Evolutionary Design of Efficient and Robust Switching Image Filters

Zdenek Vasicek[1], **Michal Bidlo**[1], **Lukas Sekanina**[1], **Kyrre Glette**[2]

[1] Faculty of Information Technology, Brno University of Technology
Bozetechova 2, 612 66 Brno, Czech Republic
E-mail: {vasicek,bidlom,sekanina}@fit.vutbr.cz

[2] Department of Informatics, University of Oslo
P.O. Box 1080 Blindern, N-0316 Oslo, Norway
E-mail: kyrrehg@ifi.uio.no

Abstract

This paper proposes an evolutionary approach based on Cartesian Genetic Programming to the design of image filters for impulse burst noise. The impulse burst noise belongs to more serious image distortions that cause a loss of information in a series of pixels together. The results introduced herein represent a continuation of our research in the design of high-quality image filters. Whilst the previous experiments considered only basic impulse burst noise in which a burst corrupting a series of pixels could take a single value, this paper is devoted to the filtering of more realistic noise of this type where the pixels in a burst can take different values. In order to increase the probability of removing the noise pixels while retaining other pixels unchanged, the concept of switching filter will be applied. In our case it means that the filter system is designed by evolution of both a filter circuit and a noise detector. We show that the proposed method is able to design an efficient and robust impulse burst noise filter that exhibits better filtering properties in comparison with several conventional approaches and, moreover, it is also suitable for a high-speed image processing.

1 Introduction

In some cases the process of acquiring or transmitting images leads to the corruption of certain image pixels so that these pixels do not possess their original value which causes the loss of information. This corruption is referred to as a noise. There are several different variants of the noise in the image data that are less or more difficult to suppress (e.g. salt & pepper noise, impulse noise, impulse burst noise etc.). The impulse burst noise belongs to more serious image corruptions that is difficult to eliminate in order to restore the original image in a satisfactory quality. This paper aims to address the problem of efficient and robust filtering of images corrupted by impulse burst noise using evolutionary techniques.

The impulse burst noise typically occurs in remote sensing images such as satellite images. The main reason for the occurrence of bursts is the interference of a frequency modulated carrying signal with signals from other data sources. This interference can occur several times during a transmission of a single image and corrupt several image pixels in one or more neighboring rows.

Various filters have been proposed to suppress this type of noise in the recent years. For the purposes of this paper, we can divide these filters into two major groups. The first group will contain general purpose filters for impulse noise removal which can be relatively easily implemented in hardware: median filter [1], adaptive median filter [6] and weight median filter [3]. The second group will consist of specific filters developed for impulse burst noise such as training-based optimized soft morphological filters and variational approaches [9, 8, 12, 5]. Unfortunately, it is much more difficult to implement these filters in hardware than the filters of the first group and hence they are not suitable for applications that require high-speed image processing.

Evolutionary algorithms have been employed to design complete filter structures for various noise types in the recent years. In particular, evolved shot noise filters outperform conventional filters (such as median and adaptive median filters) in terms of the quality of filtering as well as the implementation cost on a chip [14, 17, 18]. Another advantage of filters evolved for the shot noise is that they utilize a small filtering window of 3×3 pixels. The success of the shot noise filters evolution is the main motivation for this paper. However, the shot noise represents a model instance of a noise rather than a real image corruption. In

practice, the impulse burst noise represents a more common case which we investigated in the recent years. In [16] we proposed a concept of a selector representing an extra circuit in front of the filter itself that selects a subset of pixels from the filter window and thus reduces the search space needed to be explored by the evolution during the design process. This concept allowed us to design filters with 5x5-pixel filter window that outperform the conventional median filters. Moreover, we showed that this approach is suitable for hardware implementation using FPGAs [20].

In [15] a concept of a switching filter was introduced in order to prevent the degradation of non-noise pixels during the filtering process. The switching filter operates in two steps: In the first step, the noisy pixels are detected using a detection algorithm. Then, the new values of the corrupted pixels are estimated using a filtering algorithm.

In this paper we will continue in the research of the automatic design of image filters using evolutionary algorithms. In particular, the goal is to perform evolutionary design of efficient and robust switching filters with the focus on improving the filtering quality in comparison with existing solutions. The main idea is to evolve a circuit using Cartesian Genetic Programming (CGP) at the functional level that encapsulates the noise detection algorithm and the filter itself. The experiments will deal with the design of filters for the impulse burst noise. The obtained results will be compared with the conventional filters and solutions obtained from our previous experiments presented in [16] and [20].

2 Impulse Burst Noise

The noise model considered in this paper represents an extension of a simple impulse burst noise. The simple impulse burst noise can be characterized by means of two parameters p and q. Let p denote a probability that a certain pixel belongs to an impulse burst. In fact, this parameter determines the maximal amount of the corrupted pixels of an input image. Let q be a parameter which determines the maximal length of burst (i.e. the maximal number of consecutive pixels which are affected by an impulse). The number of burst fragments in the image depends on both these parameters; the higher q, the lower number of burst fragments for a given (constant) value of p.

Figure 1 shows an image (256×256 pixels) which is corrupted by (a) 10% ($p = 0.1$) and (b) 40% ($p = 0.4$) impulse burst noise; the parameter q possesses the value 128. If the images are transferred as one-dimensional arrays in which the rows of the image pixels are stored in sequence, the interferences during the transmission leads to the noise demonstrated in Figure 1.

For the purposes of this paper the simple variant of the impulse burst noise is extended so that the corrupted pixels can take different values. This noise model is closer to the burst noise that may occur in real images. We will consider the following scheme to model the extended impulse burst noise. If a given pixel is corrupted according to the model presented for the simple burst noise, then this pixel can take a value from $\mathcal{N}(255, \sigma^2)$. Note that only the valid noise values (i.e. no greater than 255) are considered. A sample image corrupted by the extended impulse burst noise ($p = 0.2$) is shown in Figure 1c.

3 Evolutionary design of image filters

Every image filter is considered as a digital circuit of several 8-bit input values and a single 8-bit output (filtered) value, which processes grayscale (8-bit per pixel) images. The basic concept of an image filter working with a 5×5 filtering window is shown in Figure 2a. The circuit accepts 25 input values of the pixels from the filtering window and produces the filtered value. The potential obstacle of this concept may be the fact that every pixel is filtered by the same circuit (i.e. the corrupted pixels as well as the pixels possessing correct values) which may cause global degradation of the resulting image quality. Therefore, in this paper we focus on the evolution of a filter that is equipped with a noise detector.

The concept of an image filter combined with a noise detector (i.e. the switching filter) is illustrated in Figure 2b. In our case the image filter produces a filtered value O_1 and a noise detector output O_2 (both are 8-bit values). The MSB of O_2 controls the multiplexer that implements the switching algorithm. The switching filter works as follows. If O_2 is greater than 127 (i.e. the MSB of O_2 equals 1), then the value I_C was detected as noise and the final output of the filter O_F equals the filtered value O_1, otherwise O_F equals the original value I_C. In fact, the noise detector represents an additional logic of the filter circuitry that is capable of determining whether the value of the pixel to be filtered is a noise value or a correct (uncorrupted) value. The main idea of this concept is to prevent the degradation of the non-noise pixels.

In addition to the conventional approaches to the filter design, evolutionary techniques have successfully been applied in the design of filters for various kinds of noise. In this paper, we focus on the evolutionary design of switching filters by means of Cartesian Genetic Programming.

3.1 Cartesian Genetic Programming for Filter Evolution

The method for the evolution of image filters presented in this paper is based on Cartesian Genetic Programming introduced in [11]. In the original usage of CGP for the filter design (according to [13]), a candidate filter is represented using a graph which contains n_c (columns) $\times$ n_r

(a) 10% noise   (b) 40% noise   (c) 20% noise
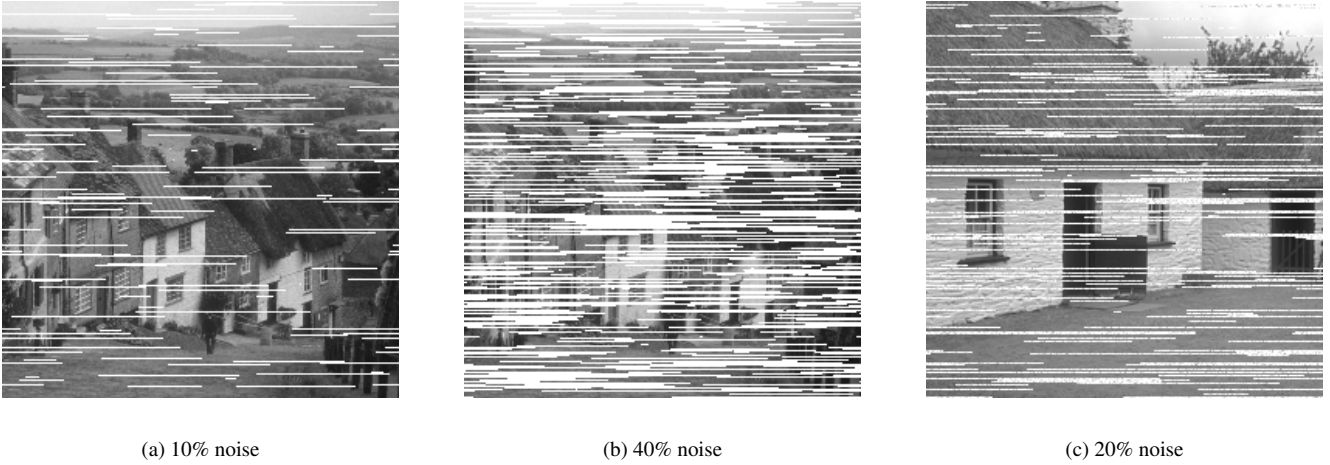
Figure 1. (a),(b) Images corrupted by a simple impulse burst noise of various intensity. (c) Image corrupted by more realistic version of impulse burst noise.

(a) common image filter   (b) switching image filter
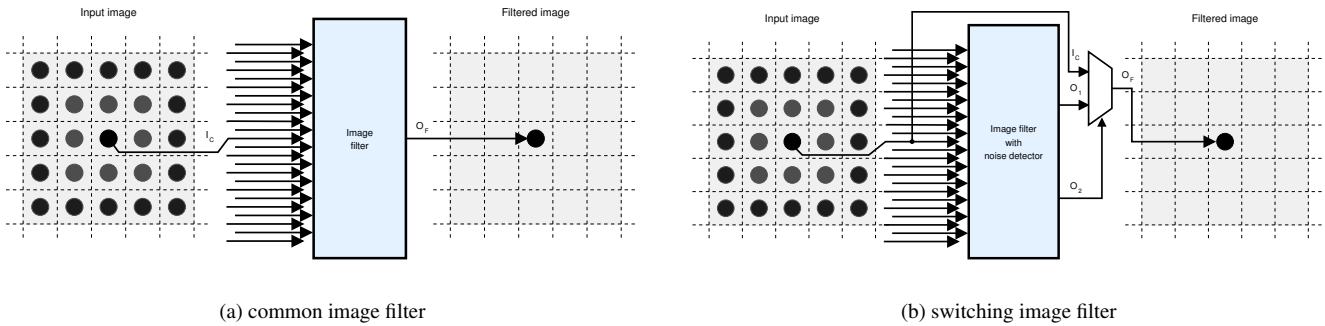
Figure 2. (a) The concept of a 5×5 kernel image filter. A new value of the central pixel I_C is calculated by the image filter whose output O_F represents the filtered value. (b) The concept of a 5×5 kernel switching filter.

(rows) nodes. The role of the evolutionary algorithm is to find the interconnection of the programmable nodes and the functions performed by the nodes. Each node represents a two-input elementary function that receives two 8-bit values and produces an 8-bit output. The functions (building blocks) that are utilized in our experiments are specified in Table 1. This function set was discovered during many previous experiments considering the image filter evolution for different noise types. A node input may be connected either to the output of another node which is placed anywhere in the preceding columns or to a primary input of the filter (this corresponds to the l-back parameter equal to n_c allowing the full connection). A switching filter circuit is encoded as a strings of integers (a chromosome) consisting of $3 \times n_r \times n_r + 2$ values (genes). For each node, three in-

tegers are utilized which encode the connection of the node inputs and its function. The last two integers of the CGP encoding specify the connection of the filter output O_1 and the noise detector output O_2.

In order to evolve an image filter capable of removing a given type of noise, we need (1) a set of suitable elementary functions (building blocks which will be utilized in the proposed filter circuit), (2) rules for interconnecting those functions and (3) training images (usually corrupted version and the corresponding uncorrupted version of an image is sufficient) to measure the fitness values of the candidate filters (i.e., to evaluate the quality of the candidate filters). The goal of the evolutionary algorithm is to minimize the difference between the original uncorrupted version of a training image and filtered image. Since this evolutionary de-

Table 1. The list of functions that can be implemented in each programmable node

code	function	description
0	255	constant
1	x	identity
2	$255 - x$	inversion
3	$max(x, y)$	maximum
4	$min(x, y)$	minimum
5	$x \gg 1$	right shift by 1
6	$x \gg 2$	right shift by 2
7	$x + y$	+ (addition)
8	$x +^S y$	+ with saturation
9	$(x + y) \gg 1$	average
10	y if $(x > 127)$ else x	condition
11	$|x - y|$	absolute difference

sign method does not guarantee that the evolved filters will be robust, the generality of evolved filters (i.e., the ability to operate sufficiently also for other images containing the same type of noise) has to be evaluated by a test set of several different images.

3.2 Fitness function

The objective of the evolutionary algorithm is to minimize the difference between the filtered image and the original image. Usually, the *mean difference per pixel* also known as the *mean absolute error* (MAE) is minimized. Let u denote a corrupted image, v is the filtered image and w is the original (uncorrupted) version of u. Let K represent the size of the image (only square images are considered in the experiments) and k denote the size of the filter kernel. The image size is $K \times K$ ($K = 256$) pixels but only the area of $(256 - k + 1) \times (256 - k + 1)$ pixels is considered because the pixel values at the borders are ignored and thus remain unfiltered. The fitness value of a candidate filter is obtained by calculating the error function:

$$f = \frac{1}{(K-2)^2} \sum_{i=1}^{K-2} \sum_{j=1}^{K-2} |v(i,j) - w(i,j)|.$$

It is evident that the robustness of evolved filter depends on the selection of the training data. In [10], it has been determined that one image containing 128×128 pixels provides a sufficient amount of training data for evolution of robust 3×3 filters. This is caused by the fact, that the fitness functions utilizes training vectors instead of a whole image. Thus a training image containing 128×128 pixels can produce up to 15876 training vectors. As we utilize a larger filter window in this work, we will choose the training image consisting of 256×256 pixels.

4 Evolutionary System Setup

The following setup of the evolutionary design system is considered for the experiments. The initial parameters were determined on the basis of our previous experience and their values were adjusted for the specific problem to be solved in a series of experiments considering some selected parameter settings. The goal was to find a setting that is able to provide filters of a reasonable quality in a given number of generations. The following setup was determined to perform the final experiments. The CGP array consists of $n_c \times n_r = 7 \times 9$ elements. The evolutionary strategy works with the population of 8 individuals. The offspring are produced by means of the mutation operator that can mutate up to 5 genes. The l-back parameter of the CGP has been set to n_c. 100 independent evolutionary experiments were performed, each experiment takes 150,000 generations. The initial population was generated randomly. The function set (building blocks) of the CGP is considered according to Table 1. The goal is to design a filter with 5×5-pixel filter window. The candidate filters were evaluated using a training image corrupted by a 20% noise (see Figure 1c).

5 Experimental Results

In this section the best resulting filter is presented and its filtering properties are compared with the conventional filters and the best filters obtained during our previous research [16].

### 5.1 Conventional Filters Considered for the Comparison

Center weighted median filter (CWMF) is a filter which is most suitable for hardware implementation because, in fact, it represents a slightly modified variant of the common median filter [7]. In this work we consider the center weight 3 and the kernel size 3×3 pixels. Another approach suitable for high-speed image processing is the adaptive median filter (AMF) [19]. In comparison with the CWMF the implementation cost of AMF is higher. However, the adaptive median filters exhibit significantly better filtering properties than standard median filters. The basic idea of the AMF is to utilize multiple stages during the filtering process in order to detect and replace the corrupted pixels only. Therefore, the AMF can be considered as a multiple-stage order statistic filter. In each stage a filtering window of different size is utilized. In this comparison, AMF that utilizes the kernel sizes up to 5×5 is used; our goal is to compare the quality of the filters working with the filter window consisting up to 5×5 pixels. Finally, we have chosen a filter that utilizes an advanced impulse detection technique based on the Pixel-Wise MAD (median of the absolute deviations

from the median) [4]. This filter is denoted as PWMAD. We have used the recommended settings of the PWMAD filter (5 iterations, the value of threshold 5 and the filter window 5×5 pixels). According to the results presented [4], this approach is capable to efficiently separate noisy pixels from the image details using the estimation based on absolute deviations from the median-MAD. However, in order to obtain reasonable results, the process of filtering has to be repeated iteratively. This leads to the increased memory requirements (to store the intermediate results) which is the main disadvantage of the iterative filters.

In order to compare the quality as well as robustness of the proposed resulting filters, the filters were evaluated using 25 randomly selected test images (384x256 pixels) from [2] that were corrupted by the aforementioned extended impulse burst noise with the intensity of 1-30% which means that each test image was corrupted by 10 different noise intensity and then filtered by a filter. Therefore, in total 250 images were utilized to evaluate the filters. During the evolutionary process, a 384x256-pixel training image was used in which 92,813 unique training vectors were identified. The noise model corresponds to the parameters $p = 0.01 \div 0.3$, $q = 128$, $\sigma = 30$.

5.2 Computational effort

The experiments were conducted on a cluster consisting of 100 PCs (Pentium IV, 2.4GHz, 1GB RAM) using the Sun Grid Engine (SGE). A highly optimized software implementation of CGP has been utilized. The evolution time of a single run is approximately 6 hours until the CGP algorithm reaches 150,000 generations.
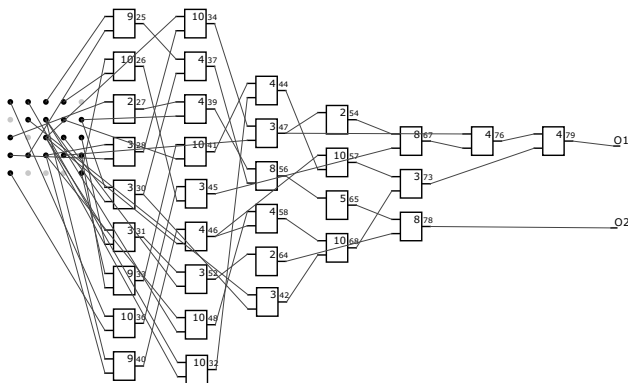
Figure 3. The structure of the best evolved filter for the extended impulse burst noise (the functions are numbered according to Table 2).

5.3 Properties of the Proposed Filter

The filter illustrated in Figure 3 exhibits the highest performance out of all the evolved filters. For evaluating the filtering quality, the average values of the peak signal to noise ratio (PSNR) and mean absolute error (MAE) were calculated over the set of test images and different noise levels. The PSNR is a widely used metric for evaluating of filtering quality, however, in some cases PSNR does not reflect the real situation correctly as it will be discussed later.

The quality of the proposed filter as well as the quality of the conventional filters from the point of view of PSNR, respective MAE, is shown in Figure 4 – parts (a) and (b). In order to evaluate the filtering quality of the proposed filter objectively, we have filtered several images corrupted with various intensity of the extended impulse burst noise and calculate the average values of PSNR and MAE. If the PSNR criterion is considered, the higher the PSNR value, the better filtering quality. On the contrary, the lower MAE value, the better filtered image. As evident, the proposed filter exhibits the best filtering quality in comparison with all the conventional filters mentioned in Section 5.1 even if we do not apply iterative filtering. As it has been mentioned, the PSNR does not reflect the real situation well especially if the noise intensity is lower; the visual quality does not correspond with the obtained results. Looking at the filtered images (e.g. see Figure 5), at least CWMF has to obtain lower score since the filtered images are smudged (CWMF modifies all the pixels regardless of certain pixels being corrupted or not). As it is clearly evident from Figure 4, the conventional AMF and CWMF filter produce images that exhibit even worse quality in comparison with the corrupted image for the noise intensity approximately lower than or equal to 4% (i.e. the MAE of the filtered image is greater than the MAE of the corrupted image).

Figure 5a-d show an image corrupted by 1% noise that was filtered using the proposed filter and various approaches. The conventional filters whose results are showed in Figure 5a-c were chosen to compare with the proposed filter because they provide the best results from the list of conventional filters mentioned in Section 5.1. Figure 5d shows that the proposed filter exhibits very good quality even for the lower noise intensity – in this case 1% impulse burst noise has been generated. In case of the image filtered by the PWMAD filter, we can see that a perceptible part of the noise remains in the image (see Fig. 5c). In contrary, the image produced by the CWMF does not contain any impulse, however, the image is smudged and lacks the details in comparison with the original image.

Similar comparison was performed considering the images corrupted with higher noise intensity (30% impulse burst noise). The obtained results are shown in Figure 5e-h. Whilst the proposed filter is able to remove most of the
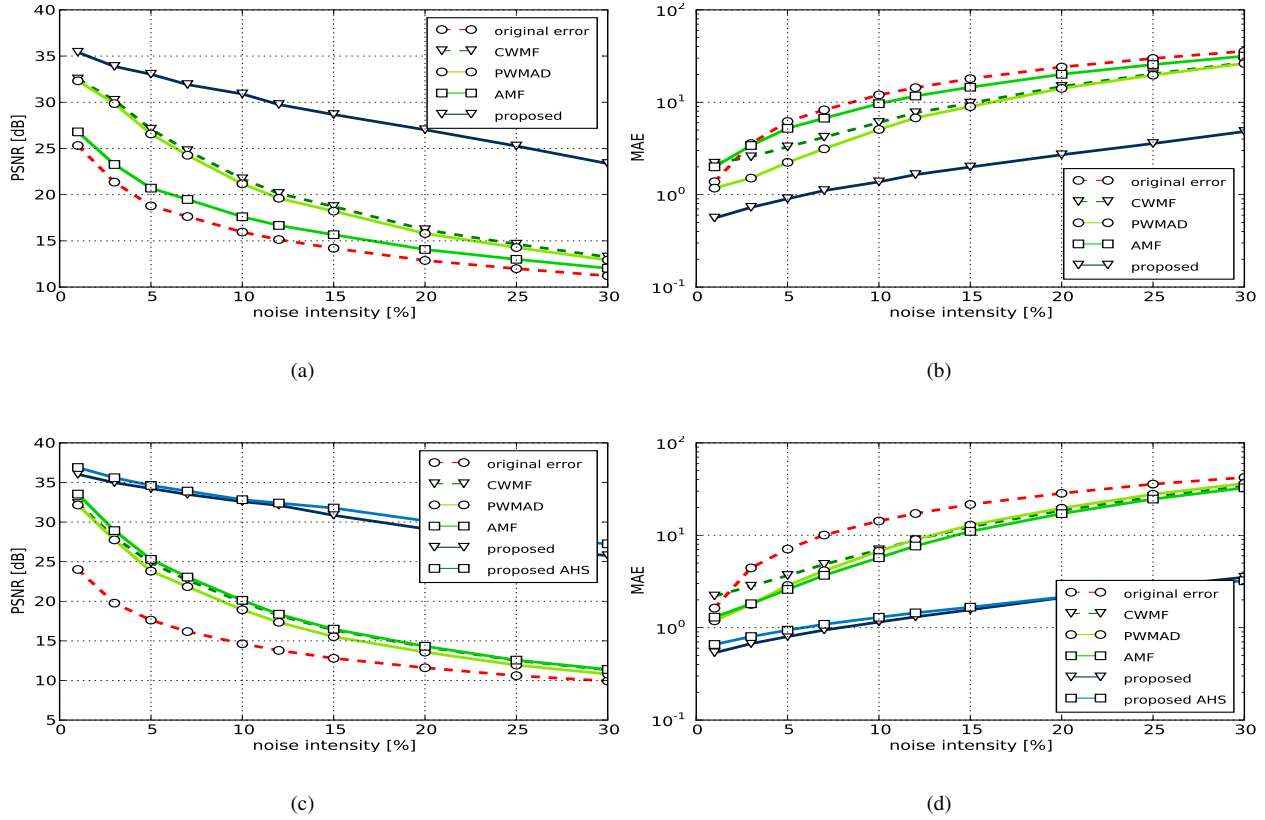
Figure 4. The average PSNR and MAE calculated using 25 test images for different levels of noise intensity. Parts (a) and (b) shows the results for the best filter proposed in this paper in comparison with the conventional filters. Parts (c) and (d) show the comparison for white burst noise considering the proposed filter, the best previously evolved filter for this kind of noise (denoted as 'proposed AHS' [16]) and the conventional filters.

noise, the conventional filters have serious problems and fail to remove the noise. The failure of the conventional filters probably lies in the fact that the bursts are accumulated in the neighbouring rows of the image an thus it is difficult to estimate the correct pixel values using median filter.

In comparison with the previous results, the following example represents a serious problem for the filters. Figure 6 shows an image containing several sharp and contrast transitions that are very similar to the noise. Even if the proposed filter is able to provide better image (shown in Fig. 6d) in comparison with the CWMF and PWMAD filter, it can be seen that the image is degraded slightly.

In order to demonstrate the robustness of the proposed filter, a comparison of the filter proposed in this paper with the best filter obtained in our previous research [16] was performed. The results of the filtering quality are shown in Figure 4 – parts (c) and (d). It is important to note that in only white impulse burst noise was considered [16] (i.e. the

entire burst only consists of white pixels; note that in this paper the bursts also contain some degrees of gray). The filter from [16] is denoted as 'proposed AHS' in Figure 4c,d. It is evident that although the proposed filter was trained to more complex impulse burst noise, it substantially outperforms the conventional filters if the white burst noise is considered. For the PSNR its results are slightly worse in comparison with the 'proposed AHS' filter (see Fig. 4c) but on the other hand the MAE is better especially for lower noise intensity (see Fig. 4d). When we performed a visual comparison of the filtered images, it was hard to see a difference. The robustness of the proposed filter is also supported by the fact that (1) it exhibits very good filtering quality even for higher noise intensity (note that the filter has been trained using a 20% impulse burst noise), overcoming the conventional filters which were considered for comparison, and (2) the filter is able to successfully process different images (affected by the same or similar kind of im-
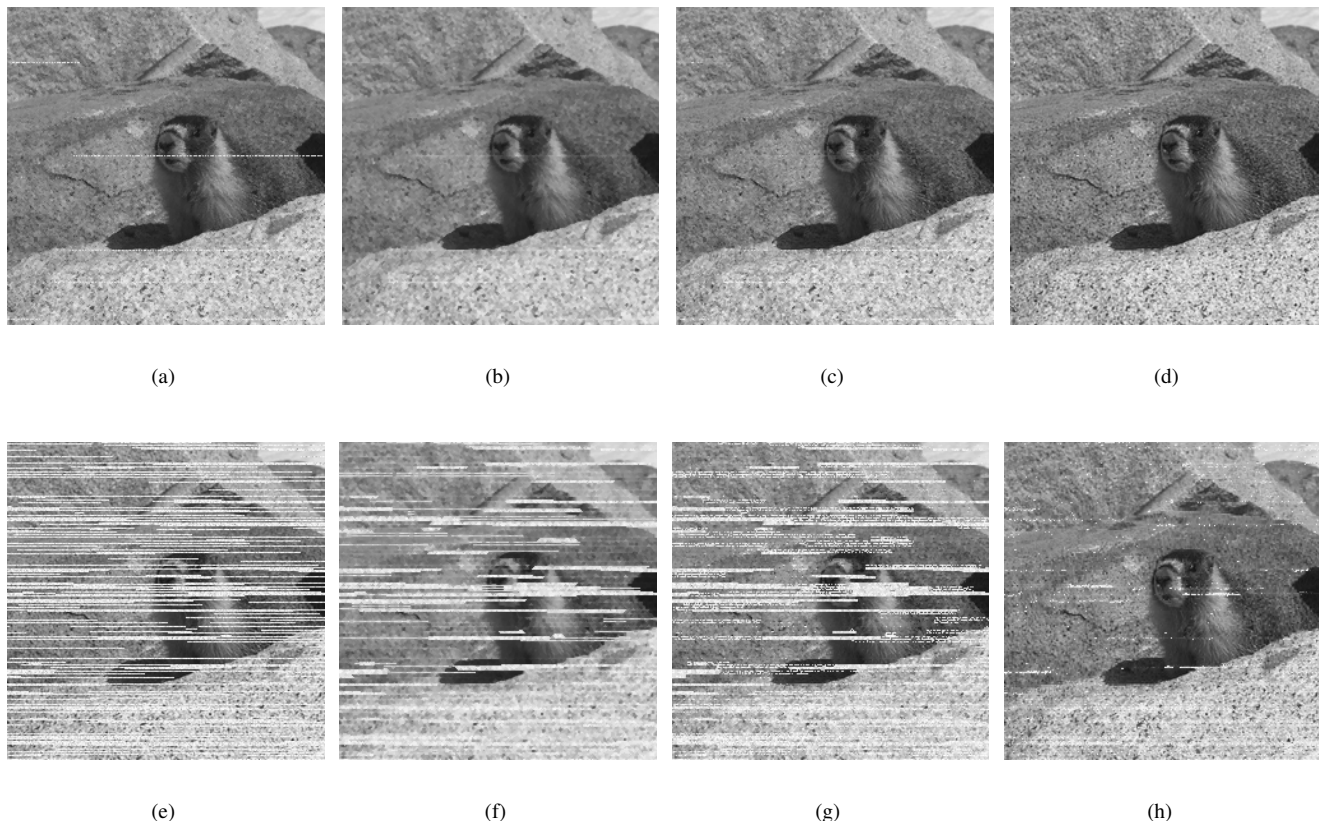
Figure 5. The results (a)-(d) show the 1% extended impulse burst noise filtered by (a) AMF, (b) CWMF, (c) PWMAD and (d) the proposed filter. The results (e)-(h) show the 30% extended impulse burst noise (e) by means of (f) CWM, (g) PWMAD and (h) the proposed filter.

pulse noise) which were not considered during the evolution of the filter.

It is interesting to note that the proposed filter is efficient not only from the point of view of the filtering quality but also from the point of hardware/software implementation – it consists of simple operations and does not require iterative processing.

6 Conclusions

The paper presented an evolutionary approach based on CGP for the automatic design of switching image filters. The concept of so-called switching filters was utilized that combines the filter logic with a noise detection algorithm. The idea of this algorithm is to determine whether the filtered pixel is a noisy pixel or not. In particular, we focused on designing a filter for an extended variant of impulse burst noise which is close to the type of noise occurring in real images.

The best filter that we presented in this paper exhibits an efficiency from the point of view of the filtering quality in which it overcame the conventional filters it was compared with. A training image was utilized by means of which the evaluation of the filters during the evolution was performed. The proposed filter showed its ability to remove most of the noise of different intensity from a set of test images. The resulting quality of the filtered images was very good in comparison with the outcomes of the conventional filters. These features of the proposed filter were demonstrated on different types of images from a test set.

Acknowledgments
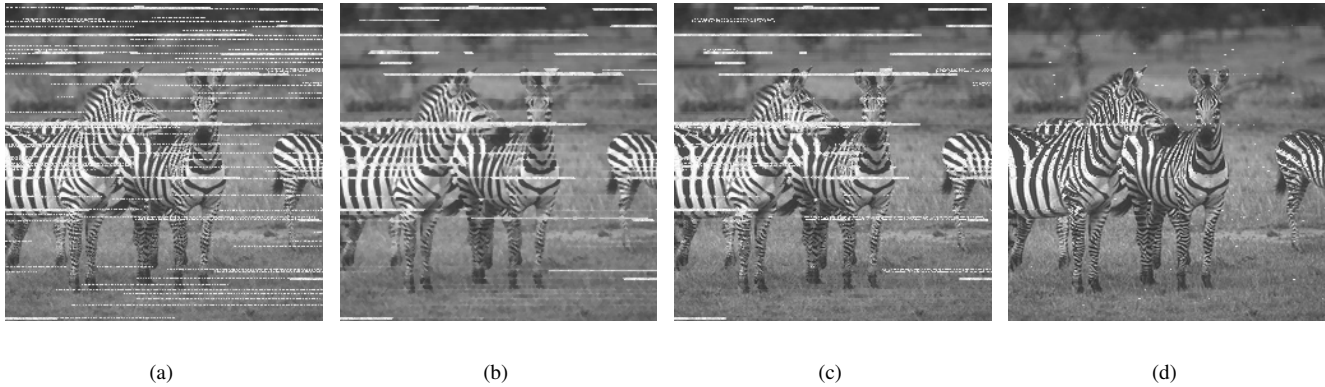
Figure 6. 15% extended impulse burst noise filtered by (a) AMF, (b) CWMF, (c) PWMAD and (d) the proposed filter.

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