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Median Filtering in Digital Images

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ABSTRACT: **In digital image forensics, it is typically accepted that intentional manipulations of the image content square measure most essential and therefore various rhetorical ways specialise in the detection of such 'malicious' post-processing. However, it is additionally useful to recognize the maximum amount as attainable regarding the general process history of an image, as well as content-preserving operations, since they'll have an effect on the responsibility of rhetorical ways in numerous ways that. during this paper, we tend to gift a straightforward nevertheless effective technique to notice median filtering in digital images—a wide used denoising and smoothing operator. As a good selection of rhetorical ways depends on some reasonably a one-dimensionality assumption, a detection of non-linear median filtering is of specific interest. The effectiveness of our technique is backed with experimental proof on an outsized image information.**

Keywords: digital forensics, median filter, processing history, image processing

I.INTRODUCTION

Digital image forensics has recently become a wide studied stream of analysis in multimedia systems security. omnipresent digital imaging devices and subtle written material package gave rise to the would like for rhetorical toolboxes which will blindly assess the believability of digital pictures while not access to the supply image or supply device1, a pair of or the help of associate auxiliary watermark signal.3 once reasoning regarding the believability of digital pictures, it's necessary to possess at least a rough operating definition of what constitutes a manipulation and what is taken into account to be a

'legitimate' post-processing.4 it's usually accepted that intentional manipulations of the image content (e.g., copy & paste operations or image splicing) a lot of essential and therefore varied rhetorical ways concentrate on detection of such 'malicious' post-processing. However, it's additionally helpful to grasp the maximum amount as attainable regarding the final process history of a picture, as well as content-preserving operations, like compression,5 distinction improvement,6 sharpening,7 and demising.

Even though such image process primitives generally don't damage the authentic price of a picture, they're of interest during a rhetorical examination of a picture since they'll have an effect on rhetorical ways in varied ways that. First, the particular state of a picture before manipulation could influence the set of tools we have a tendency to ar victimization to investigate the image or our interpretation of the proof derived from these tools. this is often connected to the sphere of steganalysis, where, as an example, the selection of an appropriate spatial-domain detector ought to be created conditional to the cowl properties.8

Second, bound post-processing steps could interfere with or diminish delicate traces of previous manipulations and so decrease the reliableness of rhetorical ways.

In the course of this paper, we have a tendency to shall concentrate on the median filter, a well-known denoising and smoothing operator.9 within the line with what was mentioned higher than, we have a tendency to believe that a detection of median filtered pictures is of explicit interest since a good selection of image rhetorical techniques consider some quite dimensionality assumption. as a result of median filtering may be a extremely non-linear operation, it's probably to have an effect on the reliableness of those ways. A typical example is that the detection of resampling, that employs a neighborhood linear predictor of component intensities and was shown to be vulnerable to median filtering.

The rest of this paper is organized as follows: ranging from a brief review of basic properties of the median filter in we are going to center on the questionable streaking artifacts in Sect. three and show however this characteristic will truly be accustomed find median filtering in electronic image pictures.

II. MEDIAN FILTERED IMAGES

Given a set of random variables $X = (X1, X2, \ldots, XN)$, the order statistics $X(1) \leq X(2) \leq \cdots \leq X(N)$ are random variables, defined by sorting the values of Xi in an increasing order. The median value is then given as

$$X(K+1) = X(m), \quad \text{for } N = 2K+1$$

$$\text{median}(X) = 1/2\ \ X(K) + X(K+1), \quad \text{for } N = 2K, \qquad (1)$$

where $m = 2K + 1$ is the median rank. The median is considered to be a robust estimator of the location parameter of a distribution and has found numerous applications in smoothing and denoising, especially for signals contaminated by impulsive noise.[9]

For a grayscale input image with intensity values $x_{i,j}$, the two-dimensional median filter is defined as

$$y_{i,j} = \underset{(r,s)\in W}{\text{median}}(x_{i+r,j+s}),$$

where W is a window over which the filter is applied. For the rest of this paper, we assume symmetric square windows of size M × M with M = 2L + 1, i. e., the median rank m equals m = (M 2 + 1)/2. This is probably also the most widely used form of this filter.

In order to describe some characteristics of median filtered images and compare the median filter to other filters, it is useful to study the output distribution of the median filter. Due to its non-linearity, however, theoretical analysis of the general relation between the input and output distribution of the median filter is highly non-trivial. For this reason, it is often assumed that the input samples are i.i.d. The general cumulative distribution function (CDF) FY for output samples yi,j and i.i.d. input samples xi,j with CDF FX is given by12

$$y_{i,j} \sim \mathcal{N}(\mu, \sigma_m), \text{ where } \sigma_m = \sqrt{\frac{\pi}{2}} \cdot \frac{\sigma}{M}.$$

Since, in filtered images, pixels in a close neighborhood originate from overlapping windows, they are corre- lated to some extent and thus the joint distribution of adjacent pixels is generally of interest. For an M × M median filter with i.i.d. input FX (x), Liao et al.15 derive an expression for the bivariate distribution of two output pixels yp and yq (H pixels window overlap), FY (yp , yq). The formula, which can be found in Appendix A, highlights how cumbersome the theoretical description of median filtered images can become even under the unrealistic assumption of i.i.d. pixel intensities.

For this reason, many studies in the literature have focused on more specific features of interest when analyzing the median filter. As such, the median filter was found to preserve edges better than, for instance, the moving average filter.16 It is also known that median filtered images exhibit regions of constant or nearly constant intensities.17 A further stream of research addresses the so-called roots of the median—signals which are invariant to median filtering—as well as the convergence of arbitrary signals to such roots.18

III. STREAKING ARTIFACTS

One of the main variations between the median filter and different sorts of linear and non-linear filters is that, for Associate in Nursing odd filter dimension, its output samples square measure directly drawn from the set of input samples, cf. Eq. (1). For discrete-valued signals, this means that, especially, that no miscalculation to integers has to be performed once filtering. as a result of of overlapping filter windows, there exists a non-zero likelihood that the output pixels in a very sure neighborhood originate from the same position of the input image. This result is termed streaking and

was quantitatively analyzed by Bovik.17 For continuous-valued i.i.d. input samples, he derived expressions for the likelihood that 2 pixels with a precise distance have equal intensity. Whereas being a operate of the filter size, it turns out that these possibilities square measure freelance of the actual distribution of the input. Tables with possibilities for various filter sizes and element distances is found within the original publication.17

Obviously, the presence of such a particular 'probability pattern' would be a really sturdy indication of previous median filtering. However, whereas the reported distribution-independence of streaking artifacts in continuous-valued i.i.d. signals is based on the zero probability of two input samples being equal, typical digital images have discrete-valued pixel intensities drawn from a finite alphabet. Here, the streaking probabilities become distribution-dependent because the quantized intensities can a priori be equal-valued. The probability that two integer grayscale output pixels yp , yq have equal intensity can generally be written as

$$P_0 = \Pr(y_p = y_q) = \sum_i F_Y(i, i) - \sum_i F_Y$$

$$(i - 1, i) + F_Y(i, i - 1) - F_Y(i - 1, i - 1),$$

where, for i.i.d. input samples, F_Y is the joint distribution .

IV. CONCLUSION

In this paper, we've investigated the detection of median filtering in digital pictures. within the broader framework of digital image forensics, we tend to see this endeavor as a contribution to the drawback of determinative the general process history of digital pictures. whereas the applying of 'classical' image process primitives for demising, sharpening, or distinction improvement will usually not in and of itself hurt the authentic price of a picture, it's still of high interest to be told the maximum amount as doable concerning what specifically went on to a picture and to form well-read selections supported this data. in and of itself information is fascinating not solely in forensic show ever conjointly in steganalysis and watermarking, we tend to regard our ways as valuable instruments in numerous fields of transmission security.

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