Gaussian Noise Estimation Applied to Color Images

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Abstract. An important field in Digital Image Processing is related to noise estimation, since it is essential for many image-processing procedures such as Filtering, Segmentation, Pattern recognition etc.; noise is inherent to any procedure and cannot be avoided since there are many types of noise from different sources, such as: image acquisition, image compression, transmission channel, etc. Therefore, we propose a novel Gaussian noise estimator using in first instance homogeneous areas and the whole image content by obtaining mean Euclidean distances between the noisy image and the image obtained by applying a mean filter to the noisy image. We validate the proposal against another algorithm, as well as their performance analysis for noise estimation and for a real application that consist in filtering noisy images using the CBM3D algorithm. Validations consist in using general-purpose images taken from the database BSDS500, which has low detailed images as well as high textured ones. Besides, our proposals is able to deliver better results for high noise levels.

Keywords: Gaussian Noise estimator, Color Images, Euclidean distance, Absolute and Angle distances.

1 Introduction

Basic procedures in the Gaussian noise estimation consist in estimating the standard deviation in order to determine the noise level present in the image, for our case in color images. For denoising image algorithms, knowing the type and the noise level to be treated is essential, which in most real applications is not common, thereby many methods of noise estimation have been proposed, Stanislav Pyatykh et. al. [1] consider three of them, which are:

1. Wavelet transformation
2. Image filtering
3. Preclassification of homogeneous areas

Another method proposed is found in [2] where Aihong Liuonly considers image filtering and preclassification of homogeneous areas.

Nevertheless, most of them have common criteria to take into account in their algorithms such as splitting noise, and image or modelling noise as a Gaussian distribution.

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The present paper exposes two noise-estimation algorithms for Additive White Gaussian Noise (AWGN) [3,4] modeled by the equation (1), where Ar is the noisy image, A is the original image and $n(\mu, \sigma^2)$ is the AWGN, with mean $\mu = 0$ and variance σ^2. The proposed algorithms in this paper are based in filtering and splitting noise in the image, the first proposal uses the whole image and the second uses preclassification of homogeneous areas. Since these algorithms are improvements of an algorithm presented by Rosales-Silva et.al. in [5], a quickly review is needed, this explanation is given in section 2.

$$Ar = A + n(\mu, \sigma^2). \tag{1}$$

To validate the proposed noise estimators, we implemented the algorithm designed by Xinhao Liu et.al. [6] ("the reference algorithm") which uses a technic based on patches selection, and a "tuning" process according to the image in which the estimator is been applied, however this algorithm process R,G,B channels individually, so it obtains three different results for each estimation, so it does not take into consideration the correlation in the R,G,B color channels.
Xinhao Liu et.al. in [6] states, "even if the true noise level is estimated ideally, the denoising algorithm might not achieve the best performance.".

In order to make comparisons to our proposals, the algorithm Color Block Matching 3D "CBM3D" presented in [9] by Dabov et.al. is implemented. The algorithm CBM3D consists of selecting sets of similar blocks of pixels which collaborate in the denoising procedure, this means that, each block provide information for the robustness in the denoising algorithm.

The paper is organized as follows: in Section 2 is introduced the theoretical background in which our algorithms are based; Section 3 exposes the detailed methodology of the two algorithms proposed; Section 4 exposes analysis and comparisons between the proposed and reference algorithms using images from the Berkeley Segmentation database "BSDS500" [8]; Section 5 presents the conclusions.

2 Distance Estimation Criteria

Our proposed algorithms improve the results of a previous work treated in [5], the previous work algorithm "basic algorithm" consists in three steps:

1. Filter the noisy image (Ar) by a mean filter [10] using a window processing of 3X3 pixels, so a filtered image (Af) is obtained.

$$Af = MeanFilter(Ar). \tag{2}$$

2. Obtain the angles $(Ang_{i,j})$, Euclidean $(D_{eu_{i,j}})$and absolute distances $(D_{ab_{i,j}})$, between pixels in the same spatial position ($i = 0,1,2, \dots., M$; $j = 0,1,2, \dots., N$; between the filtered image and the noisy image, assuming them to be three dimensional (R, G, B) points.

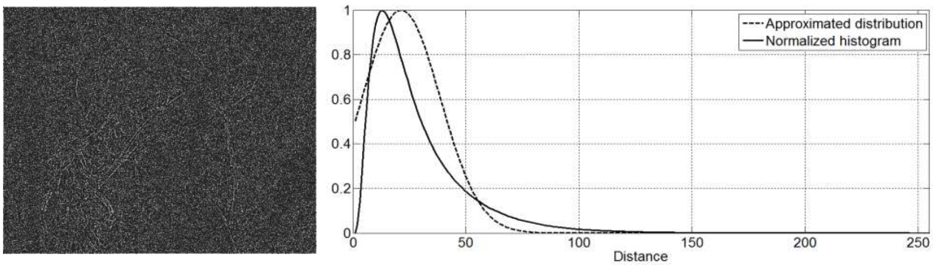
$$D_{ab_{i,j}} = \left|\left(Ar_{R_{i,j}} - Af_{R_{i,j}}\right) + \left(Ar_{G_{i,j}} - Af_{G_{i,j}}\right) + Ar_{B_{i,j}} + Af_{B_{i,j}}\right|, \tag{3}$$

$$D_{eu_{i,j}} = \sqrt{\left(Ar_{R_{i,j}} - Af_{R_{i,j}}\right)^2 + \left(Ar_{G_{i,j}} - Af_{G_{i,j}}\right)^2 + (Ar_{B_{i,j}} - Af_{B_{i,j}})^2}, \tag{4}$$

$$Ang_{i,j} = cos^{-1}\left(\frac{Ar_{R_{i,j}} \cdot Af_{R_{i,j}} + Ar_{G_{i,j}} \cdot Af_{G_{i,j}} + Ar_{B_{i,j}} \cdot Af_{B_{i,j}}}{\sqrt{Ar_{R_{i,j}}{}^2 + Ar_{G_{i,j}}{}^2 + Ar_{B_{i,j}}{}^2} \cdot \sqrt{Af_{R_{i,j}}{}^2 + Af_{G_{i,j}}{}^2 + Af_{B_{i,j}}{}^2}}\right). \tag{5}$$

3. Compute the mean and the standard deviation for angles, Euclidean and absolute distances obtained from Eq.(3), Eq.(4), Eq.(5) respectively assuming that a Gaussian distribution describes the data to be taken into account.

As an example, the results obtained from the proposed algorithm applied in the well-known image Lena by contaminating it with a noise level of 25, are shown in fig 1. Even when Absolute and angle distances were analyzed, for commodity only the process for the Euclidean distances (fig 1a) is shown, fig 1a was obtained by applying eq. (4) to each pixel, between noisy image and filtered image. Euclidean distances histogram normalized and its approximated Gaussian distribution in fig 1b are obtained in order to calculate the mean Euclidean distance and its standard deviation, this parameter is supposed to be equal to the noise level introduced in the original image in an artificial way using Matlab functions.



(a) (b)

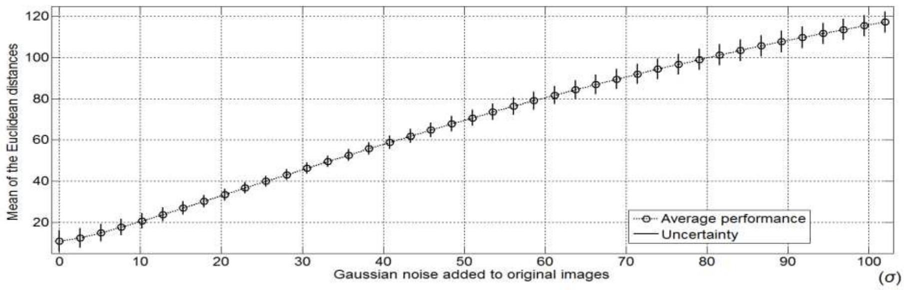
Fig. 1. a) Euclidean distances between pixels in noisy and filtered images, b) normalized histogram and approximated Gaussian distribution for Euclidean distances in (a).

The previous method has low accuracy because it assumes that filtered images have no noise, which is not true, for most of the real images to be processed. The Gaussian noise added artificially has an standard deviation of 25 and after applying the basic algorithm to estimate the noise level was obtained to be equal to 17.31 by using the histogram distances. This result shows that the estimated value is different from the original noise level artificially added; this is the main objective treated in this paper.

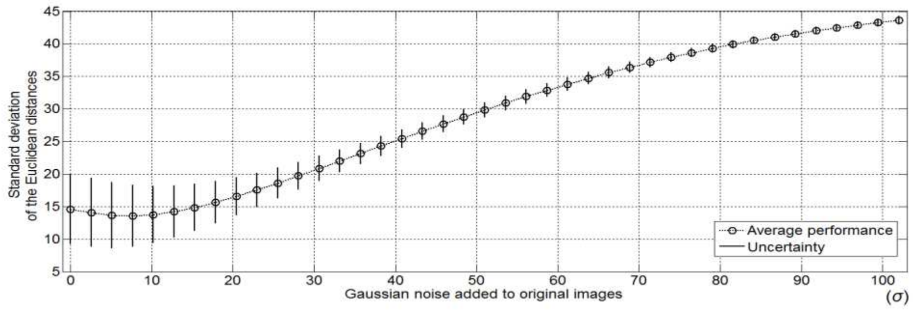
2.1 Basic algorithm performance

After several experiments, where different noise levels were added to images from BSDS500, it was found a relationship between the results obtained from the basic algorithm presented in section 2 and the standard deviation of the AWGN previously added to the images. This is shown in the fig. 2, only the analysis for mean Euclidean distances is shown because after some analysis, it was demonstrated to have a better performance for Gaussian noise estimation, also in fig 2a could be seen that the relation between the noise level added to the image and the mean of the Euclidian distances tends to be a monotonic function which could be modeled as an straight line, while in fig 2b its possible to see that the standard deviation of the Euclidian distances result in a non-monotonic function which should be modeled as a polynomial function.

In fig 2a and 2b, is shown the average performance and the uncertainty for each point from applying the basic algorithm to all images in BSDS500, adding different amounts of noise from 0 to 100 in increments of 2 in its standard deviation.



(a)



(b)

Fig. 2. Average performance for all images in BSDS500 “doted and circles line” including uncertainties “black continuous lines” for each point analyzed, a) using the mean Euclidean distance, b) using the standard deviation of the Euclidean distances.

So, our proposed algorithms were based in the results presented in fig 2 a, this proposals are explained in section three, on the basis of the basic algorithm presented at the beginning of this section.

3 Proposed Algorithms for Noise Estimation

As it could be seen in fig 2a, the average behavior can be modeled as a straight line just by applying a linearization method, while in the fig 2b this does not apply because in that case the average performance is a non-monotonic function and it produces that for certain amounts of noise two results could be obtained from the algorithm where only one of them is the correct output.

3.1 First Proposal (EstGl)

Let's suppose that the red line in the fig 2a is an straight line σ represented by eq. (6), which is equal to mean Euclidean distance "v" plus-minus its uncertainty "$\Delta\sigma$", in order to obtain a value representing the noise level from this equation its necessary to approximate it to the ideal case, which is when the value obtained is exactly the same noise level which was added artificially to the processing image. So this is an straight line with slope equal to one, first of all it is necessary to adjust σ to cero by taking from it, the minimum value "v_{min}"; then normalize it by dividing for "v_{max}" and finally multiply the value resulted by the maximum value considered for the estimator "x_{max}" which we proposed as 100 in order to avoid arithmetic overflow (arithmetic overflow will be discussed in Section 5). This procedure is simplified as "$F = (x_{max}/(v_{max} - v_{min}))$". After testing this adjustment for the basic algorithm, F was experimentally obtained equal to 0.95 and v_{min} equal to 10.96.

$$\sigma = v \pm \Delta\sigma, \tag{6}$$

$$\sigma_{aprox} = Fv - Fv_{min} \pm F\Delta\sigma. \tag{7}$$

σ_{aprox} represents a line whit the same performance shown in fig 2a, so in order to have a better estimator's response, it is proposed a piecewise linearization, developed by applying a least squares linearization, for three segments. Intervals for every segment's limits which resulted in lower errors were proposed. Then making the assumption that eq. (7) represents an straight line equal to $y_n = m_n x + b_n$; where x represents the AWGN added to the image, m_n is the slope in the *n*-th segment and b_n is the point where the line y_n crosses *y* axis, the term $\Delta\sigma$ could be omitted in order to avoid uncertainties propagation. So after Isolating *x* in algebraic treatment, we obtain the equation (9), and to simplify we propose the use of B_n and K_n variables.

$$(v - v_{min})F = m_n x + b_n. \tag{8}$$

$$x = \frac{vF}{m_n} - \frac{Fv_{min}}{m_n} - \frac{b_n}{m_n}, \tag{9}$$

$$K_n = \frac{F}{m_n}\ , \tag{10}$$

$$B_n = -\frac{Fv_{min}}{m_n} - \frac{b_n}{m_n}. \tag{11}$$

The term $\Delta\sigma_{est}$ in eq. (12) is the uncertainty of the estimator which is calculated under several experiments.

$$\sigma_{est} = K_n v + B_n \pm \Delta\sigma_{est}. \quad (12)$$

Table 1. Values for constants K_n, B_n and intervals for each segment.

n-th Segment	Proportionality constant K_n	Adjust to cero constant B_n	Values obtained from eq. (7)
1	1.02	-32.40	Lower than 13
2	0.82	-7.21	From 13 to 67
3	1.13	-10.41	Higher than 67

The estimator proposed will be called EstGl, given by eq. (12), although a specific process is necessary to determine the value of the constants to be used in eq. (12), this process is explained in the next blocks diagram.

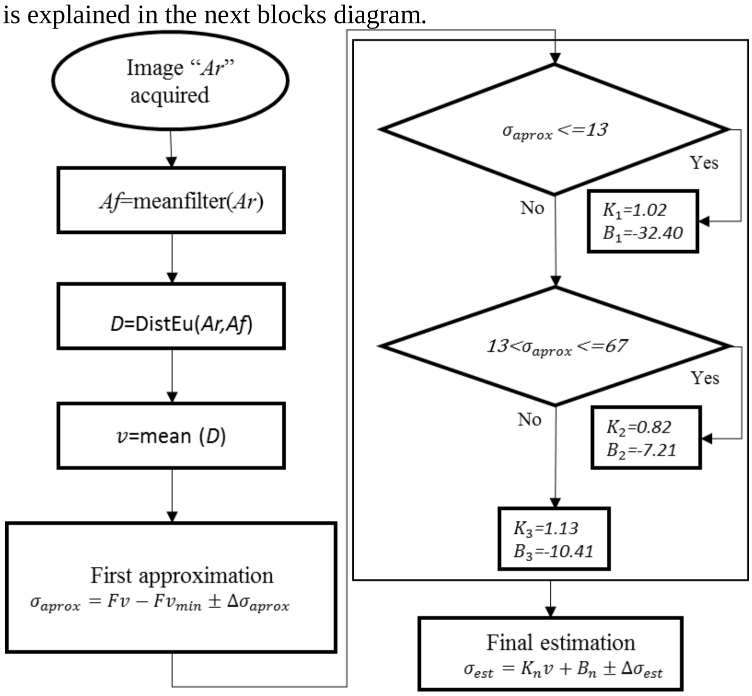


Fig. 3. Proposed Estimator EstGl.

3.2 Second Proposal (EstBl)

An adjustment on EstGl called EstBl consists in an homogeneous area pre-selection, it consists in dividing the image in blocks of 13X13 pixels and then apply the EstGl for each block as if they were complete images, taking as the result obtained by the estimator the smallest value obtained from the blocks which represents the most homogeneous area in the image, where, as mentioned in [6] is more likely to obtain the real noise level, this is mainly because homogeneous areas do not contain details which could be mistaken for noise in the noise estimation algorithm.

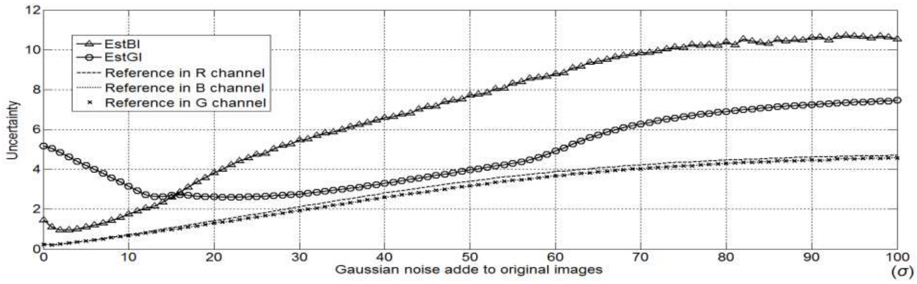
4 Results

In order to probe the performance of the proposed algorithms two tests were applied, the first one is for noise estimation (Section 4.1), which consist in contaminating the images from BSDS500 by a known noise level, then estimating the noise level using the proposed algorithms and “the reference algorithm”, the second one in Section 4.2 consists in contaminating the images from BSDS500 by a known noise level and filter those noisy images using the CBM3D algorithm taking into account the estimations obtained by the proposed algorithms, “the reference algorithm” and the real noise level.

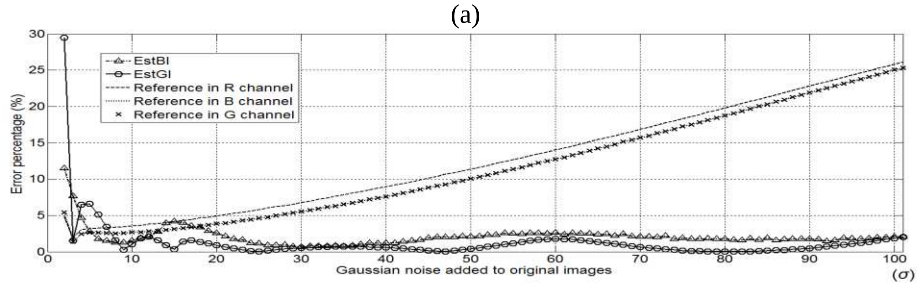
4.1 Performance Results in Noise estimation

We use all images in BSDS500, and the implementation of a comparison to “the reference algorithm”, the proposed methodology evaluation consists on the next steps:

1. Acquire an original image from the database BSDS500.
2. Add an amount of AWGN to the original image.
3. Estimate the noise level from the noisy image.



(a)



(b)

Fig. 4. Display of uncertainty (a) and error percentage (b), for proposed estimators and reference estimator. EstGl “continuous line with circles”, EstBl “continuous line with triangles”, estimation for red by reference estimator “discontinuous line”, estimation for green by reference estimator “x-points” and estimation for blue by reference estimator “dotted line”.

This procedure was applied for all images in BSDS500 and for a range of amounts of noise "from 0 to 100 in its σ in one by one increments", after obtaining results for proposed estimators and reference, their average performance was calculated as well as their uncertainty and mean percentage error which are shown in fig 4.

In fig 4 is shown the uncertainty (a) and error percentage (b), in the proposed algorithms we have a lower error for amounts of noise greater than 10, the proposed algorithms have higher accuracy for amounts of noise from 10 to 100 but with lower precision for amounts of noise from 0 to 100, this will be discussed in Section 5.

So, after proving that our proposed algorithms have an acceptable performance for noise estimation a second test was proposed which consists in filtering images artificially contaminated, this test and the results obtained from it are explained in Section 4.2.

4.2 Filtering images

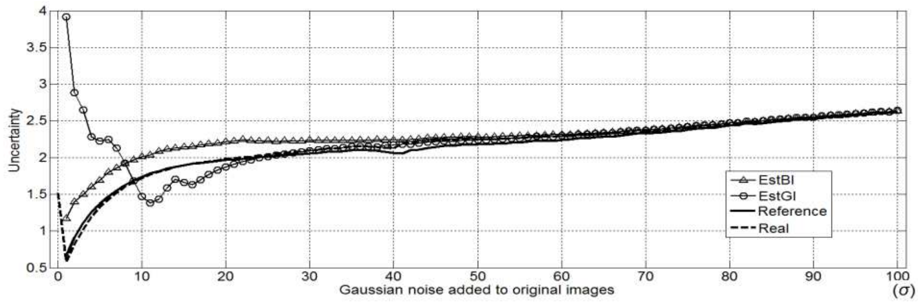
For some filtering algorithms is necessary to know a priori the amount of AWGN contained in images, one of them is the CBM3D presented in [9] and which also has been used as reference because it has proved to be one of the best denoising algorithms. Therefore, another comparison between proposed estimators and "the reference estimator" performance, is made by adding a fourth step in the procedure presented in section 4.1, which is:

4. Filter the noisy images by CBM3D, taking into account the real and estimated amounts of noise.

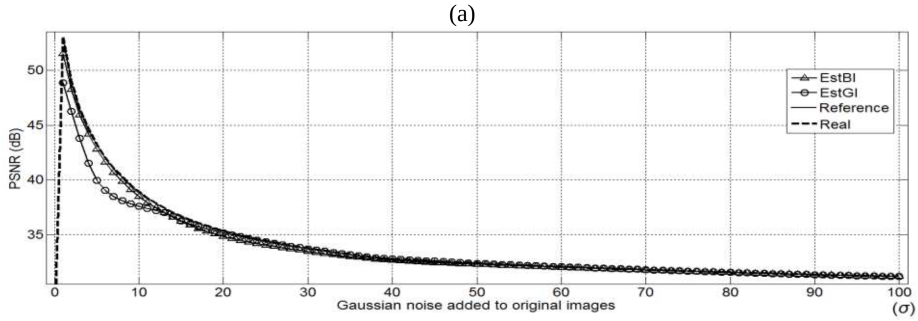
As mentioned in Section 4.1, "the reference algorithm" estimates amounts of noise for each channel in the R,G,B color space model, so in order to have just one estimation from the reference algorithm, a mean value was obtained from these results calculating the average of the noise values computed for every channel.

Results for filtered images were evaluated using the Peak Signal-to-Noise Ratio (PSNR) eq. (13) where I and k represents the evaluated and reference images respectively; the average PSNR for different noise levels and its uncertainty considering all results obtained are displayed in fig 5.

$$PSNR = 10\, log_{10}\left(\frac{255^2}{\frac{1}{3xMxN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\sum_{\beta=R,G,B}\left\|I_\beta(i,j)-k_\beta(i,j)\right\|^2}\right). \tag{13}$$



(a)



(b)

Fig. 5. Display of uncertainty (a) and PSNR (b), for filtering using CBM3D considering results obtained from EstGl “continuous line with circles”, EstBl “continuous line with triangles”, “the reference algorithm” “continuous line” and real “discontinuous line”.

In fig 5 are displayed results obtained from the analysis of 439 images, even when BSDS500 has 500 images only 439 images where used for this analysis, since “the reference algorithm” algorithm deliver complex numbers as estimation after processing 61 images at low noise levels lower than 5.

5 Discussion

In section 4.1 uncertainty and error percentage are displayed in fig 4 for results obtained from proposed and “the reference algorithm”; as mentioned, proposed algorithms have lower error with greater uncertainty especially EstBl.

However uncertainty increases as the noise level increase this effect could be a consequence of arithmetic overflow error which “cuts” and deforms distribution’s tails, for example if the AWGN added has a big standard deviation, representing the noise level and we assume that after this process is possible to split the image and AWGN, both of them would have been modified because of the arithmetic overflow error which in this case leads to the consequence of the impossibility of representing some values obtained by adding noise to an image.

In section 4.2 uncertainty and PSNR criteria are displayed in fig 5, it is remarkable that even when proposed algorithms “EstGl and EstBl” have lower errors in comparison with “the reference algorithm” (fig 4b) , they have a similar average performance in the quality of the filtered images measured by the PSNR (fig 5b), considering estimations by all analyzed methods and the “real noise level”, except for EstGl when the noise level is lower than 10.

Also it is important to say that uncertainty shown in fig 5a, is similar for estimations made by EstBl, and “the reference algorithm” and are also similar to the results obtained by considering the real noise level.

6 Conclusion.

Two algorithms were proposed the EstBl and the EstGl, was demonstrated that they have an acceptable performance, in noise estimation for images from the BSDS500 and in real applications.

However, arithmetic overflow errors are still a problem mainly for high noise levels (for our consideration greater than 35) as shown in the results of the fig 4 and the fig 5.

Another important fact is that these algorithms were proposed and tested for general-purpose images. So it is possible to apply the same principle for an specific type of images in order to have a better estimation, the variation would be the requirement of having to calculate all the constants needed, F, $vmin$, K, B and proposing limit intervals in order to obtain better results for noise level estimation as dictated in Table 1.

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