DESY Zeuthen Summer Student

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Final Report

Improving the quality of the electron beam image by means of reducing noise

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Abstract

The PITZ group measures the properties of an electron beam. Using results of measurements PITZ aims to optimize sources of high brightness electron beams. This is possible only with the condition that the measured image data correctly describes the electron beam. Thus, the problem of reducing the noise of the electron beam image is an important issue. For image denoising filters are used. Here it is explained how to choose an appropriate filter. Also results of applying some filters and filter combinations are shown. Modified minimum value filter, mean geometrical and mean harmonic filters demonstrated better result than others used ones. Next step is to implement Wiener filter as it is expected to demonstrate better result.

1. Introduction

For the purpose of testing and optimization of sources for high brightness electron beams for future free electron lasers (FELs) and linear colliders, the PITZ group measures electron beam properties like charge, transverse and longitudinal emittance, etc. Main source of information is an image of the transverse distribution of the electron beam obtained with a CCD camera. The main aim for a representative measurement is to get an image that correctly describes the electron beam transverse distribution. This is hard to be done because the photodetector signal is combined with noise. Noise is always presented in the detection area, for example noise from cables.

Each image file in PITZ is a sequence of several consequent shots - signal frames and background frames. As one can see an example of signal frame at Fig. 1.a and background frame at Fig. 1.b.

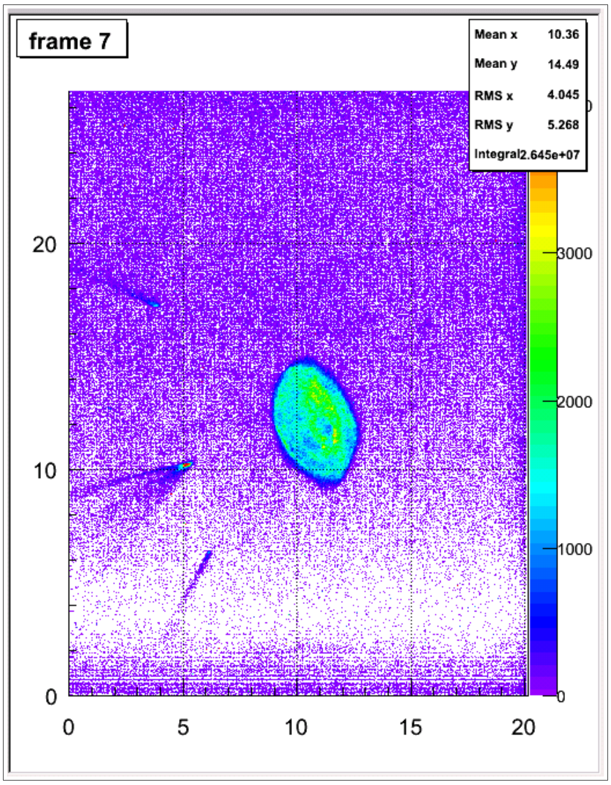

Figure 1.a Signal frame 7

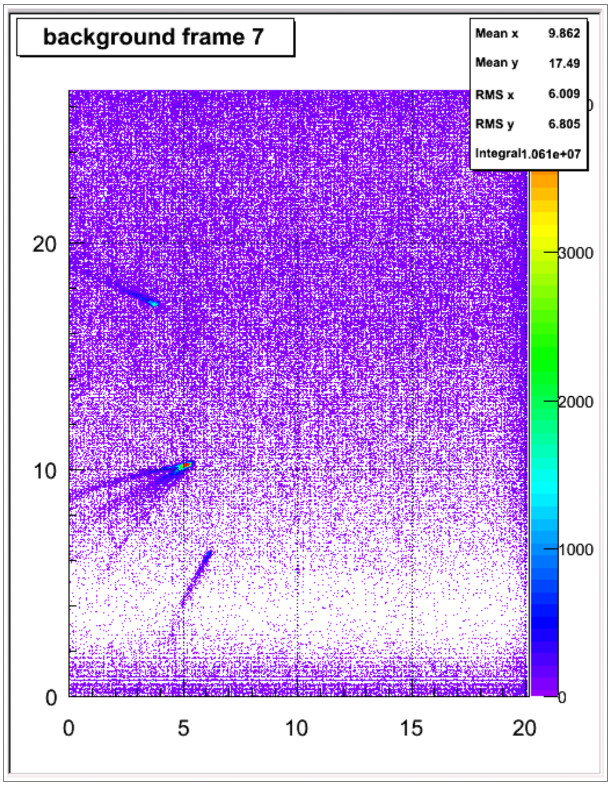

Figure 1.b Background frame 7

An image frame consists not only of a beam signal but also some noise and possible dark current. The term background describes the signal that is registered with a detector in the case of beam absence. The background is not constant, it can change depending on temperature of detector, current strength in cables, etc. In the case of present dark current the noise can change depending on the machine settings. Thus one background frame cannot be used for each shot. For the purpose of obtaining representative results, several frames of signal and background are taken. As a reminder is the probability theory - the law of large numbers (LLN) is a theorem that describes the result of performing the same experiment a large number of times. According to the law, the average of the results obtained from a large number of trials should be close to the expected value, and will tend to become closer as more trials are performed.

Here it is shown how the the noise influences the precision of the calculated electron beam parameters. Figures 2.a, 2.b, 2.c show how the centroids and the RMS spot sizes depend on the amount of noise. Figure 2.a represents the initial beam image obtained as an average of the signal frames. Figure 2.b represents the beam image after applying a median filter to the initial beam image (explanation of median filter see further), after which some noise is reduced. It is seen that the centroid coordinates and the RMS spot sizes change slightly. Figure 2.c represents the beam image after applying a mean geometric filter. It is also applied to the average of the signal frames. This filter reduces more noise, therefore the centroid coordinates and RMS spot sizes changed appreciably.

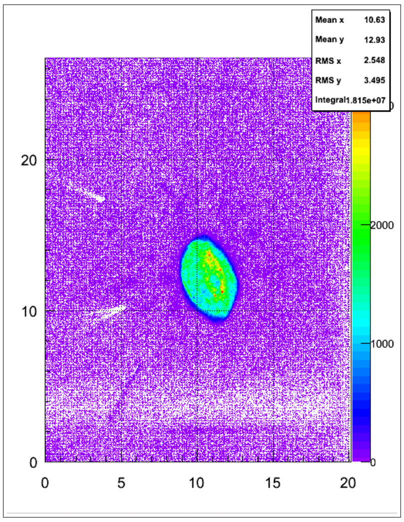

Figure 2.a Initial beam image, centroid coordinates:
x = 10.63 mm, y = 12.93 mm
RMS spot size:
σ_x = 2.5481 mm,
σ_y = 3.49753 mm

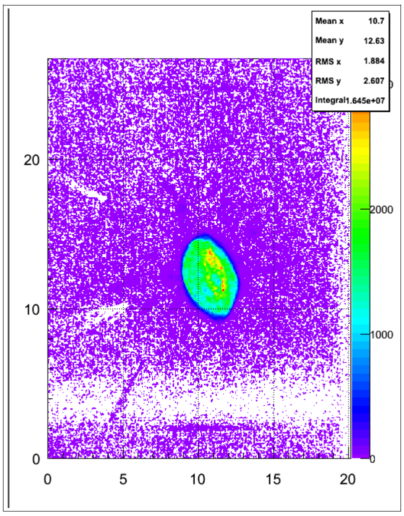

Figure 2.b Beam image after applying a median filter, centroid coordinates:
x = 10.7 mm, y = 12.63 mm
RMS spot size:
σ_x = 1.88443 mm,
σ_y = 2.60862 mm

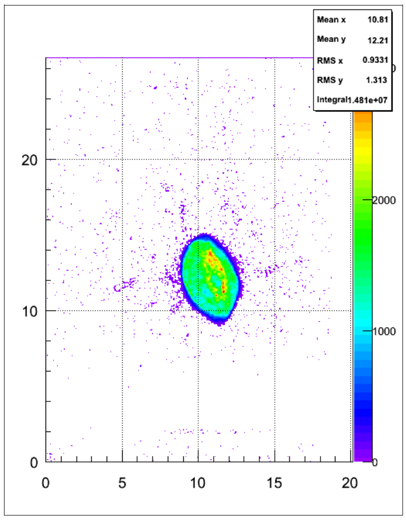

Figure 2.c Beam image after applying a mean geometric filter, centroid coordinates:
x = 10.81 mm, y = 12.21 mm
RMS spot size:
σ_x = 0.933075 mm,
σ_y = 1.31388 mm

These examples show how important it is to have an electron beam image without the presence of noise. As from now, the described filters are applied on a single image data resulting from the subtraction of the averaged background frames from the averaged signal frames.

2. Denoising. The choice of appropriate filter.

Denoising (noise reduction, noise reducing) is the extraction of a signal from a mixture of signal and noise.

Denoising can be done by means of digital filters. There are variety of filters and the most difficult problem is to choose the most appropriate one. The choice depends on several factors. First of all digital filters are divided into two big groups:

1. Filters with finite impulse response (FIR) [1]. FIR is a property of signal processing systems. FIR filter is a type of a discrete-time filter. The impulse response, the filter's response to a Kronecker delta input, is finite because it settles to zero in a finite number of sample intervals.
2. Filters with infinite impulse response (IIR). IIR systems have an impulse response function that is non-zero over an infinite length of time. Example IIR filters include the Chebyshev, Butterworth and Bessel filter.

Digital image is always a system with finite impulse response, because its impulse response function is zero within the dimensions of the image. It means that filter should be selected from FIR filters. It is very positive, because FIR filter is more stable, hence result will be better [2].

The choice of a filter also depends a priori on the information about the type of the noise. In case of PITZ image some information about the noise distribution can be extracted from the background frames. In the case when the distribution describing the noise is unknown or stochastic, it is usually supposed that the noise distribution is a Gaussian one:

$p(z)=\frac{١}{\sqrt{٢\pi\sigma}}*e^{-(z-\mu)^2/2\sigma^2}$, where p(z) is probability density function, μ and σ^2 are the mean and the variance.

An important characteristic of the noise is its correlation with the signal – i.e the noise distribution depends on the signal amplitude.

Filters also can be divided into static and adaptive. Static ones do not change their behavior depending on the input signal. On the contrary, an adaptive filter is a filter with self-adjustment of its parameters. Such filters are useful when the noise distribution is unknown. Therefore the choice of the filter mainly depends a priori on the knowledge about the noise and the system type FIR or IIR.

3. Results

The filters used can be divided into several groups: averaging filters, order statistics filters, statistical and filters adaptive filters .

3.1 Averaging Filters

The effect of averaging filters is smoothing, as they remove intensity peaks, which can result of additive noise (signal-independent noise). The averaging filters work within some range of neighbouring pixels.

Following notation will be used: S_{xy} rectangular neighbourhood (set of pixel coordinates of the image) with the size m×n and central coordinates (x, y) . g(x,y) – input image value in pixel (x,y), f(x,y) – output value of restored image in pixel (x,y).

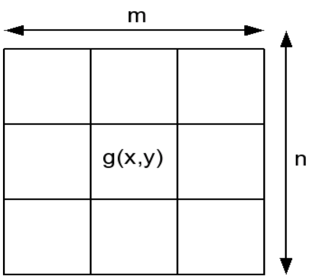

Figure 3. Area of filtering

Mean Arithmetical filter: $f(x,y)=\frac{1}{mn}\sum_{(s,t)\in S_{xy}} g(s,t)$ (1).

Mean Arithmetic filter smooths local variations of the image intensity. The result is slight reduction of the noise – Fig. 4.a.

Mean Geometric filter: $f(x,y)=\left[\prod_{(s,t)\in S_{xy}} g(s,t)\right]^{\frac{1}{mn}}$ (2). The result of applying the Mean Geometric filter is similar to result of Mean Arithmetic filter, but it loses less amount of the little details [3] – Fig. 4.b.

Mean Harmonic filter: $f(x,y)=\frac{mn}{\sum_{(s,t)\in S_{xy}} \frac{1}{g(s,t)}}$ (3). This filter is useful in the case of the “white” impulse noise and Gaussian noise – Fig. 4.c.

Comparing figures 4.a, 4.b, 4c, Mean Arithmetic filter (Figure 4.a) demonstrates insufficient result, because it decreases the noise amplitude and distributes the noise to pixels clean beforehand. The Mean Geometric and Mean Harmonic filters (Figure 4.b, 4.c) demonstrate better results than the previous one. They reduce much noise as well as signal. This result from fact that the filters are sensitive to zero values (2, 3). If a zero value pixels intensity is meet in neighbourhood, it means the input pixel is noise and the output value of pixel is also equal zero.

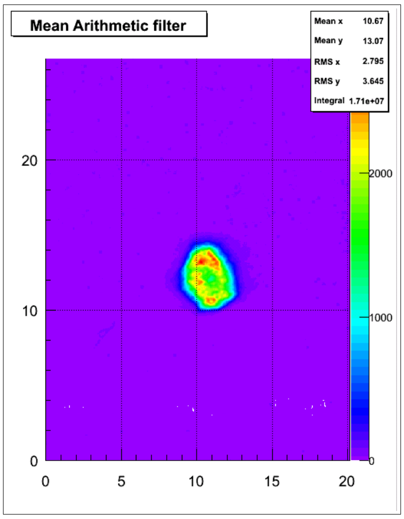

Figure 4.a Result of applying Mean Arithmetic filter.

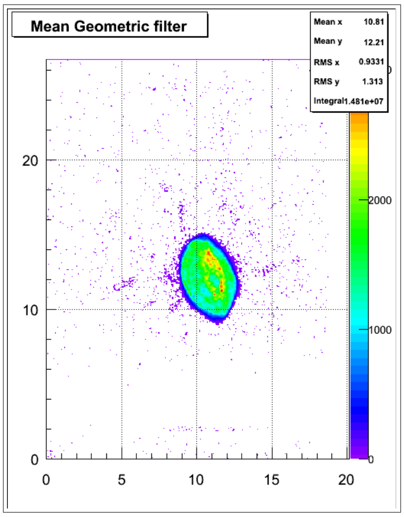

Figure 4.b Result of applying Mean Geometric filter.

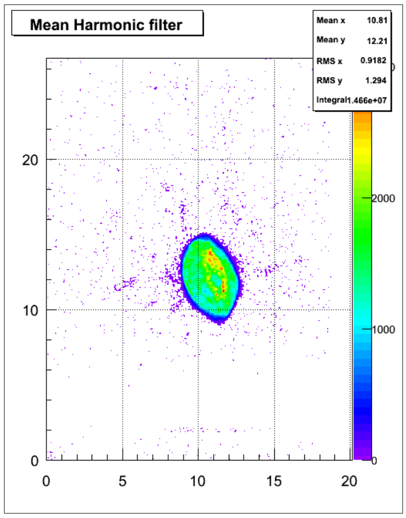

Figure 4.c Result of applying Mean Harmonic filter.

3.2 Order statistics filters

Order statistic filters work in the following way: get sequence of values from a neighbourhood, order this sequence using some rule, return as result a value that is contained in the particular position of sequence.

Median filter: $f(x,y)=med\{g(s,t):(s,t)\in S_{xy}\}$ (4). Median filter is effective in the case of impulse noise, so called noise "salt and pepper". This noise looks like combination of an image and random white and black points.

Minimum value filter: $f(x,y)=min\{g(s,t):(s,t)\in S_{xy}\}$ (5). Minimum filter is a filter for reducing the “pepper” noise. The electron beam emits not only high intensity signal but also low intensity signal on its bounds. Thus modification of Minimum value filter was used.

Modified minimum value filter: $f(x,y)=next\ \ after\ \ min\{g(s,t):(s,t)\in S_{xy}\}$ (6).

Comparing figures 5.a, 5.b, 5.c, the Median filter (Figure 5.a) demonstrates poor result, because the electron beam image contains small amount of “salt” noise. Thus the noise are is was decreased slightly. Minimum value filter (Figure 5.b) demonstrates good result, but it also reduces part of the useful signal. Modified minimum value filter demonstrates more acceptable result, it reduces enough of the noise and keeps the image part that describes electron beam.

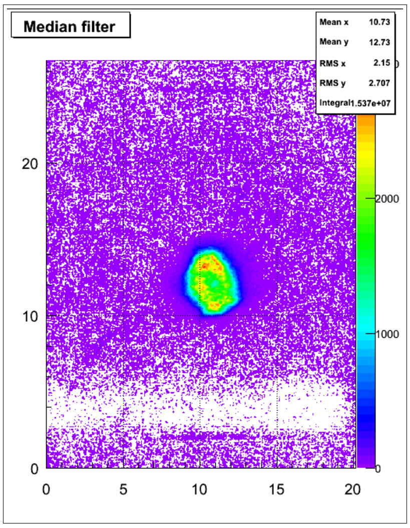

Figure 5.a Result of applying of the Median filter.

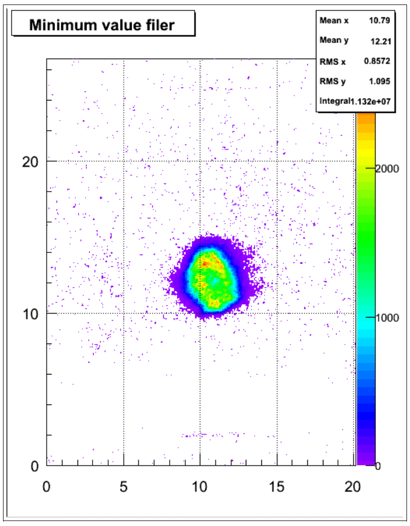

Figure 5.b Result of applying of the Minimum value filter.

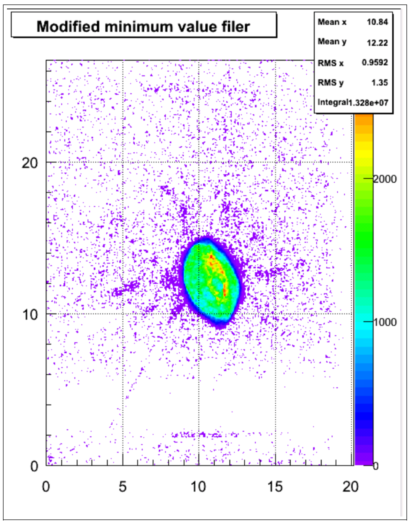

Figure 5.c Result of applying of the Modified minimum value filter.

3.3 Statistical filters

Statistical filters use statistic image information. Root mean square deviation of the electron beam noise distribution is known, so Sigma cut filter can easily be applied. This filter is useful when the signal pixel intensity is much bigger than one sigma of the noise pixel intensity. Its idea is that high signal is regarded as the electron beam signal, low signal is regarded as noise.

Sigma cut filter : $$f(x,y)=\begin{cases} 0, & (g(x,y)-\sigma_{noise})<Threshold \\ g(x,y)-\sigma_{noise}, & else \end{cases} \quad (7).$$

Sigma cut filters demonstrates insufficient result (Figure 6.a). But is a good filter for preparing the data image before applying another filter. It is rarefies noise well according to the definition. Afterwards filters, which work with big amount of the noise unsuccessful, demonstrate enough good result, for example the Median filter (Figure 6.b).

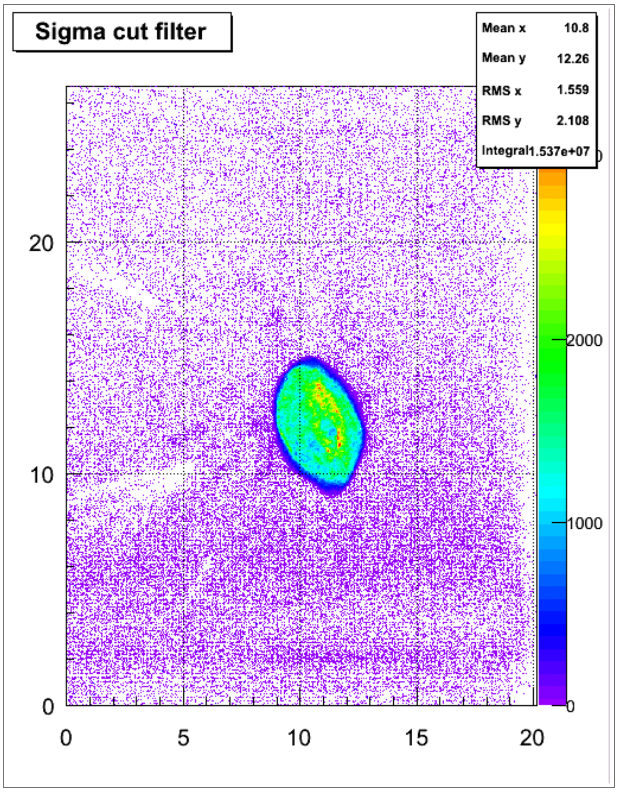

Figure 6.a Result of applying of the Sigma cut filter, Threshold = 1e - 5

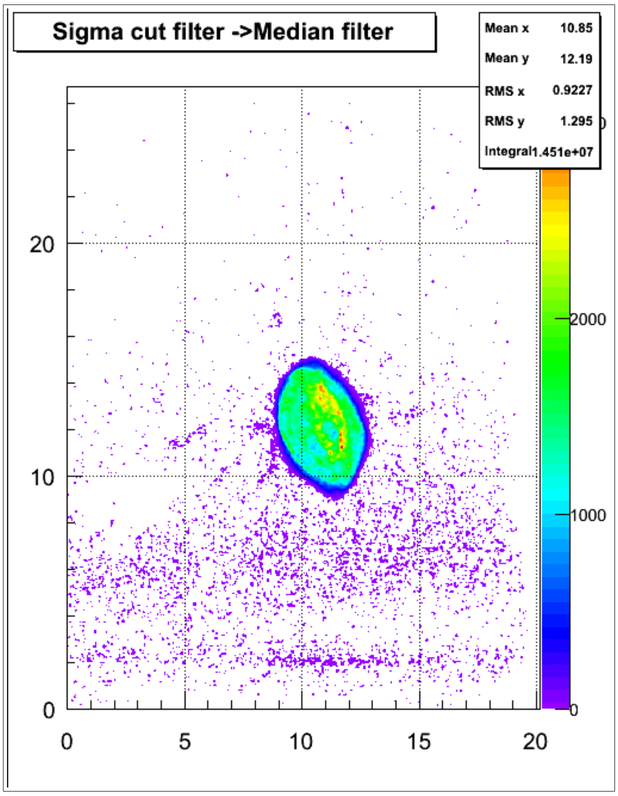

Figure 6.b Result of applying of the Sigma cut filter with Threshold = 1e - 5, then Median filter.

3.4 Adaptive filters

An adaptive filter is a filter that self-adjusts its transfer function according to an optimizing algorithm. Because of the complexity of the optimizing algorithms, most adaptive filters are digital filters that perform digital signal processing and adapt their performance based on the input signal.

The block diagram (Figure 7), shown in the following figure, serves as a foundation for particular adaptive filter realisations, such as Least Mean Squares (LMS) and Recursive Least Squares (RLS). The idea behind the block diagram is that a variable filter extracts an estimate of the desired signal.

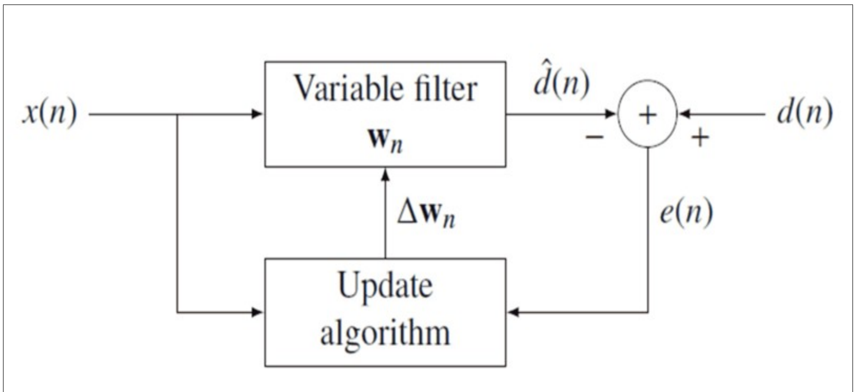

Figure 7 Block diagram of adaptive filtering

Where the input signal is the sum of a desired signal $d(n)$ and interfering noise $v(n)$:

$x(n) = d(n) + v(n)$.

The variable filter has a FIR structure. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined as

$$w_n = [w_n(0), w_n(1), ..., w_n(p)]^T.$$

The error signal or cost function is the difference between the desired and the estimated signal : $e(n) = d(n) - \hat{d}(n)$.

The variable filter estimates the desired signal as it convoluted the input signal with the impulse response. In vector notation this is expressed as $\hat{d}(n) = \mathbf{w}_n * \mathbf{x}(n)$, where $x(n) = [x(n), x(n-1), ..., x(n-p)]^T$ is an input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant $\mathbf{w}_{n+1} = \mathbf{w}_n + \Delta\mathbf{w}_n$, where $\Delta\mathbf{w}_n$ is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals. LMS and RLS define two different coefficient update algorithms.

5. Conclusion

Different filters were implemented and applied to electron beam images. Part of them demonstrates poor results, another part – acceptable ones. Result of such filters as Mean arithmetic and median filters have poor result because the electron beam image is too noisy. Mean geometric, Mean harmonic and Minimum value filters reduce much noise as well as signal. It is also not good, because real information about electron beam emittance is lost. Best result were represented by Modified Minimum value filter, it reduces enough amount of the noise as well as keeps signal.

Future work might include applying different combination of filers; filters to each frame and then calculate average image; analyze adaptive filtering, particularly implement Mean squares filter (LMS), that is approximation of the Wiener filter [4],[5].

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