similarity). We would like to remind the reader that power-law does not imply self-similarity or fractality refer to power-law distributions as fractal distribution and unlike mathematical fractals, geophysical and geological phenomena present fractal behavior within a limited scale range [3].

II. Multifractal signal and phenomena

In real world most phenomena cannot be expressed in terms of two limiting states such as: black and white, true and false, hot and cold, 1 and 0, etc. Therefore, these aspects demand more general mathematical objects for a successful description of levels between two limiting states. Those more general objects are called measures. Instead of one quantity, or measure, μ, describing the phenomenon in all scales - when we talk about fractals, a set of measures, $\sum_i \mu_i$ (a sort of weight factors) describing statistically the same phenomenon in different scales has to be used for describing such structures. Consequently, a theory of self-similarity is extended from fractals to multifractals. For instance, consider a 2D signal such as the gray scale image. For describing an object of the image, the box-counting method is not appropriate since it gives only a relation between non-empty boxes and the box size, regardless of the signal level into the boxes. Figuratively speaking, simple counting the boxes is like counting money without caring about the value of banknotes [4].

By considering multifractals the signal value (the measure μ_i) within the box is embedded into the process of signal characterization.

At the first step, the quantity α

$$\alpha = \frac{\log \mu(box)}{log\varepsilon} \tag{1}$$

called the coarse Hölder exponent, is derived. This is the logarithm of the measure of the box, μ(box), divided by the logarithm of the size of the box. In this way the coarse Hölder exponent corresponds to the fractal dimension of the measure. For a large class of multifractals the value of α is restricted to an interval $[\alpha_{\min}, \alpha_{\max}]$, where $0 < \alpha_{\min} < \alpha_{\max} < \infty$. Note that the value of α is close to the corresponding fractal dimension of the structure under observation; that means that for 1D signals (having the level m) this value is close to 1, for 2D signals close to 2, etc. Once α has been derived, the frequency distribution of this parameter has to be established, as follows. For each value of α, one evaluates the $N_\varepsilon(\alpha)$ of boxes of size ε having the coarse Hölder exponent equal to α. Since the total number of boxes of size ε is proportional to ε^{-D_E}, where D_E is the Euclidean dimension of the box, the probability of hitting the value of α is $p_\varepsilon(\alpha) = N_\varepsilon(\alpha)/\varepsilon^{-D_E}$.

Drawing the distribution of this probability would not be useful since as ε → 0 this distribution no longer tends to a limit. Instead, it is more appropriate to consider the functions

$$f_\varepsilon(\alpha) = -\frac{\log N_\varepsilon(\alpha)}{\log\varepsilon} \tag{2}$$

or

$$C_\varepsilon(\alpha) = -\frac{\log p_\varepsilon(\alpha)}{\log\varepsilon} \tag{3}$$

As , both functions tend to well-defined limits f(α) and C(α). The function f(α) is more widely used. When f(α) exists one has

$$C_\varepsilon(\alpha) = f_\varepsilon - D_E \tag{4}$$

Such definition of $f(\alpha)$ means that, for each a, the number of boxes increases for decreasing e as $N_\varepsilon(\alpha) \sim \varepsilon^{-f(\alpha)}$. Exponent f(α) is a continuous function of α. In many cases the graph of has f(α) the parabolic shape, having the maximum near α=1 (for 1D signals),or near α =2 (for 2D signals). The values of f(α) could be interpreted as a fractal dimension of the subset of boxes of size ε having coarse Hölder exponent a as ε → 0. Namely, when ε tendsto 0, there is an increasing multitude of subsets, each characterized by f(α) its own α and a fractal dimension. In this paper, for the purposes of simulating 2D multifractal spectrum by histogram method is used [4].

III. Materials and methods

In this paper, two experiments were performed. The first experiment is performed by copying an existing object in the different parts of the same image, as follows: upper right corner, upper left corner, lower right corner and the lower left corner. This affects the brightness, and thus the multifractility of the images, inserting an object that does not object which does not correspond to environment of existing image. It is expected to be incurred additional "unnaturalness" depending on the statistical nature of local parts of image. Here, that is demonstrated in the case of a typical indoor shooting (daily shooting without flash and artificial lighting) and moving the scaled object to the appropriate local parts (upper right corner, upper left corner, lower right corner and the lower left corner.) By copying the existing objects, is considered that it will not undermine the general characteristics of existing images to a large extent.

In the second experiment, it was testing the impact of statisctic of subsequently added object which can’t significantly alter the multifractal spectrum of original image. Subsequently added object was scaled and copied from other image, generated by the same camera, in the indoor environment and by use of artificial lighting.

All changes, for the purpose of testing, were performed in Photoshop. Multifractal spectrum is determined by histogram method. For the purpose of comparison of multifractal spectrum, parameters like minimum and maximum value α, and the area under $f(\alpha)$ for fixed values of α_1 and α_2 were used, in order to highlight differences in the modifications.

IV. Experiment 1

The first experiment is performed by copying an existing object in the different parts of the same image, as follows: upper right corner, upper left corner, lower right corner and the lower left corner. In the following are examples of images, the original image and the images modified by copy-move method, as well as their multifractal spectrums (Fig.3. to 6).

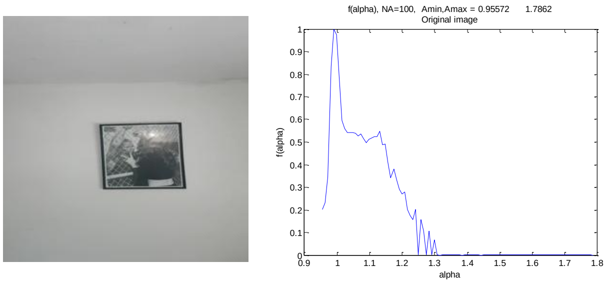

Fig. 3.Original image and its multifractal spectrum.

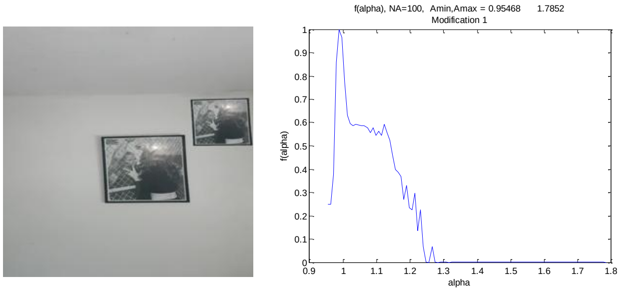

Fig. 4. Modification 1- the object (the painting) copy-moved in the top right corner, and its multifractal spectrum.

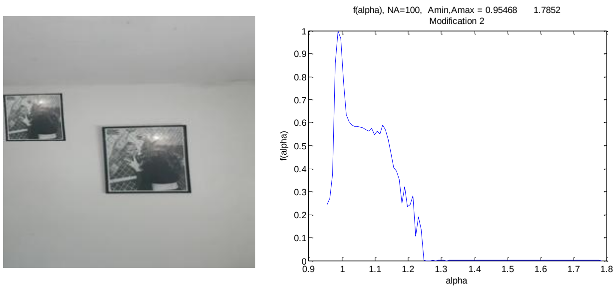

Fig. 5. Modification 2- the object (the painting) copy-moved in the top left corner, and its multifractal spectrum.

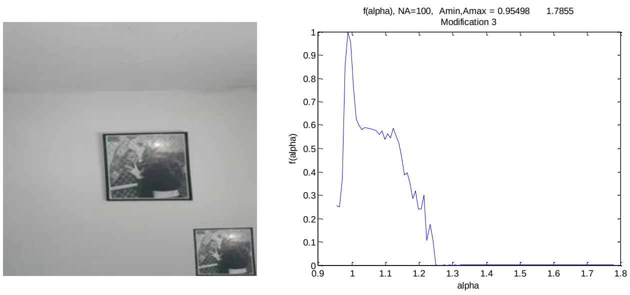

Fig. 6. Modification 3- the object (the painting) copy-moved in the bottom right corner, and its multifractal spectrum.

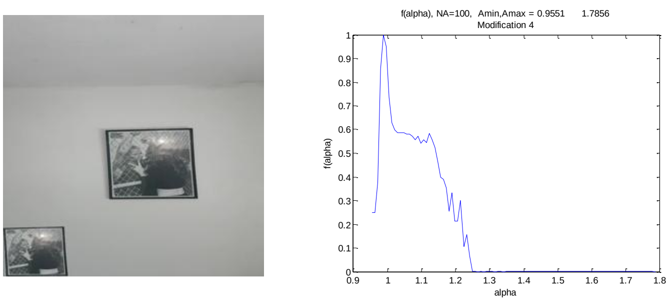

Fig. 7. Modification 4- the object (the painting) copy-moved in the bottom left corner, and its multifractal spectrum

V. Experiment 2

In the second experiment, it was testing the impact of statistic of subsequently added object which can't significantly alter the multifractal spectrum of original image. Subsequently added object was scaled and copied from an other image, generated by the same camera, in the indoor environment and by use of artificial lighting. In the following are examples of images, the original image and the images modified by copy-move method, as well as their multifractal spectrums (Fig.8. to 9).

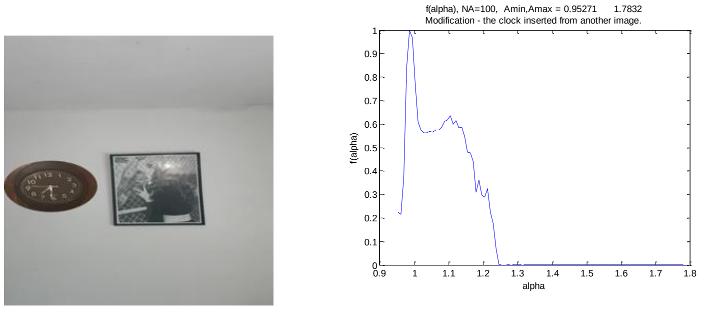

Fig. 8. Modification- the clock inserted from another image, and its multifractal spectrum.

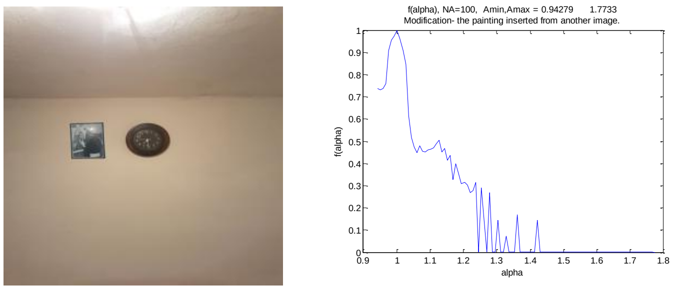

Fig. 9. Modification- the painting inserted from another image, and its multifractal spectrum.

VI. Experimental Results and Discussion

The comparations of calculated spectrums are shown in Figures 10-11, which are the result of the first experiment and Fig.12-13. as a result of the second experiment.

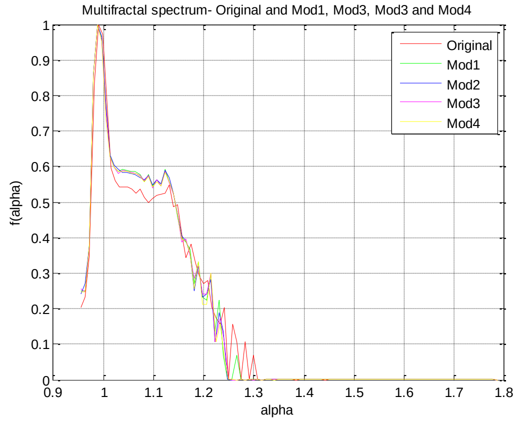

Fig. 10.Multifractal spectrums of images, original and Mod1, Mod2, Mod 3 and Mod4 (Fig. 3 to 7).

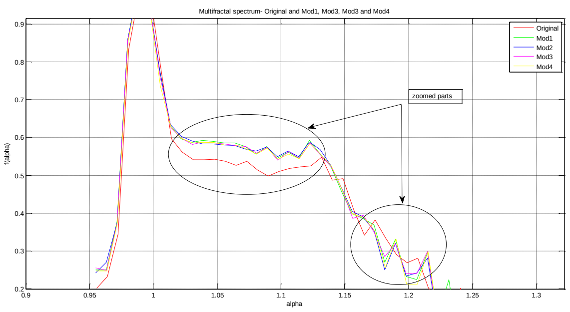

Fig. 11.Zoomed parts of spectrums- the parts which have different values.

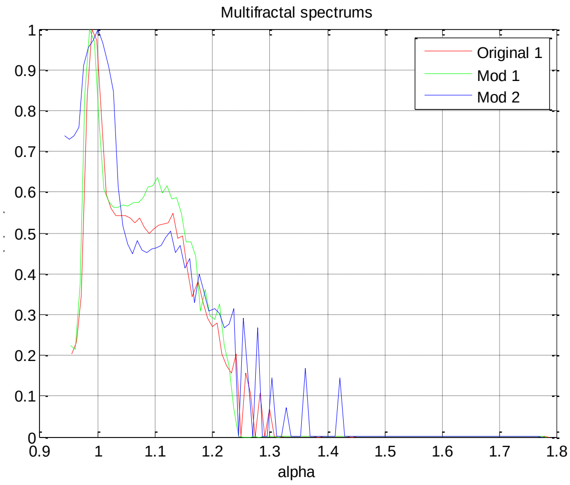

Fig. 12.Multifractal spectrums of images, original 1 and Mod1, Mod2, (Fig. 8 to 9).

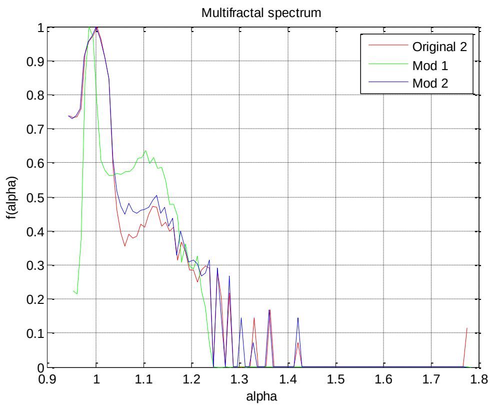

Fig. 13. Multifractal spectrums of images, original 2 and Mod1, Mod2, (Fig. 8 to 9).

Table 1 shows the values which correspond to the minimum and maximum values of the α, as well as of areas P1 and P2 for the respective intervals [α1, α2] in which the spectrums of original image and modifications are different, (Fig. 10 to 11), respectively, for each of the modification (Experiment 1).

Table 2 shows the values that correspond to the minimum and maximum values of the α, as well as of areas P1 and P2 for the respective intervals [α1, α2] in which the of original image and modifications are different, (Fig. 12 and 13), for the original 1, the original 2, and modification in relation to the original 1 and the original 2, respectively, (Experiment 2). Figure Original 1 represents the painting on the wall, while the figure Original 2 represents the clock on the same wall. Figures Mod 1 and Mod 2 represent modifications of images Original 1 and Original 2, respectively. Figure Mod 1 represents the clock inserted to Original 1 from Original 2, while figure Mod 2 represents the painting inserted from Original 1 to Original 2.

TABLE I

MIN AND MAX VALUE OF α, AND THE AREA UNDER $f(\alpha)$ FOR FIXED VALUES OF α_1 AND α_2, EXPERIMENT 1.

	α_{min}	α_{max}	P1 for [1.02,1.13]	P2 for [1.17,1.23]
Orig	0,956	1,796	0,0623	0,0175
Mod 1	0,955	1,785	0,0675	0,0175
Mod 2	0,955	1,785	0,0675	0,0166
Mod 3	0,955	1,786	0,0672	0,0169
Mod 4	0,955	1,786	0,0671	0,0162

TABLE II

MIN AND MAX VALUE OF α, AND THE AREA UNDER $f(\alpha)$ FOR FIXED VALUES OF α_1 AND α_2, EXPERIMENT 2.

	α_{min}	α_{max}	P1 for [0.95,1.02]	P2 for [1.05,1.18]
Orig 1	0,956	1,796	0,0464	0,0828
Orig 2	0,944	1,774	0,0667	0,0776
Mod 1	0,953	1,783	0,0467	0,0929
Mod 2	0,943	1,773	0,0666	0,0846

VII. CONCLUSION

Copy-Move method image forgery affects the brightness, and thus the multifractility of the images, inserting an object that does not object which does not correspond to environment of existing image. It is expected to be incurred additional "unnaturalness" depending on the statistical nature of local parts of image.

The paper presents the initial results of the study of copy-move detection and there are just two examples.

In future work, it is necessary to analyze a larger number of characteristic examples that indicate the statistical and multifractal changes on the images. It is necessary to examine the additional multifractal characteristics of these modified image and the opportunities for recognizing the changed areas of the image, which would find significant application in image forgery.

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