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Noise Generation Methods Preserving Image Color Intensity Distributions

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Abstract: *In many visual perception studies, external visual noise is used as a methodology to broaden the understanding of information processing of visual stimuli. The underlying assumption is that two sources of noise limit sensory processing: the external noise inherent in the environmental signals and the internal noise or internal variability at different levels of the neural system. Usually, when external noise is added to an image, it is evenly distributed. However, the color intensity and image contrast are modified in this way, and it is unclear whether the visual system responds to their change or the noise presence. We aimed to develop several methods of noise generation with different distributions that keep the global image characteristics. These methods are appropriate in various applications for evaluating the internal noise in the visual system and its ability to filter the added noise. As these methods destroy the correlation in image intensity of neighboring pixels, they could be used to evaluate the role of local spatial structure in image processing.*

Keywords: *Visual Noise, Gaussian Noise, Image quality, image power spectrum.*

1. Introduction

Image noise is considered a nuisance in most areas of scientific disciplines and applications. It usually occurs due to defects in the imaging technologies. As a result, random fluctuations of image brightness or color occur. However, using image noise contributes significantly to broadening our understanding of information processing of visual stimuli as noise from different sources is inseparably added to the sensory signal and complicates and changes our perception [1]. It has been applied in studies comparing the performance of different populations varying in age or health conditions in different tasks. The main idea underlying this methodology is based on the assumption that two sources of noise limit sensory processing: the external noise inherent in the environmental signals [2] and the internal noise or internal variability at different levels of the neural system [3, 4]. P e l l i and F a r e l l [5] explain that comparing sensitivity to stimulus characteristics with and without background noise allows separating the observer's ability of information processing from the observer's intrinsic noise. Visual noise, added to images is widely used to explore visual system characteristics in different diseases such as amblyopia [6], X-linked retinoschisis [7], glaucoma [8], age-related changes of visual functions [9] neural variability between children with Autism Spectrum Disorder and typical development, e.g., [10, 11].

Filtered noise allows specifying the spatial frequencies relevant to specific tasks' performance (e.g., letter identification, [12]). Filtered letters or other filtered visual objects have been used to study, for instance, contrast sensitivity [13], differences in binocular vision between emmetropia and myopia [14], spatial-frequency content for recognizing Chinese and alphabet characters [15], the effects of practice on sensitivity in a visual detection task [16], audiovisual speech perception [17], the effect of character sample density on legibility [18], etc.

Another application of image noise in studying visual information processing is in image classification [19, 20, 1] to reveal what image characteristics are essential for this task.

Using noise to mask a given image characteristic allows specifying whether this characteristic is processed independently [21, 22] and has been used to investigate unconscious visual processing [23, 24] or to an applied machine learning approach to psychophysical studies of second-order visual processing [25].

Different types of external noise have been added to the display depending on the target stimuli, technical opportunities, research purposes, etc. The most popular noise type added in visual perception studies is Gaussian [26-28]. Several studies (e.g., [29-32]) have used pixel noise, and others use white noise, e.g., [33].

Irrespective of the noise characteristics, the main problem that arises when adding background noise to the stimulus is that it modifies the original image's characteristics like luminance or color; hence, it is unclear whether the visual system responds to their change or the presence of noise. Sometimes the stimulus is temporally sandwiched by two independent external noise samples [34], or the stimulus is embedded in visual noise by using two computer displays [35]. However, it is much more convenient to use a single monitor and avoid eventual problems connected to the synchronization of the monitors or interference from the temporal characteristics of the visual system. Hence, a methodology that keeps the luminance and color characteristics unchanged would benefit a better understanding of the processing of the temporal and spatial image characteristics by the human visual system. Moreover, we could not find in the literature a methodological approach that could manipulate letters and other visual objects in such a way to produce different strictly controlled quantities of noise while at the same time preserving the main image characteristics. Consequently, we aimed to develop several methods of noise generation that keep the global image characteristics – image intensity and contrast. We have created four methods that correspond to the most widely used noise type in visual information processing studies. In the first, the noise distribution is uniform; in the second it is Gaussian; the others generate pixel noise.

This paper is organized as follows: in Section 2, is presented the methodology of the different types of noise generation briefly; Section 3 presents the results of the applications of the generated noise on selected images; Section 4 is devoted to analysing the effects of noise on the image characteristics; in Section 5 the potential application of the presented noise types is discussed; discussion and conclusion are made in Section 6.

2. Methods

2.1. Pseudo-random noise

The noise level is determined by the number of pixels (*N*) that change color. This number must be less than or equal to the total number of pixels. The procedure involves a sequential generation of triples of random integers from the uniform distribution on the set 0 to 255. We will label them “noise pixels”. The difference between the original and the noise pixels is monitored.

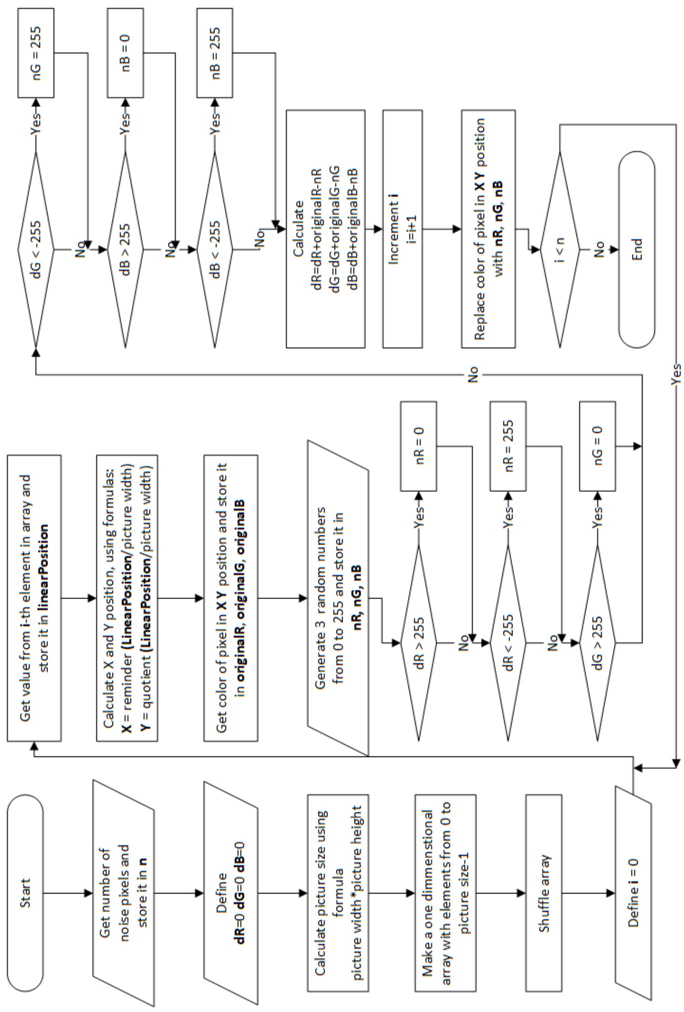

Fig. 1. Block-diagram of the pseudo-random noise generation

Fig. 1 presents a block-diagram of the pseudo-random noise generation. At each step of the procedure, a new noise pixel (*nR*, *nG*, *nB*) is generated, and its components can be modified depending on the difference (delta) between the original pixel color and the noise pixel color from the previous step. For the first pixel in the shuffled array, delta is set to 0. For the next pixels, if any of the components of delta is greater than 255, the value of the corresponding channel *nR*, *nG*, or *nB* is set to 0. If some of the differences *dR*, *dG*, or *dB* are less than 255, the corresponding channel of the noise pixel is set to 255. The original pixel is replaced by the noise pixel, and the value of delta is modified by adding the new color difference. Hence, the dynamic range of the images is kept in the range 0-255.

The procedure is repeated *N* times. As a result, we have an image with added random noise whose mean colors differ from the original image very little,

(1)
$$nK(1) = \text{randi}(0, 255),$$
$$dK(i) = \begin{cases} 0, i = 1, \\ K(i) - nK(i), i = 2, \dots, N, \end{cases}$$
$$nK(i+1) = \begin{cases} 0, \text{randi}(0, 255) + dK(i) > 255\,, \\ 255, \text{randi}(0, 255) + dK(i) < -255, \\ \text{randi}(0, 255) + dK(i), \end{cases}$$
$$K = \{R, G, B\}, i = 1, \dots, N.$$

In (1), randi(0, 255) stands for random scalar integer generation from a uniform distribution with a range between 0 and 255.

2.2. Modified Gaussian noise

The noise level is defined as the number of pixels (*N*) to which noise values are added or subtracted. The value of *N* should be less or equal to half of image pixels.

The noise pixels are generated as triples drawn from a normal distribution with a predefined mean and variance corresponding to the three color channels. For each odd pixel up to *N*/2, the values of the noise pixels are added. For the even values, the noise pixels are subtracted from the original ones (Fig. 2). In this way, the magnitude of change in each channel *R*, *G*, and *B* values for every two subsequent pixels in the shuffled array is the same but differs in sign. If some of the resulting values of *R*, *G*, or *B* are greater than 255, this value is set to 255. If some resultant *R*, *G*, or *B* values are smaller than 0, this value is set to 0. In this way, the brightness of the image varies in the range of 0-255. This procedure is repeated *N*/2 times. As a result, we have an image with added random noise from a normal distribution whose mean color intensities differ from the original image very little. The next equation represents the noise generation method:

(2)
$$dK(i) = \text{nrand}(\mu, \sigma), i = 1, \dots, N/2,$$
$$nK(i) = \begin{cases} K(i) + dK(i), i = 2n + 1, n = 1, \dots, N, \\ K(i) - dK(i), i = 2n, n = 1, \dots, N, \end{cases}$$
$$K = \{R, G, B\}.$$

In (2), nrand(μ, σ) stands for random number generation from a normal distribution with mean = μ and standard deviation equal to σ.

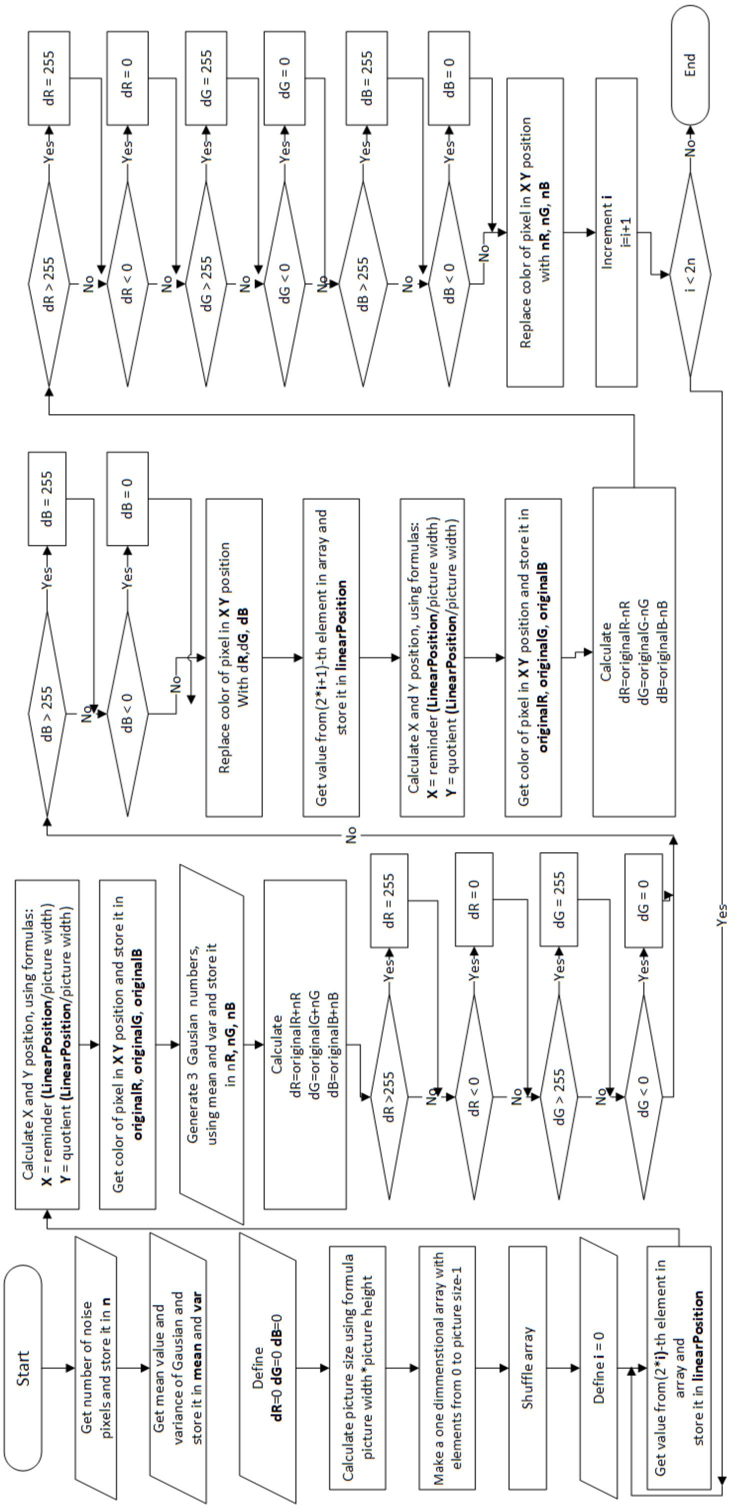

Fig. 2. Block-diagram of the modified Gaussian noise generation

2.3. Two colors exchange

The exchange noise methods generate pixel noise. The two-colors method is similar to the “Salt-and peper” noise:

$$\text{PDF}(g) = \begin{cases} P(\text{color1}), g = \text{color1}, \\ P(\text{color2}), g = \text{color2}, \\ 0, g \neq \text{color1}, \text{color2}. \end{cases} \quad (3)$$

In (3), PDF is the Probability Density Function of the noise, P – the probability of replacement of image pixels with color1 or color2. Contrary to the common method of generation of this type of noise, in our method P(color1) = P(color2), and the pixel replacement is spatially restricted. The value of P depends on N – the number of pixels to be changed.

Two colors – “color 1” and “color 2”, are chosen. Each of these colors must be present in the original image. The noise level is defined as the number of pixels (N) that will exchange color. This number should be less or equal to the smallest number of pixels with either “color 1” or “color 2”. In order to have a visible effect on the image appearance, the smallest number of pixels for color1 or color2 should be 10%. The block-diagram of the procedure is shown in Fig. 3.

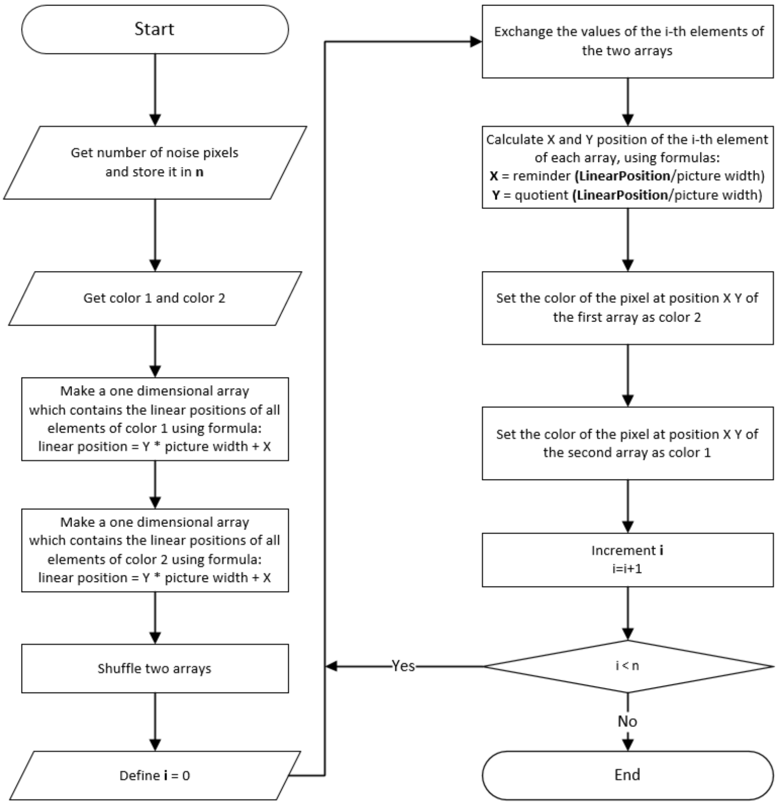

Fig. 3. Block-diagram of two colors-exchange noise generation

Each pixel in the array of coordinates is tested for having either “color 1” or “color 2”. The coordinates of the pixels with “color 1” and “color 2” are stored in two arrays. The members of both arrays are shuffled. The first *N* elements in the two arrays are exchanged. In this way, exactly *N* pixels with “color 1” change their color to “color 2” and vice versa. As a result, the number of pixels with “color 1” and “color 2” in the transformed image is the same as the initial image. This procedure could be repeated for any pair of colors in the image.

2.4. Random exchange

The noise level is defined as the number of pixels (*N*) that will exchange color. This number must be less than or equal to half the total number of pixels. Fig. 4 presents the block diagram of this noise generation. Essentially, each pair of subsequent elements in the shuffled array of size 2*N* exchange colors. As a result, the final image has the same color pixels as the original, but these pixels may be in a different location.

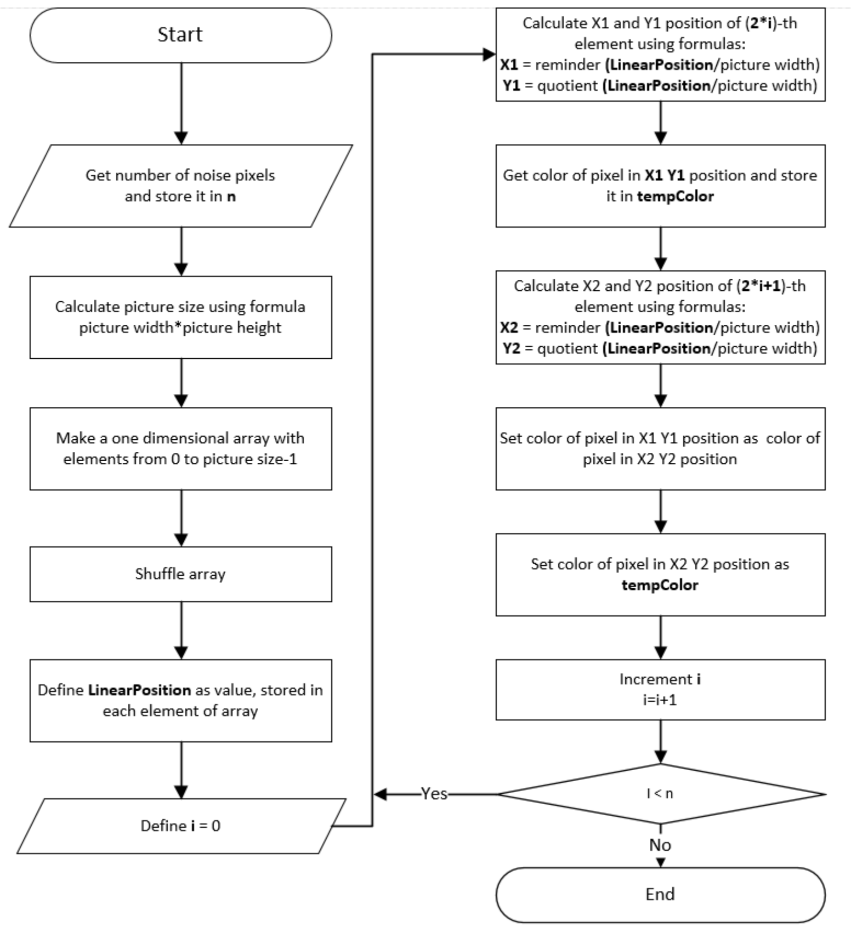

Fig. 4. Block-diagram of the random exchange noise generation

3. Results

We have tested the proposed methods for generating noise on two different images. The first was just a geometrically created image that contains only six colors. The image have approximately the same number of pixels of each color. It allows for evaluating the effects of the noise application in simplified conditions. The second image is a natural picture. Both images have been processed to a size of 1000×1000 pixels. The results of the applied noise are presented in Fig. 5 and Fig. 6. For the pseudo-random and modified Gaussian methods, we have used a noise level of 50%. For the modified Gaussian noise, the mean has been set to 64 and the standard deviation – to 32 for each color component. For the 2-colors exchange method, the noise level has been 50% from the color with minimal pixel numbers. The noise level for the random exchange noise method has been set to 30%. This is the highest level at which the original image could be resolved.

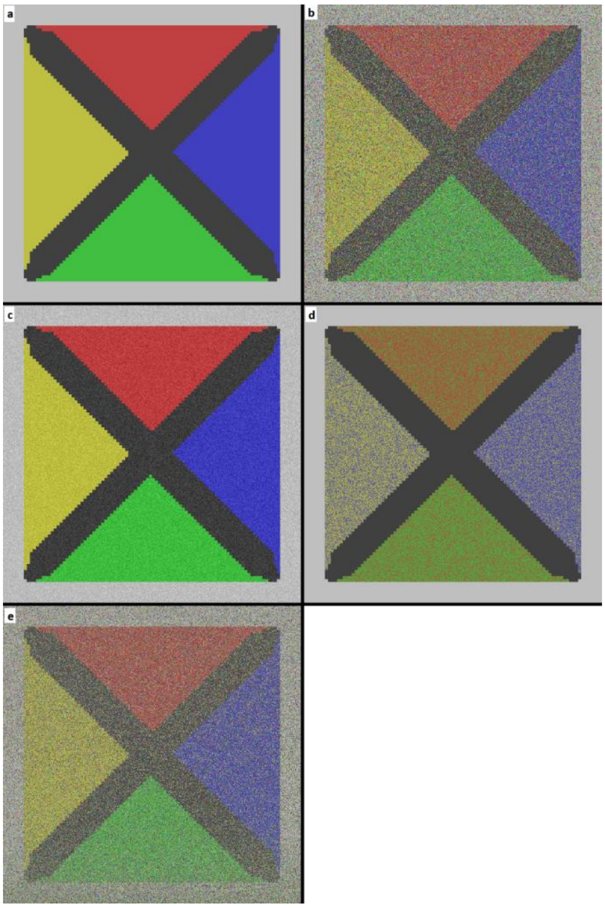

Fig. 5. Different noise types applied to the geometric designed image with six colors: original image (a); pseudo-random noise (b); modified Gaussian noise (c); two colors exchange noise (d); random colors exchange noise (e)

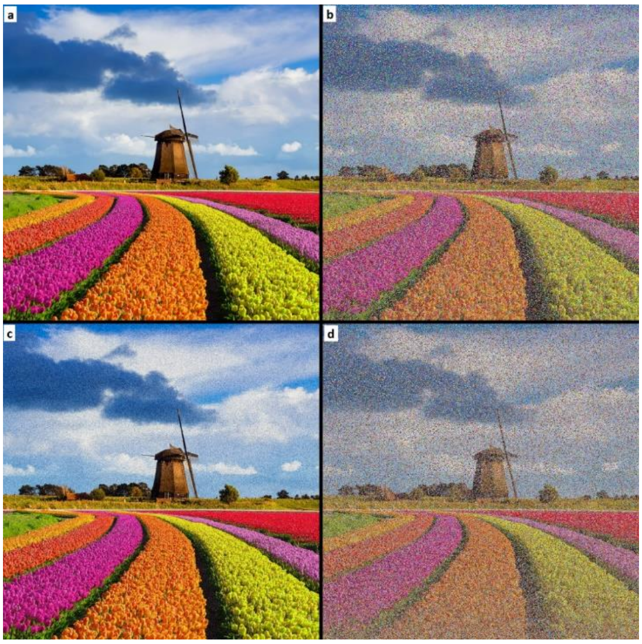

Fig. 6. Different noise types applied to the natural image with multiple colors: original image (a); pseudo-random noise (b); modified Gaussian noise (c); random colors exchange noise (d)

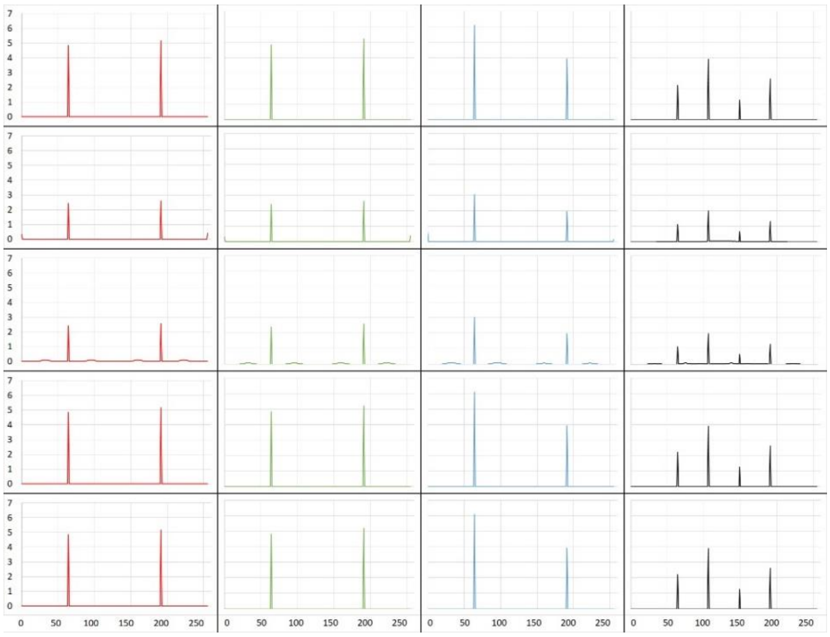

Fig. 7. Image histogram for the geometric image. The colors correspond to the *R*, *G*, *B* components, black – to the luminosity. The abscissa represents the brightness values; the ordinate – the number of pixels times 10^5. First row – original image; second row – pseudo-random noise; third row – modified Gaussian noise; fourth row – 2-color exchange noise; fifth row – random-color exchange noise

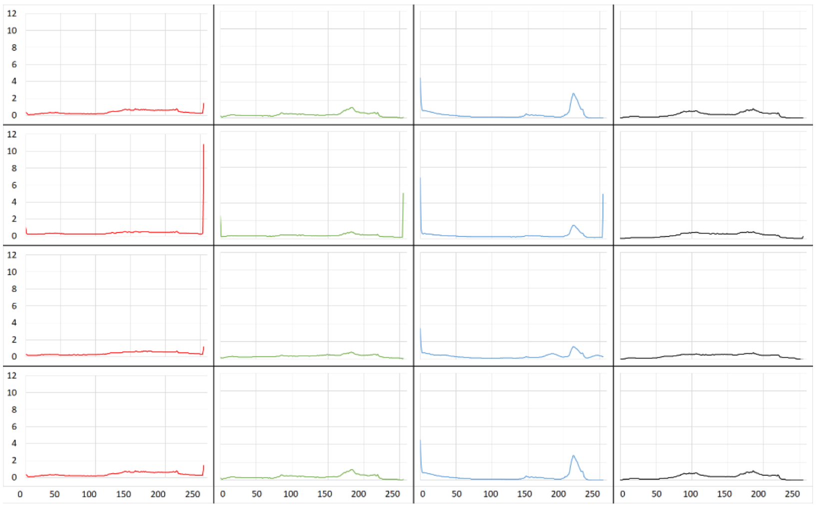

Fig. 8. Image histogram for the natural image. The colors correspond to the *R*, *G*, *B* components, black – to the luminosity. The abscissa represents the brightness values; the ordinate – the number of pixels times 10^4. First row – original image; second row – pseudo-random noise; third row – modified Gaussian noise; fourth row – random-color exchange noise

The spectral distribution of each component of color (*R*, *G*, *B*) and luminosity of the original and the modified by noise images are presented in Fig. 7 and Fig. 8. Table 1 and Table 2 show the average values of the color components (*R*, *G*, *B*) and luminosity in each image. We do not apply the two-colors exchange method to the natural image as there are very few pixels of a single color and the results of its application are not apparent.

Table 1. Average values of the color components (*R*, *G*, *B*) and luminosity in the Geometric images with added different noise types

IMAGE	*R*	*G*	*B*	*L*
Geometric without noise	129.48	129.91	113.76	124.30
Geometric with random noise	129.48	129.91	113.76	124.34
Geometric with Gaussian noise	129.48	129.91	113.76	124.30
Geometric with 2 colors exchange noise	129.48	129.91	113.76	124.30
Geometric with random colors exchange noise	129.48	129.91	113.76	124.30

Table 2. Average values of the color components (*R*, *G*, *B*) and luminosity in the Natural images with added different noise types

IMAGE	*R*	*G*	*B*	*L*
Natural without noise	150.80	133.89	128.22	137.63
Natural with random noise	150.80	133.88	128.22	137.64
Natural with Gaussian noise	150.35	134.34	129.62	138.10
Natural with random colors exchange noise	150.80	133.89	128.22	137.63

4. Effect of the noise type on the image characteristics

The common characteristic of the methods of noise generation considered here is that they change very little the spectral characteristics of the images. Due to range effects, the pseudo-random noise method induces more significant differences in the color intensity distribution. Both exchange methods preserve the spectral image distributions; however, they change the spatial correlation of image intensities of the neighboring elements, an essential characteristic of the natural images to which the visual system has evolved.

Interestingly, entropy – a measure used to describe the randomness of a texture is equal to the original when the exchanged noise is applied to the image. It changes most for images with random noise. We have estimated (Table 3) also some of the metrics used for evaluating the image quality like the mean squared error, the peak signal-to-noise ratio (psnr), and the structural similarity index (ssim). The psnr gives the ratio of the mean-squared error and the maximal range of image pixels. The ssim assesses the impact of the noise on the luminance, contrast, and structure of the images [36]. The changes in these image characteristics are evaluated considering the peculiarities of the human visual system – its sensitivity to a relative, not absolute, luminance change and lower sensitivity to high than to low contrast. It evaluates the structural changes after luminance subtraction and variance normalization used to account for the contrast changes. The mse metric shows that the difference with the original is least for the image with added Gaussian noise and maximal – when the added noise is random. Similarly, the ssim measure evaluates the image with added Gaussian noise as most similar to the original and the images with random and random exchange noise as equally dissimilar to it. The psnr metric determines the image with added Gaussian noise as most deviant from the original.

Table 3. Measures comparing the modified images with the original. The entropy is also given

IMAGE	entropy	mse	psnr, dB	ssim
Geometric without noise	0.998	-	-	-
Geometric with random noise	5.243	5455.70	10.76	0.21
Geometric with Gaussian noise	4.771	511.94	21.04	0.55
Geometric with 2 colors exchange noise	0.998	2688.17	13.84	0.64
Geometric with random colors exchange noise	0.998	4744.38	11.37	0.22
IMAGE	entropy	mse	pnsr	ssim
Natural without noise	7.792	-	-	-
Natural with random noise	7.678	6284.78	10.15	0.25
Natural with Gaussian noise	7.911	454.83	21.55	0.77
Natural with random colors exchange noise	7.792	6322.16	10.12	0.22

We have performed Fourier analysis to understand better the effects of the applied noise on the spatial image characteristics. To better understand the noise effect on the spatial frequency content of the images, the logarithm of the circularly averaged spectrum has been estimated and presented in Figs 9 and 10 as a function of spatial frequency for the two sample images we have used. The total power of the spectrum is related to the root-mean-square-contrast of individual images. As the generated noise changes little the luminance and color image characteristics, the total power spectrum is almost preserved. However, the added noise modifies its distribution over the different spatial frequencies and distorts the typical dependence of the power spectrum on the spatial frequency of $1/f^{\alpha}$ with α close to 2. Applying the proposed impulse noise types – random or exchange noise changes the exponent and the linearity of the power spectrum dependence on spatial frequencies. By flattening the power spectra, these noises reduce the second-order redundancy in the corresponding image.

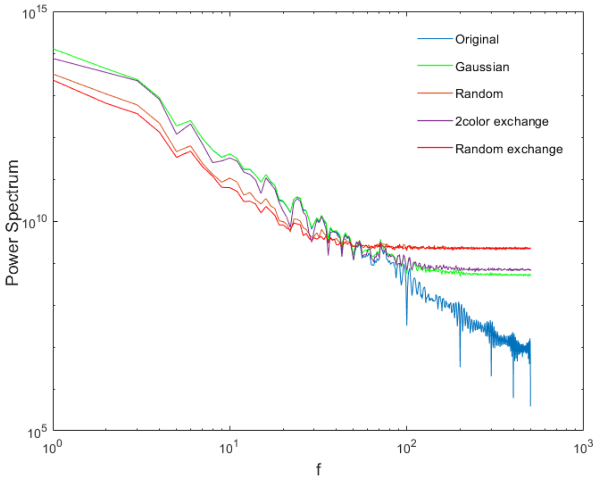

Fig. 9. The circularly averaged power spectrum of the original geometric image and itsmodified by noise vesions. Both axes are logarithmic

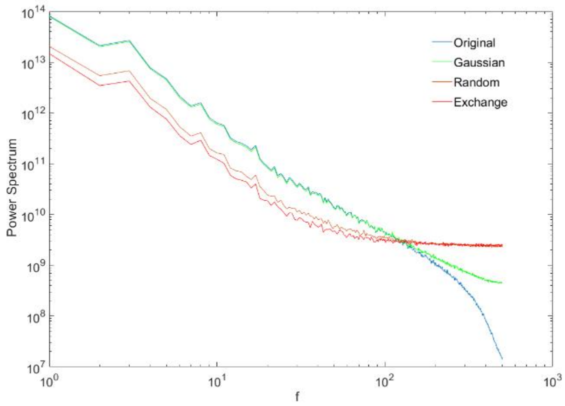

Fig. 10. The circularly averaged power spectrum of the original nature image and its modified by noise versions. Both axes are logarithmic

5. Potential application of the proposed noise types

While here we have present the results of the noise application only for two images, we have applied the proposed methods of generation on several images with different complexity. The findings we obtained confirm the conclusions about the noise effects: the proposed noise types preserve the global image characteristics – the mean luminance and the image histogram. Some distortions in the image histogram have been observed for the random and the Gaussian noise. The noise effect mostly depends on the spatial and local image characteristics.

The human visual system is supposed to be adapted to the statistical regularities in the environment [37]. Hence, adding either of the noise types we have presented may promote the understanding of the role of the environment in modeling the structure of neural computations. The exchange noise is the most appropriate of the noise types we have proposed because it preserves luminance and image color characteristics. By varying the noise level and hence, modifying the power spectrum's spatial-frequency distribution, it would be possible to study its effect in different tasks like identification and classification. This manipulation would allow investigation of the role of redundancy in visual information processing. Moreover, this noise type might be used for studying the normalization mechanisms of contrast in human vision. This mechanism is supposed to encode the total contrast in a local image patch effectively [38].

We have applied the 2-color exchange noise generation method in a study of reading [39]. The results of noise application have distorted the letters in words and allowed us to distinguish its effects on the reading performance of groups with different development.

The proposed method of Gaussian noise generation is a better alternative to the standard white noise used in the studies aiming to evaluate the internal noise in different populations and tasks as it leaves the luminance and color characteristics of the image unchanged. It also preserves the image characteristics similar to the original at low spatial characteristics. Manipulating the standard deviation would allow evaluating the range of spatial frequencies relevant for each task.

The proposed noise types may refine the similarity metrics in image quality analysis.

6. Discussion and conclusion

Our need to modify the existing methods for noise generation resulted from the necessity to add strictly controlled amount of noise to text stimuli in order to degrade the letter structure while preserving the main characteristics of the image. Adding „Salt-and-Pepper“ did not allow good control of the amount of added noise as the spatial positions of the black and white pixels are random.When black pixels fall on the text letters, they leave them unchanged. When white pixels fall on the space between the letters, nothing changes. These difficulties provoke us to seek other methods and to investigate their charasterisrics.

The standard methods of adding visual noise to an image correspond to the naturally occurring noise during image generation [40]. Irrespective of the type of added noise (additive, multiplicative, or impulse), all of them change the image characteristics. For example, the most frequently used additive noise, the Gaussian noise, changes the mean and standard deviation of image intensity even when the mean of the Gaussian distribution of the added noise is zero due to its random generation [41]. This type of noise generation ignores the pixel values in the image. Similarly, the most commonly used impulse noise – the 'Salt-and-pepper' noise changes the number of occurrences of color combinations [41], disregarding the pixel intensities in the image. When imposing either Poisson [42] or speckle [43] noises, the pixel intensities in the image are taken into account, but again, the image histogram changes significantly.

The methods of noise generation that we propose are better alternatives to the most widely used noise types. The Gaussian noise generated by our procedure keeps the color intensity distributions and the spatial structure of the image almost equivalent to the original. The exchange methods maintain the number of pixels of each color in the image, the mean color intensity, and its standard deviation and entropy. They affect the spatial structure similar to the random noise. The 2-color exchange method is suitable for images that contain a restricted number of colors. It leaves the color image characteristics constant regardless of the number of consecutive applications of the method and the choice of colors to be exchanged. The random-exchange method is appropriate for images with multiple colors, like natural scenes. It is also a good alternative to the “Salt-and-pepper” noise for adding background visual noise.

Concerning the critical steps in the protocol, it is important to correctly program the procedures. To avoid potential mistakes, we recommend using our program “BMP Noise Generator” which can be downloaded at http://autism-vision.bas.bg/.

At present, the program is limited to the processing of only bmp files. The software has been verified for all methods on images from 4 to 50.10^6 pixels. It could be supposed that it will process bigger images successfully.

In conclusion, the proposed methods of noise generation lack the disadvantages of the most widely used methods of investigating human visual information processing and offer new possibilities for its understanding.

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