

## SD LMS L-FILTERS FOR FILTRATION OF GRAY LEVEL IMAGES IN TIME-SPATIAL DOMAIN BASED ON GLCM FEATURES

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**Summary** In this paper, the new kind of adaptive signal-dependent LMS L-filter for suppression of a mixed noise in greyscale images is developed. It is based on the texture parameter measurement as modification of spatial impulse detector structure. Moreover, the one of GLCM (Gray Level Co-occurrence Matrix) features, namely, the contrast or inertia adjusted by threshold as switch between partial filters is utilised. Finally, at the positions of partial filters the adaptive LMS versions of L-filters are chosen.

### 1. INTRODUCTION

In the present communication systems, the original signal or image could be corrupted by noise [1, 3-5]. There are two main types of noises, namely, the Gaussian and impulsive noise. In the case of current system both noises create a type of noise called mixed noise.

For the suppression of mixed noise, the order-statistic filter applied into signal-dependent (SD) filter structure proves better filtration results as single filter. The L-filter or its adaptive version belongs to the class of order statistic filters. The SD filter in basic structure exploits at the position of partial filters simple LMS L-filters. Moreover, the impulse detector defines the number of partial filters.

Earlier developed SD L-filters used the SID (Spatial Impulse Detector) that can switch the signal to the limited number of partial filters. In this paper, the new modification of SD LMS L-filter with TPC (Texture Parameter Classifier) enables to divide input signal to the higher number of partial filters. Beside, the filtration results could be meaningfully improved.

The outline of this paper is as follows. In the next sections, the theory of the adaptive LMS L-filter and signal-dependending structure designs are introduced. The theory of GLCM and TPC are presented in section 4. Finally, the achieved results and the future tasks are discussed.

### 2. SINGLE CHANNEL ADAPTIVE LMS L-F

L-filter belongs to the class of nonlinear order-statistic filters that output is defined as linear combination of ordered input samples.

Let a non-stationary observed signal  $x$  is in each pixel defined by original value  $d$  and noise  $n$ . The vector of ordered input pixels  $\mathbf{xr}_i$  (in ascending or descending order) is defined as follow

$$\mathbf{xr}_i = (x_{i,1}, x_{i,2}, \dots, x_{i,K}, \dots, x_{i,N-1}, x_{i,N})^T. \quad (1)$$

The  $kx_i$  pixel represents  $k$ -th highest pixel of  $i$ -th input observation, where  $k$  is in range from 1 to  $N$ . Thus, output of single-channel L-filter (L-F) is for each  $i$  follow

$$y_i = \mathbf{w}^T \mathbf{xr}_i, \quad (2)$$

where  $\mathbf{w}=(w_1, \dots, w_N)^T$  is vector of filter coefficients. In generally, it can be obtained by Wiener-Hopf equation [1, 3, 5], but in real applications, the computations of inversion of the autocorrelation matrix  $\mathbf{R}_i^{-1}$  and the correlation vector  $\mathbf{p}_i$  are more difficult. This problem is usually solved by simple iterative algorithms. Moreover, one of frequently used algorithm is LMS (Least Mean Square) that minimise MSE (Mean Square Error) parameter. The LMS adaptation algorithm for adaptation of vector of L-filter coefficients is given by

$$\hat{\mathbf{w}}_{i+1} = \hat{\mathbf{w}}_i + 2\mu\varepsilon_i \mathbf{xr}_i, \quad (3)$$

where  $\mu$  is adaptation constant for speed adaptation control and  $\varepsilon_i$  adaptation error in  $i$ -th iteration.

### 3. ONE-LEVEL SINGLE-CHANNEL ADAPTIVE SD LMS L-F

Simple adaptive SD LMS L-filter in time-spatial domain consists of two single adaptive LMS L-filters and one classifier of type of input observation. At the position of classifier, some kind of SID (Spatial Impulse Detector) [1] based on the order-statistics is usually used. Thus, the SMD, SE, SOSD, SCOSD detectors were developed [1].

SID serves as switch between outputs of two LMS L-filters. Moreover, if impulses are detected in the input sequence, these input data are processed by high-frequency partial L-filter. On the other hand, if in the input sequence any impulses or high-frequency components are not detected, the input data are processed by low-frequency partial L-filter. The decision rule for SD L-F in combination with spatial impulse detectors is given by

$$\begin{aligned}
 &\text{IF} \\
 &\quad \sum_{k=1}^N {}_k D_i \geq \text{Level} \\
 &\quad \text{THEN } LMS_{HL-F} \\
 &\quad \text{ELSE } LMS_{LL-F}
 \end{aligned} \quad (4)$$

where  ${}_k D_i$  is the result of impulse detection for  $k$ -th image pixel in the  $i$ -th input vector. The value of level defines the number of detected impulses in the observed samples.

The main disadvantage of SIDs is linked to the limited number of partial filters, namely, for input observation with  $N$  pixels, the  $(N-1)/2$ -th number of impulses could be detected only.

#### 4. TEXTURE PARAMETER CLASSIFICATOR

The drawback of SIDs could be solved by another approach. One of them is measurement of texture parameters. There are a lot of methods, namely, statistical methods (histograms, autocorrelation functions, GLCM, GLDV, GLDS, etc.), transformation based methods (Fourier functions, Gabor functions, wavelet function, etc.), pattern based methods, etc. The TPC

The GLCM (Gray-level co-occurrence matrix) is a common technique in statistical image analysis that is used to estimate image properties related to second-order statistics. GLCM considers the relation between two neighbouring pixels in one offset, as the second order texture, where the first pixel is called reference and the second one the neighbour pixel. GLCM is the two dimensional matrix of joint probabilities between pairs of pixels, separated by a distance  $d$  in a given direction  $\theta$  [2]. Haralick defined 14 statistical features from gray-level co-occurrence matrix for texture classification [2].

The most used features are [2]:

- contrast,
- homogeneity,
- entropy,
- energy or ASM,
- correlation,
- etc.

**Contrast or Inertia** – is a measure of the local variations in an image. If there are a lot of variations in an image, the texels are concentrated away from the main diagonal and Inertia will be high. This is the opposite of Homogeneity and is defined as follows

$$\text{Inertia}_{d,\theta} = \sum_i \sum_j (i-j)^2 P_{d,\theta}(i,j). \quad (5)$$

**Homogeneity** – is a measure of monotony of an image. Homogeneity is high when an image is locally homogeneous (range of grey levels is small), and texels are concentrated along the main diagonal.

This is the opposite of Inertia and is defined as follows

$$\text{Homogeneity}_{d,\theta} = \sum_i \sum_j \frac{P_{d,\theta}(i,j)}{1+|i-j|}. \quad (6)$$

**Entropy** – is a measure of randomness of the intensity distribution. Entropy is highest when all texels are similar in magnitude and small when they are unequal. This is the opposite of ASM and is defined as follows

$$\text{Entropy}_{d,\theta} = - \sum_i \sum_j P_{d,\theta}(i,j) \log_2 P_{d,\theta}(i,j). \quad (7)$$

**ASM or energy** – is a measure of uniformity of grey level in a region. ASM is high when some texels are large in magnitude and low when all texels are almost equal. This is the opposite of Entropy and is defined as follows

$$\text{ASM}_{d,\theta} = \sum_i \sum_j P_{d,\theta}^2(i,j). \quad (8)$$

#### 5. ONE-LEVEL SINGLE-CHANNEL ADAPTIVE SD LMS L-F WITH TPC

The modification of signal-dependent with TPC is shown in the Fig. 1. The TCP is set up by two parameters. First one is the threshold and second one the GLCM parameter.

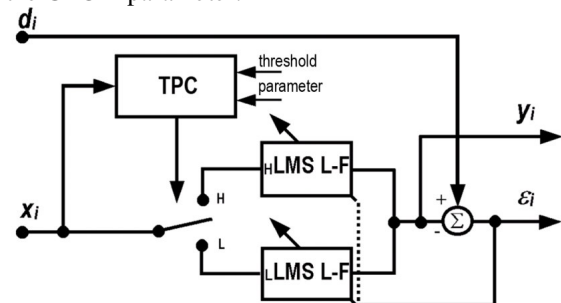


Fig. 1. Adaptive SD LMS L-F with texture parameter measurement

The GLCM matrices of gray image noised by gauss and impulse noise for distance  $d=1$  and all orientation  $\theta=0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ$  are shown in Figure 2. It is evident, that both noises are creating different structure of GLCM. The chosen GLCM parameters used for noised images in Fig. 2 are shown in Tab. 1.

Tab. 1. GLCM parameters for gray images #128 corrupted by noises G20 and I10

Image	#128G20	#128I10
<b>Contrast</b>	768.4	1017.3
<b>Homogeneity</b>	0.1036	0.8277
<b>Entropy</b>	12.6111	2.3504
<b>Energy, ASM</b>	0.00024	0.67530

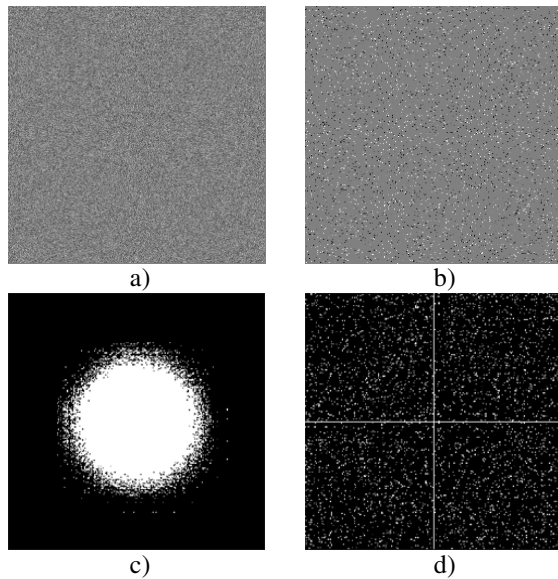


Fig. 2. Noisy images #128, a) G20, b) I10. GLCM matrix for  $d=1$  and all  $\theta$ , c) G20, d) I10

There are significant differences of GLCM parameters for noised images evaluation for energy (ratio ~2800), correlation (ratio ~9), homogeneity (ratio ~8), entropy (ratio ~5) and contrast (ratio ~1.3). The computed ratio is relative and it can be used for classification with arbitrary GLCM parameter on TCP position.

The detection of discrete number of impulses for obtain number of partial filters is disadvantage of SID detectors. For example, in case of input survey with number of pixels  $N$  is theoretically possible to detect  $(N-1)/2$  impulses. It can lead to step change of parameter level. For SID was found level=2 (optimal number of detected impulses for input survey with 9 pixels is 2). The arbitrary GLCM parameter for more accurately optimal value setup of switching among partial filters can be used. For example, in case of use integers and chess-board input model (minimal and maximal values repeating – maximal contrast), the input relay value will be  $contrast_{d,\theta}=43350$  (12 transitions  $0 \rightarrow 255$ , 12 transitions  $255 \rightarrow 0$ , 6 transitions  $0 \rightarrow 0$  and 6 transitions  $255 \rightarrow 255$ , for total number of transitions 36). For minimal contrast, i.e. same values in input survey, then  $contrast_{d,\theta}=0$ . Consequently, SD L-F can theoretically embody as many as 43350 partial filters.

One-level/one-channel SD LMS L-F with GLCM (GLCMSD LMS L-F) in time-spatial domain compared to SD LMS L-F with SID is simplest, because it doesn't need parameter level setup and decision rule is uniquely determined by threshold.

A decision rule GLCMSD LMS L-F for GLCM parameters (energy, correlation, homogeneity, entropy a contrast) is defined as follow

IF

$$\begin{aligned} &parameter_{d,\theta} \geq threshold \\ &THEN \quad LMS_{HL} - F \\ &ELSE \quad LMS_{LL} - F \end{aligned} \quad (9)$$

## 6. EXPERIMENTAL RESULTS

As training gray scale images, namely, the images of Lena (Fig. 3a-b) and 2<sup>nd</sup> Trevor corrupted by mixed noise (mixture of Gaussian white noise with standard deviation  $\sigma=20$  and impulsive noise with probably  $p=10\%$  - variable value noise) were used.

For the set up TCP classifier, the contrast parameter of GLCM for realized experiments were carried out only. It was caused by high computing complexity and large range of possible classification of TCP thresholds. Graph dependency of NR parameter and TCP threshold for contrast parameter is shown in Fig. 3. Minimal value of NR parameter was elaborated in range  $0 \div 5000$  by step equal to 250.

An experiments show, that optimal threshold for both tested images is between 1500÷2500. For more complicated image “Lena” was chosen optimal threshold 1750 and 2000 for simplest image “2<sup>nd</sup> Trevor”.

The results of image filtration are shown in Tab.2, respectively, the number of adaptation iterations of partial filters in Tab.3.

Tab. 2. The filter performance indices achieved for gray images Lena and 2<sup>nd</sup> Trevor corrupted by G20I10

Filter	MAE	MSE	NR	MAER
GLCMSD LMS L-F threshold=1750/2000 parameter=contrast	<b>Lena</b>			
	9.21	164.54	-8.33	-7.17
	<b>2<sup>nd</sup> Trevor</b>			
	7.45	94.92	-11.16	-9.20

Tab. 3. The number of partial filter adaptation  ${}_L$ LMS L-F and  ${}_H$ LMS L-F for GLCMSD LMS L-F

Filter	${}_L$ LMS L-F	${}_H$ LMS L-F
GLCMSD LMS L-F threshold=1750/2000 parameter=contrast	<b>Lena</b>	
	36956	27560
	<b>2<sup>nd</sup> Trevor</b>	
	41618	22898

From the computing complexity point of view, the adaptation of SD L-F coefficients is better realized in the spatial domain. Likewise, the computing of GLCM can be reduced to few orientation or size of matrix. Thus operation causes the reduction of gray level. In this case, number of potential filters is reduced too. For example, for gray level reduction from 8bits to 4bits, the number of partial filters is 10753 that it is still satisfactory large number for computing.

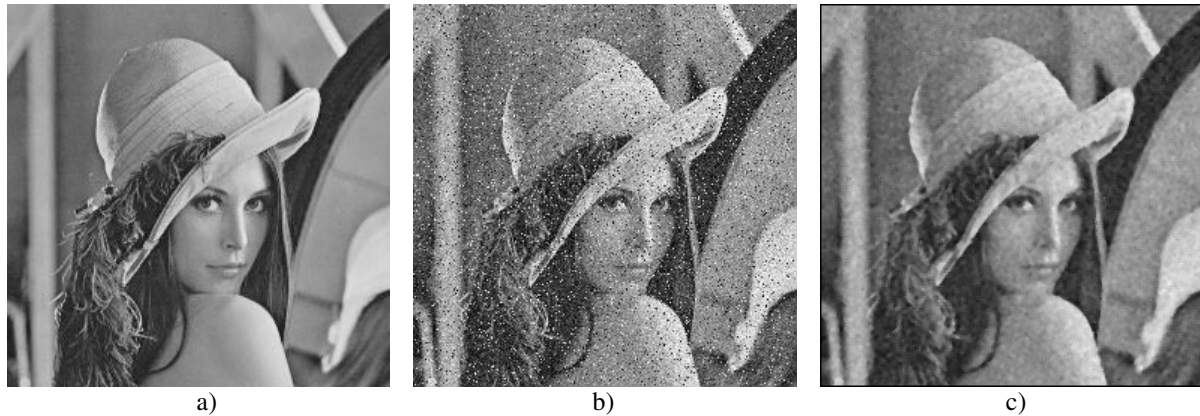


Fig. 3. Image Lena, a) original, b) noisy G20110, c) filtered by  $GLCM/GLCM\ SD\ L-F$

Moreover, the combination of several GLCM parameters (decision values can be combined, e.g. contrast + homogeneity) can provide much more number of texture parameters. SD L-F has many possibilities and it could be motivation for the future research.

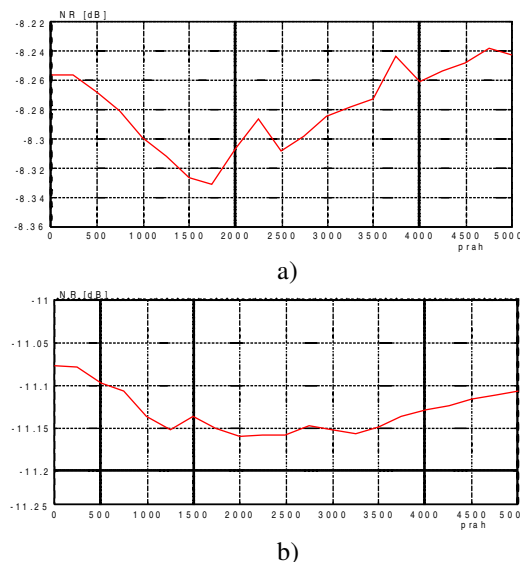


Fig. 4. NR/Contrast dependencies, a) Lena, b) 2nd Trevor

In compare with classical SID, the number of bounds is much higher and the values of bounds include not only the threshold value but also value of level that must be defined for classic SID. Moreover, the contrast parameter can divide input observations to the thousands of partial filters. The filtered image of noisy Lena by  $GLCM/GLCM\ SD\ L-F$  is shown in the Fig. 3c. By the way, for most suitable parameter in combination with contrast is homogeneity.

## 7. CONCLUSION

In this paper, the new approach for signal-dependent filter structure for mixed noise in the gray scale images was designed. The experiments proves that the impulse or kind of input observation could be effectively designated by the TCP classifier

than SID detector, because it can offer divide input observation to the more number of partial filters.

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