SUPPRESSION OF MIXED NOISE IN THE SIMILAR IMAGES BY USING ADAPTIVE LMS L-FILTERS

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Abstract

In this paper, several adaptive least mean squares (LMS) location-invariant filter (L-filter) modifications will be described. These filters are based on linear combination of order statistics. The adaptive L-filters are able to adapt well to variety of noise probability distribution, including impulsive noise. They also perform well in the case of nonstationary signals and, therefore, they are suitable for image processing, too. Following this L-filter property, applications of the adaptive LMS L-filters for filtering two-dimensional static images degraded by mixed noise consisting of additive Gaussian white noise and impulsive noise will be presented in this paper. Based on conveniently selected experiments intent on image filtering, the properties of a several adaptive L-filters modifications will be demonstrated and compared. It will follow from experiment results, that the L-filter modification called signal-dependent LMS L-filter yields the best results.

Keywords

Non-linear filters, adaptive filters, L-filters, LMS algorithm, image filtering

1. Introduction

Many problems in communications, digital signal processing and image processing involve noise removal whose characteristics are unknown or time varying or both. Such types of problems are difficult to solve because of lack sufficient knowledge about characteristics of signals to be processed. Here, adaptive filters adjusting their parameters by the statistical characteristics of the filter input signal can be applied with advantage [1].

In the field of adaptive filters, linear filters (e.g. FIR filter) have played a very crucial role. The obvious advantage of linear filters is their simplicity. Design, analysis and implementation of such filters are relatively straightforward task in many applications. However, there are several situations in which the performance of linear filters is unacceptable. Generally, non-linear filters can be applied with an advantage in comparison with that of linear once in the case of non-Gaussian signal processing or if they are applied for non-linear system modelling or identification. With regard to these facts some significant applications of non-linear adaptive filtering include e.g. echo cancellation, channel equalisation, speech and image prediction and filtering, aircraft navigation, etc.

Unlike the case of linear systems, which are completely characterised by the system's unit impulse response function, it is impossible to find a unified framework for describing arbitrary non-linear systems. Consequently, the researchers working on non-linear filters are forced to restrict themselves to certain non-linear models that are less general. Non-linear filters developed using such models include homomorfic filters, microstatistic filters, morphological filters, polynomial filters, piecewise non-linear filters, filters based on neural nets, order statistic filters, etc [2-4].

There are a number of non-linear filters based on order statistics concept [2]. Among them are the L-filters whose output is defined as a linear combination of the order statistics of a filter input signal [2,5-7]. The adaptive L-filters are able to adapt well to variety of noise probability distribution, including impulsive noise. They also perform well in the case of nonstationary signals and, therefore, they are suitable for image processing, too.

In this paper, the adaptive LMS L-filter modifications as constrained and unconstrained adaptive LMS L-filter without and with step-size normalisation are presented. Besides, a signal-dependent adaptive LMS L-filter based on a sophisticated combination of two L-filters is described, too.

The adaptive L-filters presented in this paper will be applied for image filtering, where images are degraded by mixed noise. Moreover, the mixed noise will be consisted of additive Gaussian white and impulsive noises. The ability of these filters to suppress such a noise will be demonstrated by several experiments. The obtained results will indicate that the L-filters belong to a group of robust filters, which are able to remove the mixed noise in an effective way. These filters are characterised also by the ability to suppress noise in homogeneous areas and to preserve the edges at the same time. With regard to these facts, it will be concluded that the class of adaptive L-filters represents very perspective approach for image filtering in the case of image degradation by mixed noise including impulsive noise.

2. LMS L-filters

2.1 Location-invariant LMS L-filter

In this section, several modification of the LMS L-filter applied for processing a non-constant image corrupted by zero-mean mixed noise consisting of additive Gaussian white noise and impulsive noise will be described [2, 5-7].

Let us consider that the observed image signal $x(i,j)$ can be expressed as a sum of the noise-free image $s(i,j)$ plus zero-mean additive white noise $n(i,j)$ i.e.

$$x(i,j) = s(i,j) + n(i,j),$$
$$\text{for } i = 1,2,\ldots,K; \quad j = 1,2,\ldots,L, \tag{1}$$

where (i,j) denotes the pixel co-ordinates. Then, our intention is to design a filter defined on a pixel neighbourhood (called the filter window) that aims at estimating the noise-free central image pixel value by minimising mean square error of estimation (MSE).

In this paper, the filter with the square window of dimensions Ξ x Ξ will be applied, where Ξ represents the number of rows and columns. Generally, Ξ is assumed to be an odd number, i.e. $\Xi = 2\xi + 1$. Then, the input filtered matrix for the image pixel x(i, j) has the following form

$$\mathbf{X}(k) = \begin{bmatrix} x(i-\xi, j-\xi)\, x(i-\xi, j-\xi+1) \cdots x(i-\xi, j+\xi) \\ \vdots \quad\quad \vdots \quad\quad \cdots \quad\quad \vdots \\ x(i+\xi, j-\xi)\, x(i+\xi, j-\xi+1) \cdots x(i+\xi, j+\xi) \end{bmatrix}. \tag{2}$$

In this expression, running index k defined as

$$k = (i-1)K + j \quad 1 \le i \le K \quad 1 \le j \le L \tag{3}$$

is used instead of the pixel co-ordinates i, j. K and L denote the row index and column index, respectively. This notation will be used throughout this paper.

In order to describe a filter based an order statistics, let us rearrange the Ξ x Ξ filter window (2) into Nx1 vector

$$\mathbf{x}_r(k) = \left(x_{(1)}(k), x_{(2)}(k), x_{(3)}(k), \cdots, x_{(N)}(k)\right)^T, \tag{4}$$

where $x_{(i)}(k)$ denotes the i-th largest pixel of input image and $N = (2\xi+1)^2$.

Now, we are seeking an optimum L-filter whose output at k

$$y(k) = \mathbf{a}^T(k)\mathbf{x}_r(k) \tag{5}$$

minimises mean square error of estimation (MSE) defined as

$$\begin{aligned} J(k) &= E[(y(k)-s(k))^2] = \\ &= E[s(k)^2] - 2\mathbf{a}^T(k)\mathbf{p}(k) + \mathbf{a}^T(k)\mathbf{R}(k)\mathbf{a}(k) \end{aligned} \tag{6}$$

subject to the constraint

$$\sum_{i=1}^{N} a_i(k) = 1. \tag{7}$$

In the (6), $\mathbf{R}(k) = E[\mathbf{x}_r(k)\mathbf{x}_r^T(k)]$ is the correlation matrix of the observed ordered image pixel values and $\mathbf{p}(k) = E[s(k)\mathbf{x}_r^T(k)]$ denotes the cross-correlation vector between the ordered input vector $\mathbf{x}_r(k)$ and the desired image pixel value $s(k)$. The vector

$$\mathbf{a}^T(k) = [a_1(k)\, a_2(k) \ldots a_N(k)]^T \tag{8}$$

is the L-filter coefficient vector.

By employing (7), we can partition the L-filter coefficient vector as follows

$$\mathbf{a}(k) = \left(\mathbf{a}_1^T(k) | a_\upsilon(k) | \mathbf{a}_2^T(k)\right)^T, \tag{9}$$

where $\upsilon = (N+1)/2$ and $\mathbf{a}_1(k)$ and $\mathbf{a}_2(k)$ are $(N-1)/2x1$ vectors given by

$$\begin{aligned} \mathbf{a}_1(k) &= \left(a_1(k), \cdots, a_{\upsilon-1}(k)\right)^T \\ \mathbf{a}_2(k) &= \left(a_{\upsilon+1}(k), \cdots, a_N(k)\right)^T \end{aligned}. \tag{10}$$

Taking into account the constraint (7), the coefficient $a_\upsilon(k)$ connected with the sample $x_{(\nu)}(k)$ can be obtained as

$$a_\upsilon(k) = 1 - \mathbf{1}_{\upsilon-1}^T \mathbf{a}_1(k) - \mathbf{1}_{\upsilon-1}^T \mathbf{a}_2(k), \tag{11}$$

where $\mathbf{1}_{\nu-1}$ is $(\nu-1)x1$ unitary vector.

Similarly to the filter coefficient arrangement by (9), we can rearrange the ordered input vector $\mathbf{x}_r(k)$, too. Then, $\mathbf{x}_r(k)$ can be expressed as follows

$$\mathbf{x}_r(k) = \left(\mathbf{x}_{r1}^T(k) | x_\upsilon(k) | \mathbf{x}_{r2}^T(k)\right)^T. \tag{12}$$

Let $\mathbf{a}'(k)$ is the reduced L-filter coefficient vector

$$\mathbf{a}'(k) = \left(\mathbf{a}_1^T(k) | \mathbf{a}_2^T(k)\right)^T \tag{13}$$

and $\hat{\mathbf{x}}_r(k)$ be the reduced ordered input vector of $(N-1)x1$ type described as follows

$$\hat{\mathbf{x}}_r(k) = \begin{bmatrix} \mathbf{x}_{r1}(k) - x_\upsilon(k)\mathbf{1} \\ \mathbf{x}_{r2}(k) - x_\upsilon(k)\mathbf{1} \end{bmatrix}. \tag{14}$$

The intention of ours is to present an adaptive L-filter minimising (6) and fulfilling the constraint (7). Then, following the analysis in [1,5] where the steepest-descent algorithm and stochastic approximation principle is applied for (6) minimising, the following recursive relation for adaptation, the reduced L-filter coefficient vector can be obtained in the form:

$$\hat{\mathbf{a}}'(k+1) = \hat{\mathbf{a}}'(k) + \mu\varepsilon(k)\hat{\mathbf{x}}_r(k), \tag{15}$$

where

$$\varepsilon(k) = s(k) - y(k) \tag{16}$$

is the estimation error at pixel k and constant parameter μ is so-called step-size of adaptation. The expression (15) represents the LMS algorithm of the constraint location-invariant L-filter (L-LC filter). Then, the adaptive constraint LMS location-invariant L-filter performance is described by expression (5), (15) and (16). It follows from (16) that a desired image (sample $s(k)$) has to be available for the process of constraint location-invariant L-filter adaptation.

Following the similar procedure, the LMS algorithm of location-invariant unconstrained L-filter (L-LU filter) adaptation given by

$$\hat{\mathbf{a}}(k+1) = \hat{\mathbf{a}}(k) + \mu\varepsilon(k)\mathbf{x}_r(k) \tag{17}$$

can be obtained. In the derivation of (17), the constraint (7) is not taking into account. Then, the adaptive LMS L-LU filter performance is described by expression (5), (16) and (17). Similarly, to that of the LMS L-LC filters, a desired image has to be available for the process of L-LU filter adaptation.

2.2 Normalised LMS L-filter

A difficult problem frequently met in the performance of adaptive filter based on LMS algorithm performance, such as (14) or (16), is the selection of the step-size μ. The importance of the step-size selection following from the fact that parameter μ controls the rate of convergence and stability of a filter adaptation process. It can be shown (e.g. [8]) that for achieving convergence of the average MSE to a steady-state for (15), μ should satisfy the condition

$$0 < \mu < \frac{2}{3tr(\mathbf{R})} = \frac{2}{3xtotal\ power\ of\ x(k)}. \tag{18}$$

where $tr[.]$ stands for the trace of the matrix inside of brackets.

It follows from (18) that the convergence of LMS algorithm strongly depends on the power of the filter input signal. The (18) fulfilling is complicated especially in the case that a filter operates in nonstationary environment (as in image processing). In such a case, it is reasonable to employ a time-varying step-size $\mu(k)$ dependent on the power of the filter-input signal. Following this requirement, the most frequently approach for $\mu(k)$ selection is to chose $\mu(k)$ as

$$\mu(k) = \frac{\mu_0}{\mathbf{x}_r^{\,T}(k)\mathbf{x}_r(k)} = \frac{\mu_0}{\|\mathbf{x}_r(k)\|^2}, \tag{19}$$

where μ_0 is from the interval

$$0 < \mu_0 \le \frac{2}{3}. \tag{20}$$

Then, by using (19), (15) and (17), the following LMS algorithms can be obtained:

$$\hat{\mathbf{a}}'(k+1) = \hat{\mathbf{a}}'(k) + \frac{\mu_0}{\|\mathbf{x}_r(k)\|^2}\varepsilon(k)\hat{\mathbf{x}}_r(k), \tag{21}$$

$$\hat{\mathbf{a}}(k+1) = \hat{\mathbf{a}}(k) + \frac{\mu_0}{\|\mathbf{x}_r(k)\|^2}\varepsilon(k)\mathbf{x}_r(k). \tag{22}$$

The recursive equations (21) and (22) describe the adaptation of the coefficients of the normalised LMS L-LC filter (L-NC filter) and the normalised LMS L-LU filter (L-NU filter).

2.3 Modified LMS L-filter

It is well known that the rate of convergence of the LMS algorithm is slower than that of other adaptive algorithms (e.g. RLS algorithms, XLS algorithms, etc.). This slow rate of convergence may be attributed to the fact that the only one parameter μ controls the convergence of all filter coefficients. It follows from the LMS algorithm theory (e.g. [1]) that a modification of LMS algorithm with higher rate of convergence can be obtained by employing different step-sizes μ_i for different L-filter coefficients. Then, the step-size sequence is computed as follows

$$\mu_i(k) = \mu_0 \frac{\sum_{j=0}^{k} x_{(i)}(k-j)}{\sum_{j=0}^{k} x_{(1)}(k-j)}. \tag{23}$$

By using (23), the modified LMS L-LC filter (L-MC) and modified LMS L-LU filter (L-MU) updating formula are given by

$$\hat{\mathbf{a}}'(k+1) = \hat{\mathbf{a}}'(k) + \varepsilon(k)\hat{\mathbf{M}}(k)\hat{\mathbf{x}}_r(k), \tag{24}$$

$$\hat{\mathbf{a}}(k+1) = \hat{\mathbf{a}}(k) + \varepsilon(k)\mathbf{M}(k)\mathbf{x}_r(k), \tag{25}$$

respectively. In this expressions, $\hat{\mathbf{M}}(k)$ and $\mathbf{M}(k)$ denotes the diagonal matrices

$$\hat{\mathbf{M}}(\mathbf{k}) = diag[\mu_1(k), \mu_2(k), \ldots, \mu_{N-1}(k)], \tag{26}$$

$$\mathbf{M}(\mathbf{k}) = diag[\mu_1(k), \mu_2(k), \ldots, \mu_N(k)]. \tag{27}$$

2.4 Signal-dependent LMS L-filter

In this section, the signal-dependent LMS L-filters (L-SD filters) will be described. L-SD filters adjusts its smoothing properties at each point according to the local image content in order to achieve edge preservation as well as maximum noise suppression in the homogeneous regions [5].

L-SD filters consist of two independent L-filters having different filter window and whose outputs $y_L(k)$ and $y_H(k)$ are combined to give the L-SD filter final response.

Besides, the L-SD filter employs the local signal-to-noise ratio measure

$$\beta(k) = 1 - \frac{\sigma_n^2}{\sigma_x^2(k)}, \tag{28}$$

where $\sigma_n^2(k)$ is the noise variance and $\sigma_x^2(k)$ is the variance of the noisy input observations. The coefficient $\beta(k)$ is used as switch between outputs of the two LMS L-filters. Then the L-SD filter output is given by

$$y(k) = \begin{cases} y_H(k), & \textbf{if } \beta(k) > \beta_t \\ y_L(k), & \textbf{otherwise} \end{cases} \tag{29}$$

where $0 < \beta_t < 1$ is a threshold that determines a trade-off between noise suppression and edge preservation.

3. Experiments and results

In this section we present results of two experiments demonstrating performance properties of the L-LC filters, the L-LU filters, the L-NC filters, the L-NU filter, the L-MC filters, the L-MU filters and the L-SD filters in the case of filtering images corrupted by mixed noise, consisting of additive Gaussian white noise and impulsive noise. Besides these adaptive L-filters, the median filter (with the square window of dimensions 3x3) as a reference filter has been applied for noisy image filtering, too.

For the purpose of the tested filter performance quality evaluation, the following performance indices have been used:

- mean absolute error (MAE) defined as:

$$MAE = \frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left| s(i,j) - y(i,j) \right| \tag{30}$$

- mean square error (MSE) defined as:

$$MSE = \frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left(s(i,j) - y(i,j) \right)^2 \tag{31}$$

- noise reduction in dB (NR) defined as:

$$NR = 10 \log_{10} \frac{\frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left(y(i,j) - s(i,j) \right)^2}{\frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left(x(i,j) - s(i,j) \right)^2} \tag{32}$$

- mean absolute error reduction in dB (MAER) defined as:

$$MAER = 20 \log_{10} \frac{\frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left| y(i,j) - s(i,j) \right|}{\frac{1}{(K-30)(L-30)} \sum_{i=15}^{K-15} \sum_{j=15}^{L-15} \left| x(i,j) - s(i,j) \right|} \tag{33}$$

In the expressions (30-33), $s(i,j)$, $x(i,j)$ and $y(i,j)$ are the original image pixel, the noise-free image pixel and the filtered image pixel, respectively.

In the experiments, it is presupposed that the original noise-free images (reference image) shown in the Fig.1 are available.

a b

Fig.1 Original noise-free images. (a) Lena. (b) The 2nd frame of Trevor sequence

The first experiment was performed by using the 2nd frame of Trevor sequences. Here, we would like to present the ability of adaptive LMS L-filters modifications to remove noise when this original image has been corrupted by mixed noise, consisting of the additive Gaussian white noise with variance $\sigma^2 = 400$ and impulsive noise with probability p=10%. The coefficients of the tested adaptive L-filters have been initialised randomly in the interval (0,1) and they have been normalised by their sum so as their sum equals unity.

The entire noisy as well as original image has been used in the adaptation of the adaptive filters. Here, a single run on the training images has been performed. As adaptive filters, the L-LC filter, the L-LU filter, the L-NC filter, the L-NU filter, the L-MC filter, the L-MU filter and the L-SD filters have been used. In the case of adaptive filter training, the coefficients derived during the last window within the last image row processing have been applied to filter the entire image. By using this approach, the filtered images have been obtained.

For the adaptive L-filters, a suitable value of the step-size μ_0 has been found experimentally. Fig.2 shows the NR achieved by the L-NC and L-NU filters for a several values of parameter μ_0. In our experiments, we have used this value of μ_0 for which NR performance index attains a minimum. The μ_o=0.15 for the L-NC filter and the μ_o=0.25 for the L-NU filter were found. In the experiments, the step-size μ_o=0.2 has been used as compromise between them.

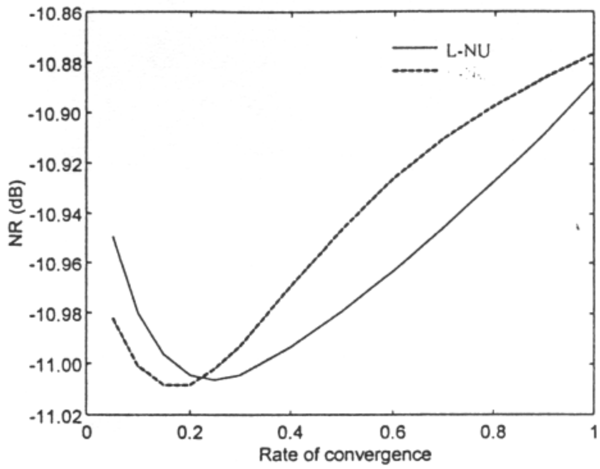
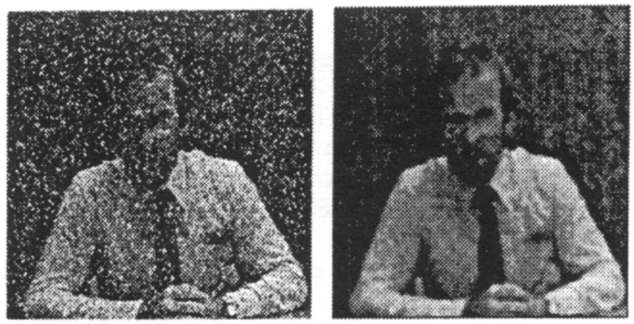


Fig.2 Plot of noise reduction (NR) performance index achieved by the L-NC and L-NU filters versus step-size parameter μ_0

By using the original and filtered 2nd frame of Trevor sequences, the filter performance indices have been evaluated. The results are shown in the Table 1. It can be observed from this table, that the best result has been achieved by the L-SD filter consisting of two L-NC filters. The original image corrupted by mixed impulsive and additive Gaussian noise as well as the output of L-SD filter is shown in the Fig.3. Here, the filter window with dimension 5x5 for edge preservation and the window of dimension 3x3 for noise suppression in homogeneous regions were applied. The threshold was chosen $\beta_t=0.75$. It can be seen from Table 1, that the L-SD filter has yielded an almost 1.1dB better NR and 1.6dB for MAER compared to the median filter.

Table 1. The filter performance indices achieved for the 2nd frame of Trevor sequence processing

Method	Performance indices			
	MAE	MSE	NR	MAER
Noised	21.4890	1240.2	-	-
Median 3x3	8.1560	113.0060	-10.4039	-8.4148
L-LC $\mu=5.10^{-7}$	7.5536	97.3064	-11.0535	-9.0812
L-LU $\mu=5.10^{-7}$	7.5313	96.8655	-11.0732	-9.1070
L-NC $\mu_0=0.2$	7.5651	98.3294	-11.0081	-9.0680
L-NU $\mu_0=0.2$	7.5559	98.4054	-11.0047	-9.0786
L-MC $\mu=5.10^{-7}$	7.6254	99.5852	-10.9529	-8.9991
L-MU $\mu=5.10^{-7}$	7.5948	98.3285	-11.0081	-9.0341
L-SD $\beta_t=0.75$	6.7528	87.6792	-11.5059	-10.0547



a b

Fig.3 The second frame of Trevor sequence. (a) Original image corrupted by mixed impulsive and additive Gaussian noise. (b) Output of the L-SD filter

By using the results of this experiment, we would like to demonstrate also the ability of the L-filter class to suppress noise in homogeneous areas and to preserve the edges at the same time. This property of the L-LU filter is illustrated in the Fig. 4 and Fig. 5, where the image row #128 of the 2nd frame of Trevor sequence for an original, noised and filtered images are presented.

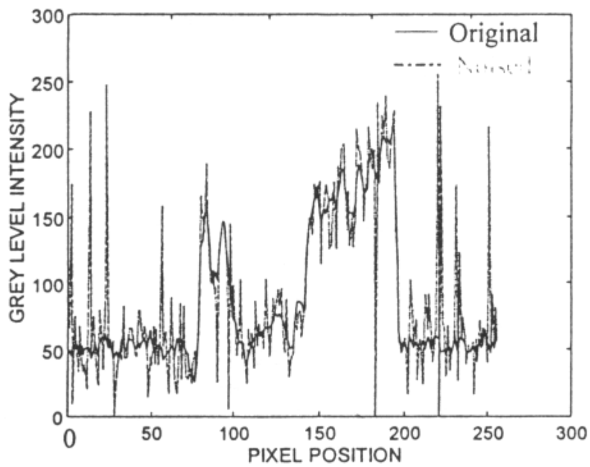


Fig.4 Row #128 of the 2nd frame of Trevor sequence for original and noised image

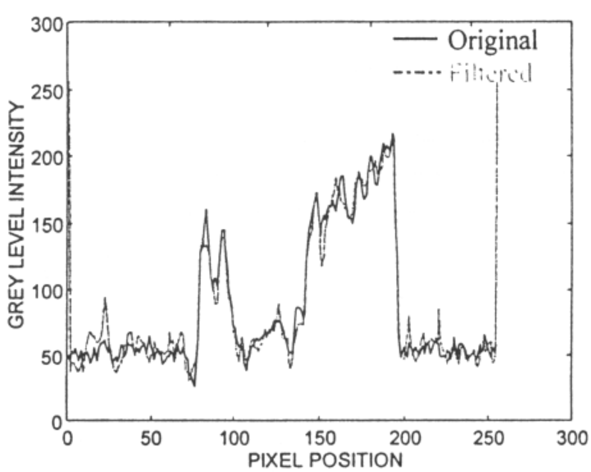


Fig.5 Row #128 of the 2nd frame of Trevor sequence for original image and the image filtered by the L-LU filter

We can see from these figures, that the L-LU filter has a high ability to suppress noise in homogeneous areas and to preserve the edges. The similar results have been obtained for the other tested L-filters.

The second experiment has been intent on analysis of robustness of the above described adaptive L-filters. In this experiment, the optimum coefficient vectors obtained in the first experiment were applied for filtering the different image (image of Lena) and similar image (the 6th frame of Trevor sequence). The noise applied for the different and similar images corruption had the same statistical properties as the noise applied in the first experiment. Results of these experiments achieved by the particular filters are given in the Table 2 and Table 3.

As it can be seen from these tables, each modification of the L-filters is more robust for different image than that of L-SD filter. It follows from the fact that the image of Lena includes more details than the 2nd frame of Trevor sequence. The weight coefficients of the L-SD filter were originally obtained by using threshold $\beta_t=0.75$, but for image of Lena other threshold have to be used. Furthermore, we can see from the Table 2, that the L-MC filter has yielded about 0.3dB better result than that of median filter for both NR and MAER criterion.

Table 2. The filter performance indices achieved at filtering image of Lena by using the optimum coefficients vectors obtained within the 1st experiment

Method	Performance indices			
	MAE	MSE	NR	MAER
Noised	21.0991	1120.1	-	-
Median 3x3	9.7984	184.8124	-7.8253	-6.6622
L-LU $\mu=5.10^{-7}$	9.4689	173.3323	-8.1038	-6.9593
L-MC $\mu=5.10^{-7}$	9.3807	170.9787	-8.1632	-7.0406
L-SD $\beta_t=0.75$	9.2424	208.6145	-7.2991	-7.1696

Table 3. The filter performance indices achieved at filtering the 6th frame of Trevor sequence by using the optimum coefficient vectors obtained within the 1st experiment

Method	Performance indices			
	MAE	MSE	NR	MAER
Noised	21.5347	1243	-	-
Median 3x3	8.1686	114.3186	-10.3635	-8.4198
L-LU $\mu=5.10^{-7}$	7.5564	98.5254	-11.0092	-9.0965
L-MC $\mu=5.10^{-7}$	7.6541	101.4692	-10.8813	-8.9849
L-SD $\beta_t=0.75$	6.8212	92.4386	-11.2861	-9.9855

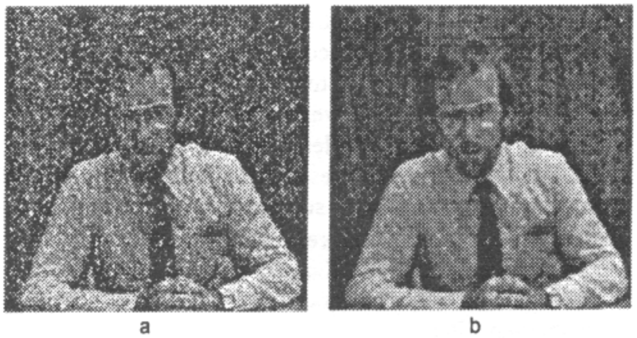
Original image of Lena corrupted by mixed impulsive and additive Gaussian noise and the output of the L-MC filter obtained by using the optimum filter coefficients obtained within the 1st experiment are shown in the Fig.6.

a b

Fig.6 Image of Lena. (a) Original image corrupted by mixed impulsive and additive Gaussian noise. (b) Output of the L-MC filter by using the optimum filter coefficients obtained within the 1st experiment

In the case of similar images processing, it can be seen from the Table 3 that the all L-filter modifications are robust. Here, the best results were achieved by using the L-SD filter. For this filter, we obtained an almost 0.9dB better NR and 1.5dB MAER compared to median filter.

Original image of the 6th frame of Trevor sequence corrupted by mixed impulsive and additive Gaussian noise and the output of the L-MC filter obtained by using the optimum filter coefficient vectors obtained within the 1st experiment are shown in the Fig.7.



a b

Fig.7 The 6th frame of Trevor sequence. (a) Original image corrupted by mixed impulsive and additive Gaussian noise. (b) Output of the L-SD filter by using the optimum filter coefficient vector obtained within the 1st experiment

5. Conclusion

In this paper several adaptive LMS L-filters applied for filtering constant images corrupted by mixed noise have been described. These filters are characterised by the ability to suppress noise in homogeneous areas and to preserve the edges at the same time. Besides, they possess the robustness property i.e. they can be applied with success for filtering some classes of similar and different images. It is evident from the experiments that the best results have been provided by adaptive signal-dependent LMS L-filter. With regard to these L-filter properties we believe that the L-filter class can be successfully applied for filtering constant images corrupted by mixed noise, including impulsive noise.

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