COMPARISON OF SECOND AND THIRD ORDER STATISTICS BASED ADAPTIVE FILTERS FOR TEXTURE CHARACTERIZATION

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ABSTRACT

In the framework of parametric texture modeling, a question arises: are adaptive approaches based on higher order statistics (HOS) more appropriate to characterize texture models than those based on second order statistics (SOS)? In order to give some responses to this question, we have compared two fast adaptive filters for texture characterization: the 2-D FLRLS filter (2-D Fast Lattice Recursive Least Square) based on SOS only and the 2-D OLRIV filter (2-D Overdetermined Lattice Recursive Instrumental Variable) based on third order statistics. Extensive experiments to study the characterization performance of each filter are presented and interpreted. They show that the 2-D FLRLS filter provides a very good performance for texture characterization, even when with important noise. Furthermore, the third order based algorithm presents higher variance than second order one. We believe that for 2-D adaptive modeling, there is no advantage to use a HOS based adaptive algorithm for characterizing textures.

1. INTRODUCTION

As far as we know, in the framework of parametric texture modeling and characterization, no complete comparison between SOS and HOS based adaptive approach has been presented. Furthermore, many authors claim that textures have some non gaussian properties and the use of HOS improves the description of the textural properties, especially in a noisy context [5][14]. They also claim that it is a difficult task to characterize diverse textures having the same SOS. Apparently, cumulants and polyspectral based random models have many good properties, such as amplitude and phase sensitivity, which are used by some authors as an appropriate model for texture characterization [7][8].

Various inverse filtering criteria derived from HOS for estimating the random 2-D field models are presented in [7]. These criteria are tested for texture classification and synthesis. The authors conclude that, contrary to the texture synthesis case, the features constructed from these criteria did not offer any advantage in terms of texture classification accuracy over those constructed from SOS based models.

In [14], a third-order cumulant based criterion is applied to noisy texture classification. However, the authors note that the third order estimators present higher variances than second order ones. We note generally that the global (non adaptive) calculation of higher order cumulants would require a large number of samples and would present a large computational load. Thus, the use of an adaptive approach based on HOS could be an eventual alternative.

In this work, we compare second and third order based adaptive filters for texture characterization. We consider two adaptive filters: the 2-D FLRLS filter [12], based on SOS and the 2-D OLRIV filter [2], based on third order statistics. We study the capability of these two adaptive filters to yield non biased estimates of the 2-D AR model even when the texture image is disturbed by additive gaussian noise. The 2-D AR model coefficients will be used as characterization features. Some preliminary tests that we have carried out show that the reflection coefficients are better as characterization features than the transversal ones. This confirms the conclusion reported by Alata et al [1]. In fact, texture classification using the 2-D FLRLS filter's reflection coefficients was investigated in [1] but the noisy case was not deeply investigated. Furthermore, the AR transversal coefficients provided by the 2-D OLRIV filter have been used in [15] to characterize texture models without a comparison to the work reported in [1].

The simulation results presented in this paper are the average of several experiments carried out for various SNR values. Texture synthesis is not our goal. In this paper, we did not take into account the variation of the texture scale or orientation.

2. RECALL OF THE 2-D FLRLS AND 2-D OLRIV FILTERS:

The reflection or lattice coefficients appear in the 1-D case for fast resolution of linear systems i.e. Levinson-Durbin, Schur algorithms [9] and model based approaches. The lattice structure compared to the transversal one has nice properties, e.g. modularity, robustness and stability which can be easily checked. In the 2-D case, i.e. image processing, 2-D reflection coefficients have been proposed and recursively estimated via a large family of adaptive filters [13]. Both 2-D FLRLS and 2-D OLRIV belong to this family. The lattice structure is based on the calculation of a forward and a backward error at sequential recursions of growing orders [12]. At each stage, forward and backward matrices of 2-D reflection coefficients are calculated.

2.1. The 2-D FLRLS adaptive filter

The 2-D FLRLS filter is a bidimensional fast adaptive lattice filter developed by Liu et al [12]. It is based on the RLS criterion and the SOS (autocorrelation matrix). It updates the filter coefficients in growing-order form with a linear computational complexity. After appropriately exploiting the relationship between 2-D and 1-D multichannel, order recursion relations and shift invariance property are derived. The 2-D FLRLS algorithm uses the geometrical approaches of vector space and orthogonal projection for solving the 2-D prediction problem [10]. A complete derivation of the algorithm is given in [12].

2.2. The 2-D OLRIV adaptive filter

The 2-D OLRIV filter [2] is an extension to the bidimensional case of the OLRIV fast filter developed by Buzenac et al [3] to solve overdetermined systems having rectangular-block Toeplitz. It has been applied to perform blind adaptive identification of AR channels using HOS.

The 2-D OLRIV algorithm is based on the equivalence of the cumulant matrix involved in the 2-D normal equations with the cumulant matrix of a multichannel process. This equivalence is used to derive a 2-D adaptive lattice algorithm based on third order cumulants, which can be seen as an extension of Swami's method [16]. The 2-D OLRIV algorithm uses an instrumental variable which can have more components that the original process to take into consideration the rectangular character of the blocks. It lies on a double lattice structure, one lattice predicting the original process and the other the instrumental process, which allows the exploitation of the third order moments. Both reflection coefficients and 2-D AR coefficients are deduced from the multichannel forward prediction operators. For more details, the reader is referred to [2]. We just note that the computational complexity of this algorithm is higher than that of the 2-D FLRLS algorithm.

3. COEFFICIENTS MEAN DEVIATION DUE TO THE ADDITIVE NOISE:

Before considering the classification problem, we first study the effect of additive noise on the estimated texture models. Both 2-D FLRLS and 2-D OLRIV filters are used to identify the 2-D AR models of the set of 8 texture images (256×256 pixels) from Brodatz Album [4] (Figure 1) providing 36 non zero reflection coefficients for the first filter and 48 for the other one. We have used order (2,2) quarter-plane support.

First, the coefficients corresponding to the noiseless case are calculated and stored. They are then respectively compared to those corresponding to noisy contexts. Three values of SNR are used: 20 dB, 5 dB and 0 dB.

Let K_i^0 and K_i^n be the reflection coefficients corresponding respectively to the noiseless and the noisy cases. We define a Mean Deviation Rate (*MDR*) value of the coefficients, with respect to the noiseless case, as : $MDR = E\left[\dfrac{\left|K_i^n - K_i^0\right|}{\left|K_i^0\right|}\right]$.

This *MDR* is introduced in order to compare the rate of coefficient disturbance caused by the additive noise for the two algorithms. For each texture, the expectation is experimentally calculated with a set of 200 independent images. Theses images of 64×64 pixels are randomly chosen from the 8 initial texture images. We only use the coefficients having an absolute value less than a threshold of 2.

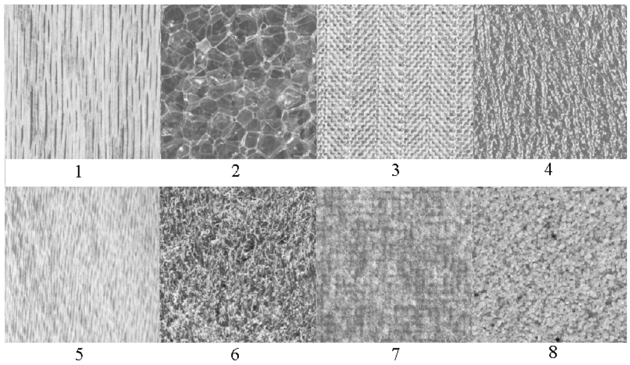

Figure 1: The eight original textures from the Brodatz Album: 1:wood, 2:bubble, 3:canvas, 4:ivy, 5:water, 6:grass, 7:wool, 8:sand

We present in Figure 2 the *MDR* for both algorithms with respect to the textures index. In Table 1, the *MDR* corresponding to all the textures is presented for SNR= 20, 5 and 0 dB.

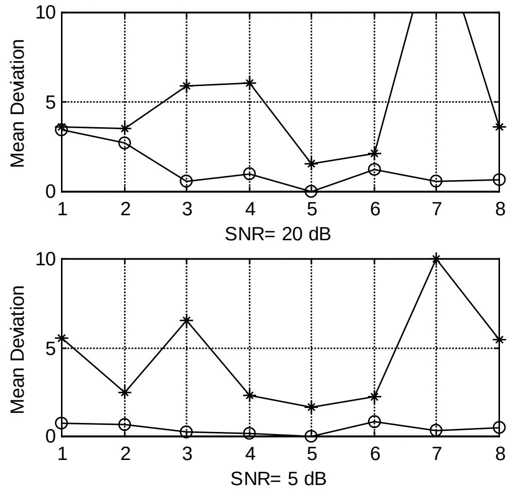

Figure 2: Mean deviation rate of all the coefficients for the 2-D OLRIV (o) and 2-D FLRLS (*) filters for each texture : 1:ivy, 2:sand, 3:wool, 4:grass, 5:water, 6:canvas, 7:bubble, 8:wood

SNR	20 dB	5 dB	0 dB
2-D F LRLS	**1.89**	**5.16**	**4.56**
2-D OLRIV	**0.44**	**1.28**	**0.42**

Table 1: Mean deviation rate of the coefficients for all textures.

Clearly, for all the SNR values, the *MDR* of the 2-D FLRLS is higher than the one corresponding to the 2-D OLRIV. We conclude that the additive noise affects the coefficients of the 2-D FLRLS filter more than the coefficients of the 2-D OLRIV filter. This confirms the insensitivity of the 2-D OLRIV algorithm to gaussian noise, even with large variance.

Furthermore, we note that the water texture model provided by the 2-D OLRIV filter is the least disturbed by the gaussian noise. Plotting the texture's histogram and calculating the odd order moments values show that this texture seems to be rather gaussian. On the other hand, the bubble texture model provided by the 2-D FLRLS filter is highly disturbed when the SNR increases. It has a non gaussian histogram and all its odd order moments have high values.

4. CHARACTERIZATION ABILITY RATE:

The objective of this experiment is to compare the capability of the 2-D FLRLS and the 2-D OLRIV filters to provide uncorrelated coefficients which permit the classification of texture models. So we define a "Characterization Ability Rate" (CAR) as the ratio between "inter-class" and "intra-class" deviations.

For a given estimated coefficient, we define the "inter-class" (i.e. between-class) deviation as the standard deviation of this coefficient with respect to the texture class variation. The "intra-class" (i.e. within-class) deviation is defined as the standard deviation of this coefficient into the same texture class with respect to various realizations. Total "inter-class" and "intra-class" deviations are calculated by averaging out all the coefficients standard deviations obtained with 200 independent realizations. The best case is to get a large "inter-class" deviation and a small "intra-class" one. Then the greater the CAR, the more robust the classification process will be.

In Figure 3, we plot the CAR with respect to the SNR value for the two algorithms. The "characterizing ability rate" of the 2-D FLRLS filter is greater than that of the 2-D OLRIV filter. In fact, HOS estimators generally present higher variances than SOS.

Moreover, in the case of 2-D OLRIV filter, we note that for SNR 5 or 0 dB, the CAR decreases respectively with respect to the noiseless case by 42 % and 56 % (Table 2). On the other hand, for the 2-D FLRLS filter, the decrease is only 16 % and 22 %, respectively. Clearly, the 2-D FLRLS filter has a higher classification robustness for low SNR values.

SNR	Noiseless	20 dB	5 dB	0 dB
2-D F LRLS	1.58	1.64 **(+3%)**	1.31 **(-16%)**	1.23 **(-22%)**
2-D OLRIV	0.54	0.67 **(+22%)**	0.31 **(-42%)**	0.24 **(-56%)**

Table 2: The variation of the characterization ability rate with respect to the SNR value.

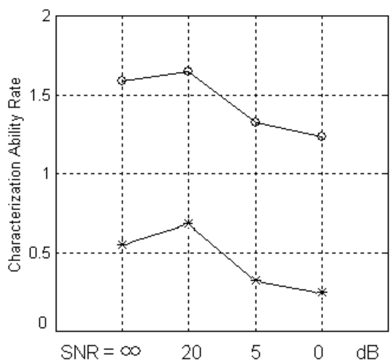

Figure 3: Characterization ability rate of the 2-D OLRIV (*) and 2-D FLRLS (o) filters for various SNR values.

5. TEXTURE CLASSIFICATION WITH A NEURAL NETWORK:

After comparing the CAR, we wish to classify the set of 8 textures with a multilayer neural network to compare the use of the 2-D FLRLS and 2-D OLRIV filters. A total set of 1600 images of 64×64 pixels (200 images of 64×64 pixels for each texture) is randomly chosen from the 8 initial texture images. The corresponding estimated reflection coefficients are used as input vectors to the multilayer neural network. The network is trained using the gradient descent back- propagation algorithm [11] with 75% of the available texture images (1200 images of 64×64 pixels, i.e. 150 images for each texture) and tested with 25% of the available texture images (400 images of 64×64 pixels, i.e. 50 images for each texture). The training examples were grouped into sets of *n* examples for each texture. The network weights were updated on each presentation of a feature vector. The set of training examples is changed each iteration and the order of presentation of the training examples is random within each set. For each texture, we define the "Classification Sensitivity" (CS) as the ratio of the number of positive tests to the total number of tests. In order to determine the optimum neural network to achieve the best CS for each algorithm and each SNR value, we carried out several experiments using various architectures, that is: various training coefficient and various numbers of neurons in each layer. We use two hidden layers and three binary coded outputs. The momentum is 0.9 and the initial random values of the weights were set between –1 and 1. The threshold value of the network sigmoid was 0.2.

In Table 3 and Table 4, we present respectively the CS for each texture and the total CS for the 2-D FLRLS and 2-D OLRIV filters.

Texture	Noiseless	SNR 20 dB	SNR 5 dB	SNR 0 dB
Wood	100 %	100 %	100 %	98 %
Bubble	100 %	100 %	98 %	84 %
Canvas	100 %	100 %	100 %	100 %
Ivy	100 %	100 %	100 %	96 %
Water	100 %	100 %	100 %	100 %
Grass	100 %	100 %	100 %	98 %
Wool	100 %	100 %	100 %	94 %
Sand	100 %	100 %	100 %	96 %
8 textures	**100 %**	**100 %**	**99.75 %**	**95.75 %**

Table 3: Classification sensitivity for each texture for the 2-D FLRLS filter

Texture	Noiseless	SNR 20 dB	SNR 5 dB	SNR 0 dB
Wood	90 %	82 %	33 %	40 %
Bubble	96 %	88 %	54 %	3 %
Canvas	98 %	100 %	78 %	33 %
Ivy	100 %	100 %	81 %	48 %
Water	50 %	50 %	19 %	20 %
Grass	66 %	69 %	38 %	20 %
Wool	88 %	92 %	64 %	40 %
Sand	90 %	82 %	79 %	17 %
8 textures	**90.84 %**	**88.24 %**	**67.74 %**	**28.89 %**

Table 4: Classification sensitivity for each texture for the 2-D OLRIV filter

The results we provide show that the 2-D FLRLS filter provides a good performance for texture characterization, even when an important gaussian noise is added. On the other hand, the CS of the 2-D OLRIV is small, specially for low SNR value, where classification robustness can't be assured. These results confirm the conclusion of the last paragraph.

For the 2-D FLRLS filter, the bubble texture is the most difficult to be classified, it is the most strongly non gaussian texture. Moreover, considering the result obtained with the 2-D OLRIV filter, the water texture has the least Classification Sensitivity. It is close to being gaussian. This proves the result of paragraph 3 and confirms the conclusion of [6].

Finally, to verify the result of paragraph 3 on the coefficient deviation due to the SNR variation, we test the neural network, only trained with the coefficients of the noiseless case, with the data corresponding to the noisy cases. The results are given in Table 5. Apparently, unlike the 2-D FLRLS filter, the 2-D OLRIV filter better recognizes the noisy textures because the noisy case coefficients are close to the noiseless case ones.

Algorithm	20 dB	5 dB	0 dB
2-D FLRLS	90 %	32 %	19 %
2-D OLRIV	86 %	62 %	29 %

Table 5: Classification sensitivity when the network is only trained with noiseless case data.

6. CONCLUSION:

Although the effect of the additive gaussian noise is more important on the 2-D FLRLS filter than the 2-D OLRIV filter, the first one can provide an excellent characterization of the texture model. It presents a large "inter-class"-"intra-class" variance ratio and a high classification sensitivity, even when the texture is disturbed by additive noise. From this study, we can prove that, although HOS based filters have some advantages, and although textures have some non gaussian properties, the use of an adaptive filter based on higher order moment is not the best solution to exploit this non gaussianity. Compared to a SOS based filter, the HOS based one provides coefficients with a larger variance. In other words, there is no need to use an HOS based adaptive algorithm to characterize the texture model. More studies developing HOS approaches with parametric and nonparametric models and providing more independence of the orientation and the scaling of the texture images still remain to be done.

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