

RAFAŁ PETRYNIAK\*

## EDGE PRESERVING TECHNIQUES IN IMAGE NOISE REMOVAL PROCESS

TECHNIKI USUWANIA SZUMU Z OBRAZU  
MINIMALIZUJĄCE STRATĘ OSTROŚCI GRANIC  
MIĘDZY OBIEKTAMI

### Abstract

The paper describes how to prepare dynamic graphic filters, which main goal is to remove noise from an image and also to preserve information on edges between objects. These types of filters are able to focus on operations inside objects, and at the same time weaken the process at objects borders.

*Keywords: image noise removal, graphic filter, edge detection, adaptive methods*

### Streszczenie

W artykule przedstawiono metody dynamicznego konstruowania filtrów graficznych, których głównym zadaniem jest usuwanie szumu z obrazu, przy jednoczesnym zachowaniu informacji o krawędziach między obiektami. Tego typu filtry potrafią samodzielnie wzmacniać swoje działanie wewnątrz obiektów i jednocześnie osłabić je na ich granicach.

*Słowa kluczowe: usuwanie szumu z obrazu, filtry graficzne, detekcja krawędzi, metody adaptacyjne przetwarzania obrazu*

\* PhD. Eng. Rafał Petryniak, Institute of Applied Informatics, Faculty of Mechanical Engineering, Cracow University of Technology.

## 1. Introduction

The quality of the input image is one of the most important factors that influences the image analysis process. The preferred quality shall reproduce the actual structure of the existing objects. Unfortunately, many factors affect the result of image capturing process, so it is difficult to achieve the perfect data. Simple examples of quality reduction are poor image sharpness and accompanying noise.

In the design phase of an algorithm, we need to take care of the algorithm performance objectives. For instance, we do not want the algorithm to destroy the image information, which might be important for us. Applying of dynamic methods for filter construction allows us to process the image fragments step by step.

## 2. Filters based on point neighbourhood

One of the simplest methods of noise removal from an image is to use the filter which is based on the local neighbourhood of each point. This approach requires the simplified assumption that point and its closest surrounding belong to the same object. So the points shall have similar values or the values should change gradually. Based on that, a value that differs significantly from the other is considered to be affected by an external factor (like noise) and should be modified. Taking an average value of surrounding points is a popular technique. Two types of average values are usually used:

- **Arithmetic mean** – smoothes the image by setting the point with the mean value of its neighbourhood.
- **Median** – does not introduce new values to the image, but choose the central value from the neighbourhood.

## 3. Linear image smoothing based on the Gaussian function

When we use the arithmetic mean in a filtering process, all points from neighbourhood are treated in the same way. Applying of arithmetic mean to remove a noise may lead to much smoothing, and to losing of some important data regarding object edges (Fig. 1c). To minimize this effect, we may apply the *weighted mean*, which distinguish the points nearest to the central one from the further located. *Gaussian function* may help us to choose the weights.

$$G(x, y) = \frac{1}{2\pi\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

where:

- $x$  – distance from the  $X$  axis,
- $y$  – distance from the  $Y$  axis,
- $\sigma$  – standard deviation of normal distribution (*sigma*).

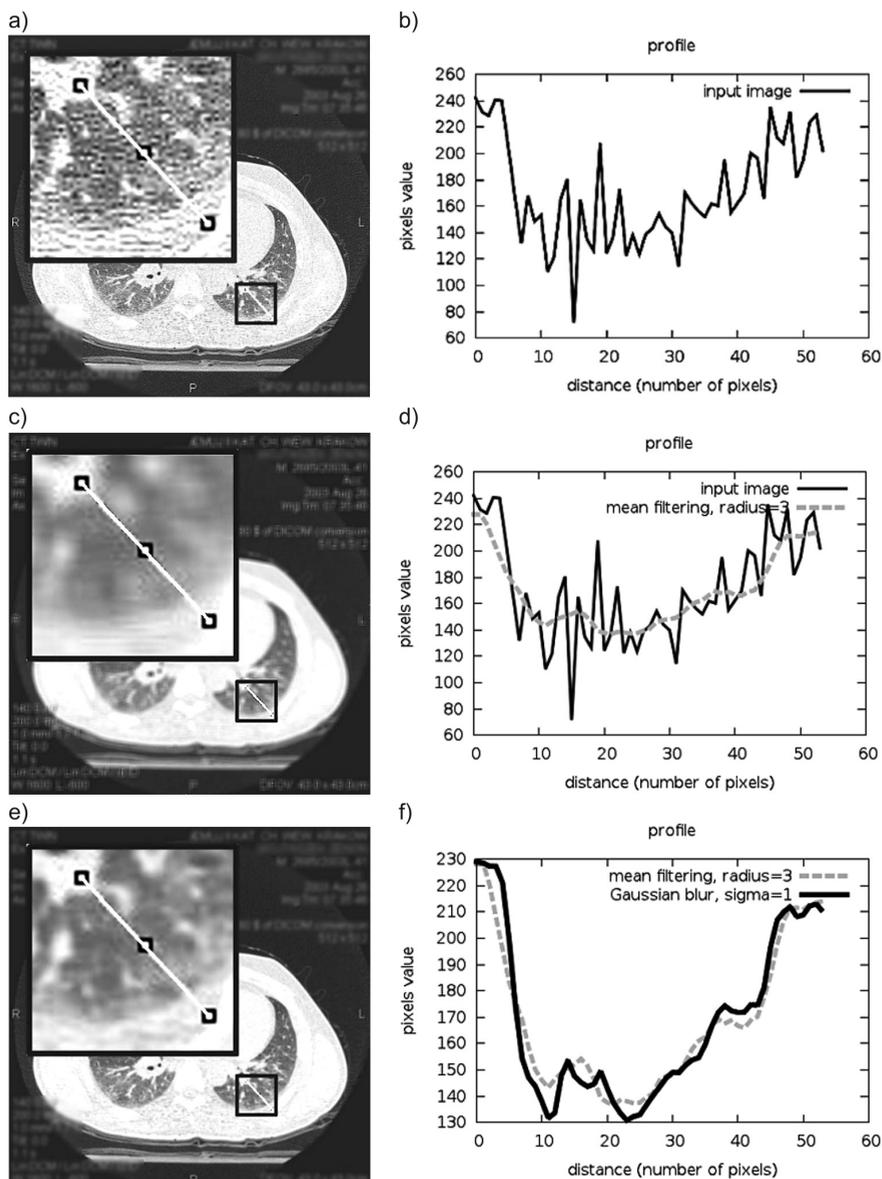


Fig. 1. The results of linear smoothing filters for a example tomographic image of the chest: (a) original image, (c) mean filtering, (e) Gaussian blur. The right column shows the profiles of the pixels values for the selected line

Rys. 1. Wyniki działania liniowych filtrów wygładzających dla przykładowego obrazu tomograficznego klatki piersiowej: (a) obraz oryginalny, (c) filtracja uśredniająca o promieniu = 3, (e) filtracja Gaussa o wartości sigma = 1. W prawej kolumnie przedstawiono profile wartości pikseli dla wybranej linii

#### 4. Non-linear image smoothing based on the Gaussian function

Gaussian smoothing helps to keep the object edges, however, it still treats all points in the same way. This is typical for linear filters. To improve the process, we might want to modify it in a way that it takes into account the localization of the point – whether it is in the middle of the object, or close to the edge. Then the smoothing process shall focus on similar fragments on the image, and not on the edges.

One of the first publications in this area was paper about *Perona-Malik model* [1]. The authors introduced a variable  $g$ , which decides on smoothing level, based on  $E$  value – estimator for edges. For  $E$  estimator the authors suggested to use gradient operator.

$$E(x, y) = \|\nabla u(x, y)\| \quad (2)$$

In the mentioned paper, there were described also two functions  $g$ , that influence the smoothing level.

$$g_1(E) = \exp\left(-\left(\frac{E}{K}\right)^2\right) \quad (3)$$

$$g_2(E) = \frac{1}{1 + \left(\frac{E}{K}\right)^2} \quad (4)$$

Additional parameter  $K > 0$  represents the minimal value required to decide if a point belongs to the edge or not.  $K$  may be considered as difference of pixel value between the edge and its surrounding. This parameter may be set by the user or may depend on the histogram of image noise [1].

Comparing with previously described linear filters, the *Perona-Malik model* operates on the points from the nearest neighbourhood (filter radius = 1), and not on the wide neighbourhood. To manipulate with the level of smoothing, it is recommended to run the filter several times on the image (this is an iterative approach).

The algorithm results are presented on Figure 2. Selected image fragment was zoomed out (Fig. 2a) and its profile (pixel values) was put on chart (Fig. 2b). The image profiles of *Perona-Malik model* and *Gaussian function* were compared and shown on Fig. 2b. Although both profiles look similar, we can see differences in edge areas. With *Perona-Malik model* we observe bigger values changes in these areas, whereas *Gaussian filter* provides smoother values. Additionally, we can notice that edges on the Figure 2a are sharper than on Figure 1a. The noise removal process seems to clean up the image.

In *Perona-Malik model* edge estimator  $E$  may be the thin throat. If we use a local gradient for  $E$  calculation, it may happen that a point may be classified to an edge, and not to the body of an object, and such areas will not be smoothed. High noise may influence the local gradient method significantly and may change the results. To mitigate the noise influence, in the paper [2] there was proposed additional step with **model regularization**. For this purpose the linear filter can be selected (*Gaussian function* is recommended), which smoothes the biggest value changes. On such filtered image the value of  $E$  will not be much influenced by local noise, and *Perona-Malik model* will provide better results.

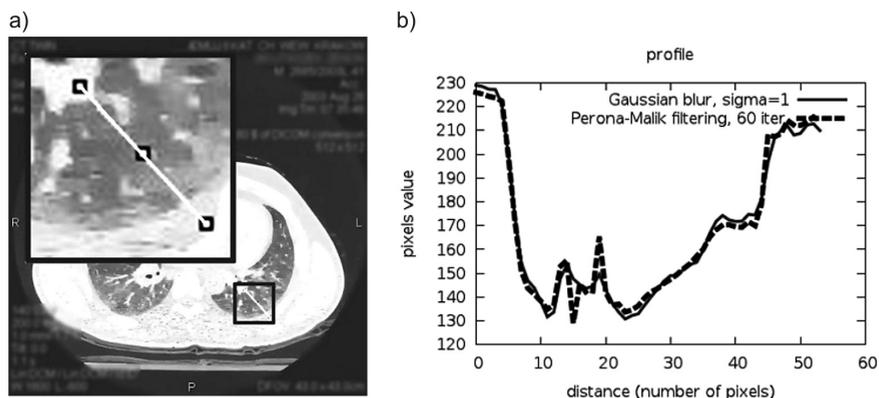


Fig. 2. The results of the non-linear image blur filter based on the *Perona-Malik model*: (a) result image after filtering (60 iterations), (b) profile of the selected line compared to blurred image profile of Gaussian function

Rys. 2. Wyniki działania nieliniowego filtru rozmycia obrazu opartego o *model Perona-Malik*: (a) obraz po filtracji (60 iteracji), (b) profil wartości dla wybranej linii porównany z profilem obrazu po rozmyciu funkcją Gaussa

Regularization is performed only once before first calculation of estimator  $E$ , in order not to lose too much data on edges.

## 5. Summary of the practical aspects of non-linear filtering methods usage

Non-linear filtering method described above may give better results than linear methods, like mean filter or *Gaussian blur*. However, in some cases it is not the perfect solution. Main weakness is the time needed for calculation due to iterative approach [3]. For instance, to reach the results on Figure 2a, 60 iterations for the whole image were performed. It is much more effort, than for other popular filters like mean or median, which need to be performed only once for each point. Additional issue with the non-linear filters is to define the optimal number of iterations.

Generally, the algorithm is not much influenced by small changes in number of iterations. Nevertheless, for a person using this method rarely, it might be not obvious what number of iterations shall be applied – 30, 60, or 120 iterations. Another issue is with the popularization of the non-linear algorithms. It is very likely, that we will not have them implemented in our daily used tools. The implementation of these methods is more difficult, than the implementation of linear methods.

If described weaknesses (calculation time, defining number of iterations, implementation effort) are uncomfortable, then a simpler non-linear method may be applied – *median*, already mentioned in this paper. It also has some drawbacks (possible change of object geometry due to smoothing of sharp edges or thin lines [4]), however it may give results good enough. If we look at the Figure 3a, we can see that edges are still sharp. The profile was presented on Figure 3b.

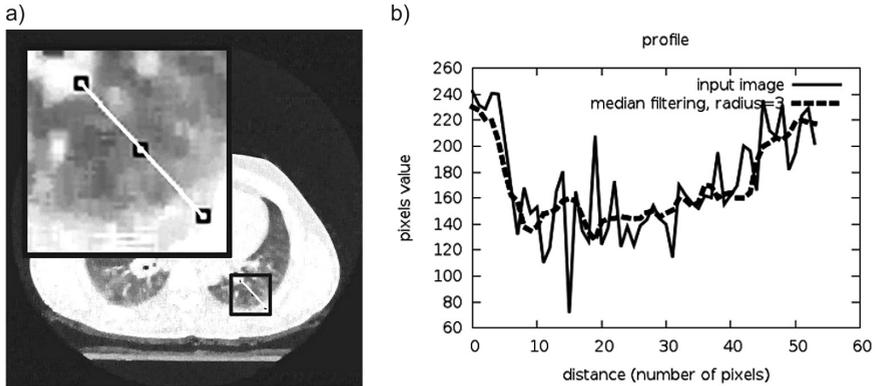


Fig. 3. The results of the median filter: (a) image after filtration, (b) profile of the selected line  
 Rys. 3. Wyniki działania filtru medianowego: (a) obraz po filtracji, (b) profil wartości dla wybranej linii

In opposite to the mean filter, removal of extreme values, does cause much smoothing and allows to keep edges of objects (Figure 4). Despite the fact that both filters – mean and median works good in areas of pixel values shocks, it seems that *Perona-Malik filter* profile suits better with original image profile in areas where two objects are connected (Figure 5).

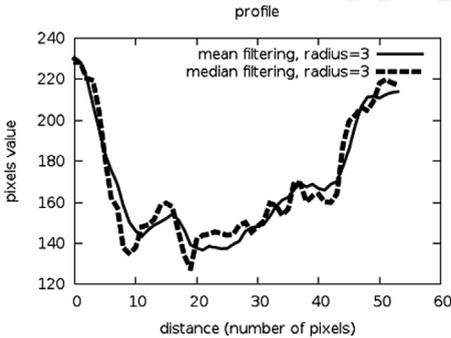


Fig. 4. Comparison of mean filter profile (Figure 3.1c) with a median (Figure 3.3a)

Rys. 4. Porównanie profilu filtracji średnią arytmetyczną (rys. 3.1c) z medianą (rys. 3.3a)

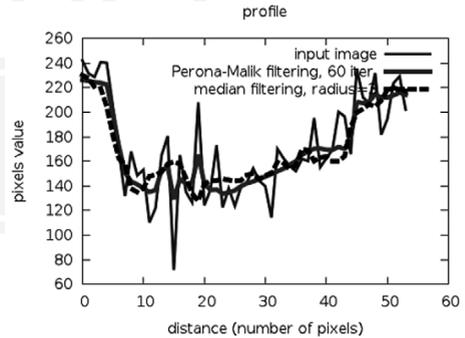


Fig. 5. Comparison of median filtering profile (Figure 3.3a) and Perona-Malik filtration (Figure 3.2a) to the original image (Figure 3.1a)

Rys. 5. Porównanie profilu filtracji medianowej (rys. 3.3a) i filtracji Perona-Malik (rys. 3.2a) z obrazem oryginalnym (rys. 3.1a)

## 6. Conclusions

Presented in this paper non-linear image filters are suitable for images with high noise. Applying popular linear image filters, like arithmetic mean or *Gaussian filter*, in such cases may cause too much smoothing of object edges, which may lead to failures in further image analysis process.

## References

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