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ANALYSIS ON THE EFFECT OF A GAUSSIAN NOISE IN IMAGE FILTERING AND SEGREGATION

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ABSTRACT

The effects of convolution of a Gaussian function with an image are investigated in this paper on both a qualitative and quantitative level. This paper studies a methodology of segmentation utilising Gaussian blurring in addition to evaluating the generally known "Gaussian-blur" in image filtering. Noise is an unavoidable part of the acquisition process. As a result, knowing the impacts of a filtering technique is critical for selecting the suitable technique to effectively filter the image, as the segmentation process can be costly and time-consuming. It's usually preferable to have an automatic segmentation method that saves time and human labour. In order to analyse the impacts of the convolution in a quantifiable method, we chose a Quality Index to measure the filtering properties. The Gaussian Blur approach should be used in photographs with a lot of noise and a small variance Gaussian function, whereas a higher variance Gaussian function should be used in images with a lot of noise and a large variance Gaussian function.

INTRODUCTION

Medical diagnosis is improving: we can now check inner organs without requiring surgery, and we can even use imaging technology like Positron Emission Tomography to study metabolic processes. Noise, on the other hand, is unavoidable: it is sometimes inherent in the process of obtaining photographs and might obstruct a specialist's diagnosis if, for example, a little structure, such as a small tumour, vanishes in the image due to excessive noise. As a result, data must be filtered before being used.

The filtering process' purpose is to remove as much noise as possible while preserving as much information as possible. Noise can actually be detrimental to diagnosis: little tumours that would vanish in the filtered image would jeopardise the diagnosis. As a result, it's critical to understand the implications of the filtering algorithms we use, as well as the situations in which they should be used.

Before moving on to a segmentation application that employs the Gaussian blur to produce a mask, the proposed work investigates the effects of a Gaussian blur on a chosen image and analyses the results of the filtering using a qualitative index given in [1].

MATERIALS AND METHODS

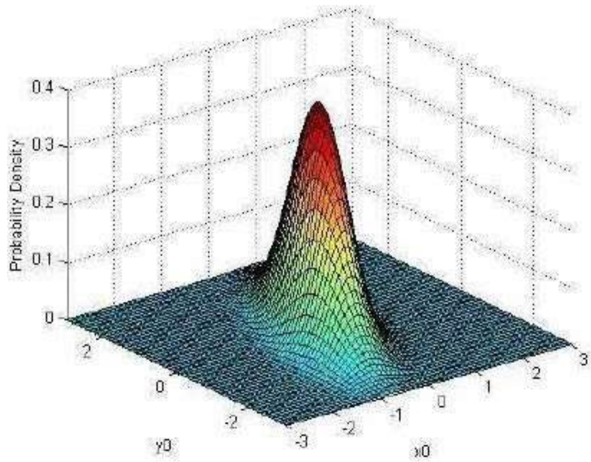
ImageJ ("Bridge") [2] provided the inspiration for the original image. It was added noise with ImageJ's built-in "Add noise" function, and then filtered with ImageJ's "Gaussian Blur" function. The "Gaussian Blur" is created by convolutioning a kernel with the image's pixels using a Gaussian function. In the discrete instance, [3] gives the following convolution:

$$f*g[n] \overset{def}{=} \sum_{m=-œ}^{œ} f[m].g[n-m] \qquad (1)$$

The function used to generate the kernel is the two-dimensional Gaussian function. In the following function, *A* is the amplitude, (x_o,y_o) the center, σx, σy the standard deviations in the x and y directions:

$$F(x,y) = A.e^{-(x-x_0)^{2}/2\sigma x2 \; + \; -(x-y_0)^{2}/2\sigma y2} \qquad (2)$$

The kernel size will be detailed in further section. One example of Gaussian distribution is the Fig. 1:A convolution



kernel is used to approxim ate the Gaussian distribution in image processing. As a result, the values of the distribution are used to construct a convolution matrix, which is then applied to the original image. The new value of each pixel is a weighted average of pixels in its near vicinity. As a result, the value of the first pixel (owing to its biggest Gaussian value) receives the most weight, whereas subsequent pixels receive less weight as their distance from the original pixel grows. The Gaussian kernel convolution [2] is a low-pass filter that straightens the edges of an image. Because the variance of the Gaussian distribution has a major impact on the filter, we utilise it to define it. The filtering results are shown in [2]. We will compare the filtered and original photographs using the quality factor recommended in [1] because the current research focuses on the impacts of Gaussian blur, as described in [2] and [3].

$Q(f,g) = (\sigma_{f,g}/ \sigma_g^2 \sigma_f^{2)} (2 f*g/f^2g^2)(\sigma_g^2 \sigma_f^2/ \sigma_g^2 + \sigma_f^2)$ .3

The gold standard (unfiltered original image) is denoted by g, and the filtered image is denoted by f. The covariance between the two pictures is t2, the image f variance is t2, the image g variance is g2, and the image f and g means are f and g, respectively. The covariance between the two images, luminance distortion (mean values), and contrast distortion are all evaluated by this quality factor (the variance values). Other approaches [5], [6] presented in the literature are more human-like than this one.

The indicator we used to evaluate the noise level in the images is the Signal-to-Noise Ratio (SNR), given by:

$$SNR = 20.\log(\sigma_{Signal} /\sigma_{Noise})$$

The signal-to-noise ratio (SNR) compares the signal's intensity to the noise's intensity. A higher SNR indicates that the image quality is better.

We picked ImageJ [2] and Eclipse [6] since they had documentation and allowed us to create our programmes as Plugins. "Bridges," which can be found in ImageJ examples [2], was the image on which we worked. This image was chosen to make modifications after filtering easier to see. The filter's performance was tested using a Gaussian Noise model with varied SNR values of 5, 10, and 15. The image's high, medium, and low noise levels are depicted in this manner. We used an impulsive noise called "Salt and Pepper noise" on the original image as well.We utilised ImageJ's noise function ("Noise" function) to introduce noise. The first step was to compare the original image's mean and standard deviation to the resultant images. The noise variance was then calculated using (4), and the selected noise was then added to the image. The computed variance for each SNR is shown in Table 1.

TABLE 1-Variance of the Signal and Noise in Images

Image	Variance
Original	54.63
SNR 5	30.78
SNR 10	17.31
SNR 15	9.73

There is no need to inform a noise variance due to the nature of impulsive noise. The original image, as well as the noisy photos, are shown in Figure 2.

EVALUATION OF THE FILTER

Because the kernel window size in the ImageJ implementation is calculated using the variance values, the variance of the Gaussian function is the major attribute to be analysed. We employed three different variances in this study: 1, 3, and 10. Table 2 shows the quality indicators for the resulting filtering.

Variance	SNR(5)	SNR(10)	SNR(15)	Impulsive
1	0.9536	0.9677	0.9716	0.9560
3	0.8633	0.8743	0.8768	0.8629
10	0.7924	0.8057	0.8085	0.7978

TABLE 2- Q index for filtered images

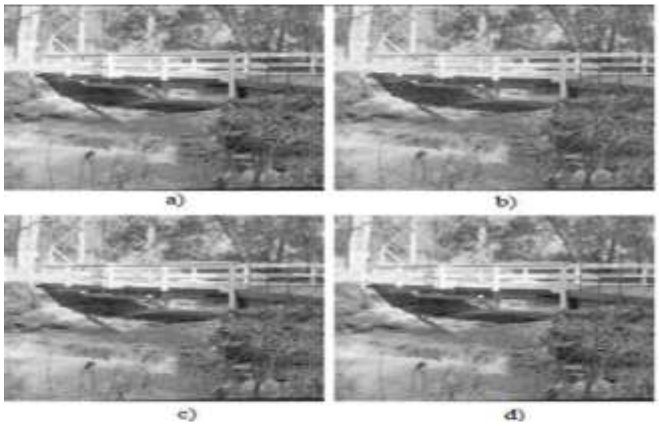


Figure 2. a) Original Image b) SNR 5 c) SNR 10 d) SNR 15

In all SNR circumstances in the first row, the Gaussian blurring method delivers comparable results. As the variance of the Gaussian function increases, the quality values in the second row get closer to each other and lower than the quality values in the first row. By comparing this data to the least variance data, we discover that the variance of the Gaussian function has a greater influence than the SNR values. The last row shows that the Gaussian variance is more important than the noise variance in determining the final quality index, especially when the function has a lot of volatility. We can conclude from the data in Table 2 that the Gaussian filter response is closely related to the variance of the Gaussian function, rather than the variance of the picture noise (Signal to Noise Ratio). As a consequence, Gaussian filtering should be employed in photos with low SNR (i.e., images with a lot of noise), as the results are similar in all SNRs tested.

Other filters may be more effective for photographs with less noise. Figure 3 depicts how image quality is affected by filtering. The image is not as fuzzy after filtering because the Gaussian function's variance is tiny.

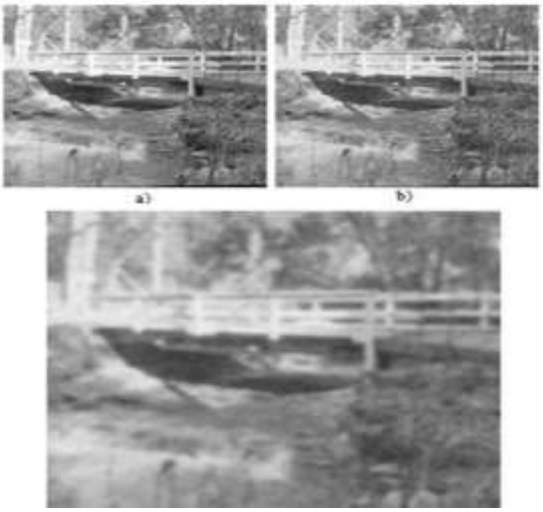


Figure 3. a) Original Image b) Noisy image c) Filtered Image

I. APPLICATION TO SEGMENTATION OF MEDICAL IMAGES

The technique of extracting sections of an image is known as segmentation [4]. This is necessary in order to take precise measurements. When done manually, it is often challenging for the computer and costly in human work. As a result, the development of an automatic and reliable method of segmentation is critical.

Due to the distortion that occurs in the borders, the Gaussian blur tool is not particularly useful as a filter when used with larger variance values, especially in the case of medical photographs. Nonetheless, [7] proposes one application that demonstrates how big variance values can be used to generate masks for segmentation in medical imaging.

Because each tissue in the human body reacts to tomography differently, the image's intensity values are all distinct. When a tissue absorbs more radiation, it glows brighter than when it absorbs less radiation. This might be seen as each tissue having its own zone in the intensity histogram. After some processing and blurring, we could isolate a region from the histogram and use it as a mask to the original image. We may eventually be able to do an automated segmentation of the liver, as proposed in [7].

The approach begins by picking the peaks on the histogram that correspond to the liver. These figures were derived from clinical trials [7]. Because the method concentrates on the liver, the algorithm chooses the upper section of the image to avoid the presence of other organs with comparable structure [7]. The next step is to create a mask with a Gaussian blur. It has a variance of 7 in this example. We employ a binary operation after the mask is ready: if the mask pixel is white, the picture original pixel is maintained; otherwise, it is discarded. From the original image to the segmented image, the entire process is depicted in Fig. 4. The impact of a substantial variation in can be seen.

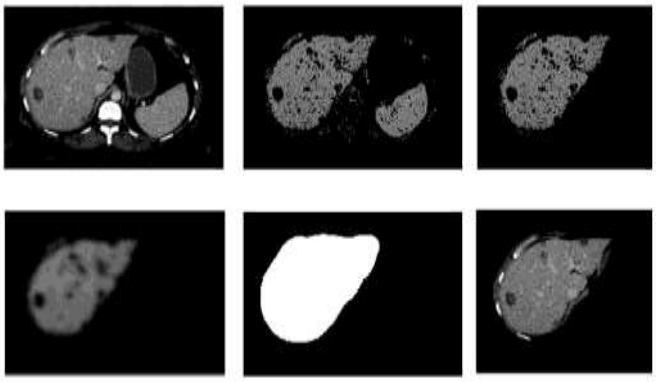


Figure 4. Segmentation process of a liver tomography

CONCLUSIONS

Because the results of the filtering demonstrated a relative independence on the noise features and a substantial dependence on the variance value of the Gaussian kernel, the Gaussian blur approach is particularly useful for filtering photos with a lot of noise. In fact, if the image has a high SNR, using the technique described here may make the image worse. When the original image has a low SNR, the Gaussian blur is a preferable option. Furthermore, while using a big variance in the Gaussian function to filter photos blurs and degrades the image, it may also be used to generate a mask to segment it. The ability to use an automated segmentation approach is the most crucial characteristic of this segmentation. Future research could focus on improving the segmentation technique, expanding the range of tissues used, or incorporating this technology into other medical imaging approaches.

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