
13	7.8	3.6	53×53
14	8.7	3.8	51×51
15	9.6	4.0	49×49

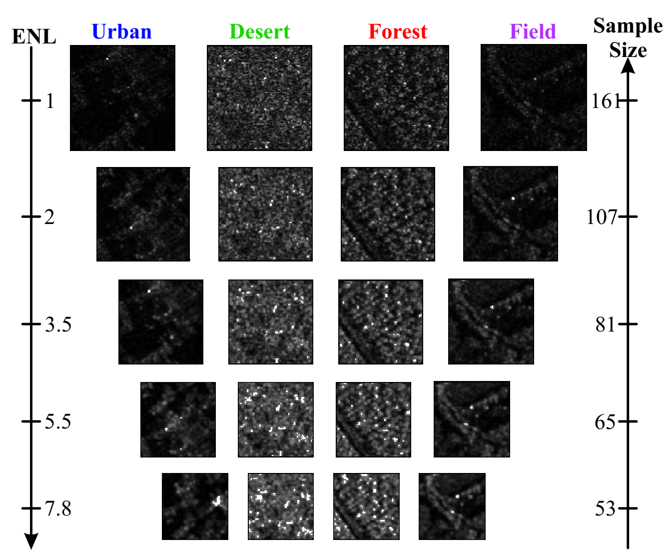


Fig. 3. Samples from the multi-look/multi-resolution TerraSAR-X databases.

V. Experimental results

It is worth to note that all the PCA performances computed in the following, are expressed as the average of 5 repetitions with randomly selected train and test data. In each repetition, 50% of the data is used for training and the rest for testing.

A. How does the PCA perform after the pixels sorting?

Fig. 4 shows the PCA performances, as a function of the used PCs sets, before and after the pixels sorting.

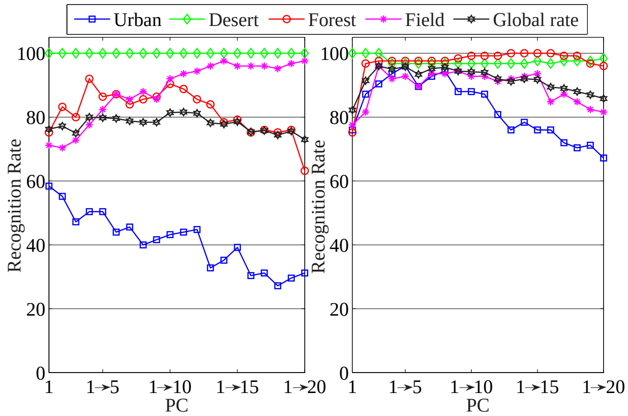


Fig. 4. From left to right: PCA performances as a function of the used PCs, before and after the pixels sorting.

According to Fig.4, the pixels sorting improves advantageously the PCA performance, especially for urban areas, where a gain of about 40% was mostly achieved. In fact, the electromagnetic scattering in these areas, is characterized by a variety of single or multiple scattering mechanisms with a wide range of scattering amplitudes, and a sorting of the backscattering magnitudes is thus gainful. For forests, where the backscattering response is very relevant ([12]), an increase of about 20% was also gained. The steadiness of the deserts recognitions could be explained by the uniformity of the backscattering in this class.

B. How much is the optimized PCA based feature extraction algorithm performance sensitive to speckle?

Fig. 5 summarizes the optimized PCA based feature extraction algorithm performances, obtained for the 15 multi-look/multi resolution databases, when only the first 5, 10, 15 and then 20 PCs, are used.

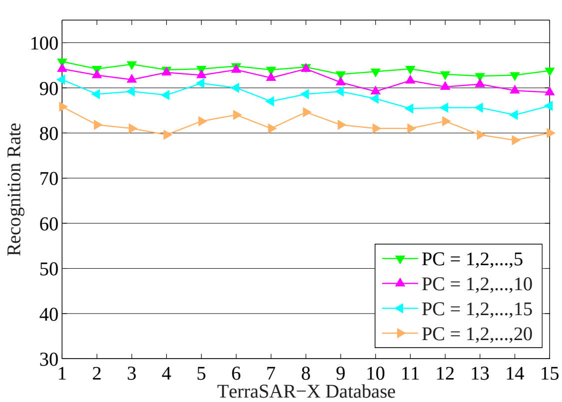


Fig. 5. The optimized PCA based feature extraction algorithm performances for the 15 multi-look/multi-resolution TerraSAR-X databases, when different sets of PCs are considered.

Fig. 5 does not show a clear dependency between the PCA performance and the amount of speckle included in principle, in the images.

⇒ A POSSIBLE EXPLANATION: Since the multi-looking results simultaneously, in an increase of the ENL and a decrease of the resolution. We carried out the same tests on simulated databases first, with a decreasing resolution and an unchanging ENL, and then with an increasing ENL and an unchanging resolution. In fact, the non-dependency between the PCA and the multi-looking might be a simple compensation between a dependency between the PCA and a decrease of the resolution from one side, and a dependency between the PCA and an increase of the ENL from another side.

- **Simulated SAR databases I: a decreasing resolution and an unchanging ENL:** To simulate a SAR image, the propriety of the multiplicative noise should be maintained. Thus, to generate our first databases, we have started by multiplying 6 Brodatz textures, with the same speckle noise ($ENL = 6$). Then, the multi-resolution databases are obtained by sub-sampling the speckled textures with different factors, ranging from 1 to 6. Samples from some of these databases are given by Fig.6.

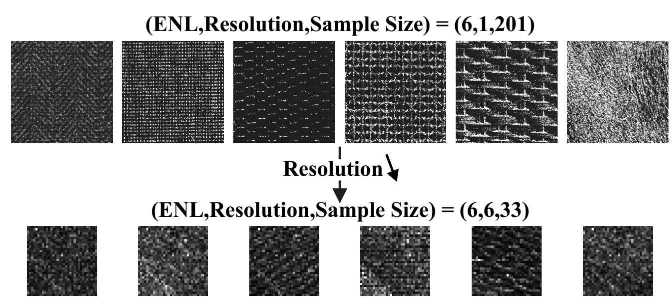


Fig. 6. Samples from some of the **simulated SAR databases I** (a decreasing resolution and an unchanging ENL).

When applied on the multi-resolution **simulated SAR databases I**, the optimized PCA based feature extraction algorithm shows the performances summarized in Fig.7.

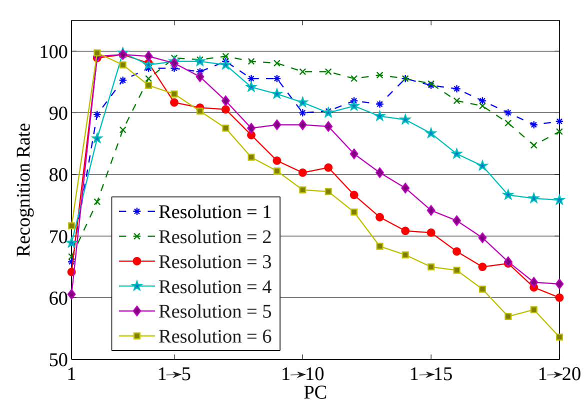


Fig. 7. The optimized PCA based feature extraction algorithm performances as a function of the used PCs, for the **simulated SAR databases I** (a decreasing resolution and an unchanging ENL).

From Fig.7, it is clear that, when more than 2 PCs are considered, our optimized PCA based feature extraction algorithm is more sensitive to the size of the used PCs sets, for the low-resolution databases (solid curves), than it is for the high-resolution ones (dashed curves).
Fig.8 provides the classification results of our algorithm as a function of the resolution, when only the first 5, 10, 15 and then 20 PCs, are considered.

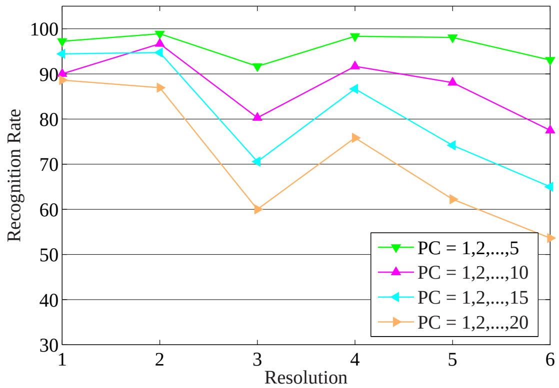


Fig. 8. The optimized PCA based feature extraction algorithm performances as a function of the resolution, for different PCs sets, when the ENL is unchanging.

Fig.8 demonstrates that, when the ENL does not change, the larger is the used PCs set, the stronger is the dependency of our algorithm with the resolution. In this case, the algorithm performs better for the high-resolution databases. It seems that, using only the first PCs, the features extracted from all the resolutions, hold almost the same information. However, when dealing with larger feature subspaces gathering also the further PCs, this information starts to be less relevant when the resolution lowers (some details are lost during the sub-sampling).

- **Simulated SAR databases II: an increasing ENL and an unchanging resolution:** To simulate our second SAR databases, we have multiplied the same 6 different Brodatz textures with speckle noises having an increasing ENL ($ENL = 1, 2, \dots, 9$). Samples from some of these multi-look databases are provided by Fig.9.

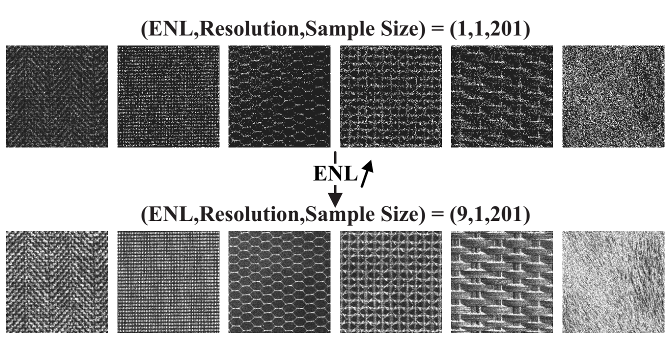


Fig. 9. Samples from some of the **simulated SAR databases II** (an increasing ENL and an unchanging resolution).

Fig.10 shows the performances of the optimized PCA feature extraction algorithm, obtained for the multi-look **simulated SAR databases II**.

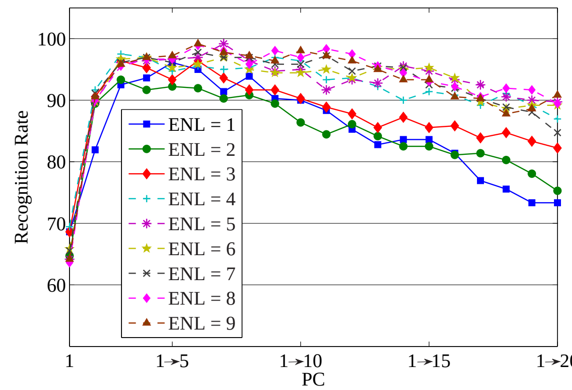


Fig. 10. The optimized PCA based feature extraction algorithm performances as a function of the used PCs, for the **simulated SAR databases II** (an increasing ENL and an unchanging resolution).

We could notice from Fig.10 that the dependency of our algorithm performance, with the size of the used PCs sets is stronger, for the databases where the speckle level is high (solid curves), than it is for the ones where the speckle was well-reduced (dashed curves).
Fig.11 illustrates the sensitivity of our optimized PCA based feature extraction algorithm, to a change only in the ENL, when only the first 5, 10, 15 and then 20 PCs, are used for classification.

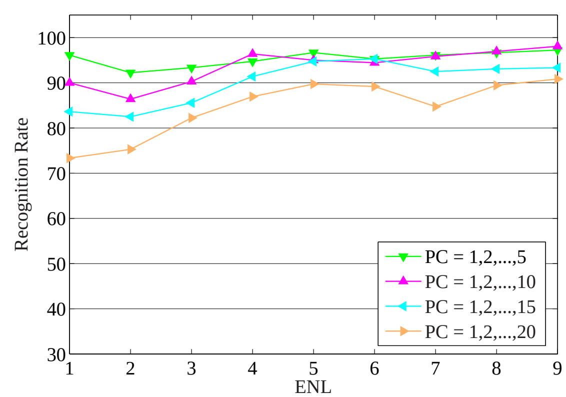


Fig. 11. The optimized PCA based feature extraction algorithm performances as a function of the ENL, for different PCs sets, when the resolution is unchanging.

From Fig.11, it is clear that, when keeping the same resolution, the larger is the number of used PCs, the more sensitive is our algorithm regarding the ENL. If large sets of PCs ($PC = 1, 2, \dots, N$, with $N \geq 10$) are considered, the features extracted by the PCA get more relevant and better discriminating, with an increasing ENL (the reduction of the noisy appearance of the SAR image results in a better information retrieval). The results confirm also that, the information extracted from SAR images at different ENL levels, starts to vary more when the features subspaces get larger.

VI. Conclusions

In this paper, an optimal pre-processing, consisting in pixels sorting, was proposed for a better PCA feature extraction from a four-class TerraSAR-X database, made of urban areas, deserts, forests and fields. In fact, this sorting generates a more organized input data for the PCA. An advantageous improvement was noticed in the PCA performance, more particularly for the recognition of the urban areas and forests, where a gain of more than 40% and 20% was respectively achieved.

Then, a study on the sensitivity of the PCA to the amount of speckle, that might be included in the SAR image, was carried out. We have used a 15 multi-look/multi-resolution TerraSAR-X databases obtained after, a speckle reduction by means of multi-looking with 15 different levels. It was demonstrated that there is no clear dependency between the PCA and the multi-looking. This non-dependency was explained:

- for the small feature subspaces, by the fact the PCA is extracting almost the same information at the different multi-looking levels.
- for the large feature subspaces, by a compensation between the PCA performance improvement regarding an increase of the ENL from one side, and the PCA performance deterioration regarding a decrease of the resolution from another side. In fact, when taking into account the further PCs, the PCA is no more extracting the same information from the different multi-look/multi-resolution databases.

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