NOISE AND SIGNAL ACTIVITY MAPS FOR BETTER IMAGING ALGORITHMS

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ABSTRACT

In this work, we propose noise and signal activity estimation method that discriminates noise from signal based on local and global properties of the image data. The method yields pixel-wise maps of the noise variance and of the signal activity. Using these maps to guide imaging algorithms such as image enhancement and print defect detection improves their performance. The proposed method does not assume a white Gaussian noise model; it is very efficient computationally and, as such, is useful for a wide variety of applications.

***Index Terms*—** Noise estimation, signal activity, texture

1. INTRODUCTION

Noise in images has become a more serious problem recently as the pixel size in the image sensors have been shrinking dramatically to allow for the large megapixel counts that consumers demand for digital cameras. The noise problem can also be exacerbated by low quality optics and sensors included in camera phones and PDA cameras. Thus, noise affects most images and compromises all imaging algorithms. Visual perception of noise depends on both the noise and the underlying image content; this phenomenon is known as the masking effect. Therefore, for imaging applications to be effective, maps of both noise and signal activity are required. We substantiate this claim by showing significant improvement in image enhancement application relative to a noise-estimate-only driven enhancement.

The main technological hurdle we face in implementing the proposed approach is accurate estimation of local noise and signal activity. Indeed these are challenging and related problems. Noise estimate (either local or global) should not be affected by image structures, and therefore should be derived from featureless areas, that is the areas not containing edges or textures. Unfortunately, many natural irregular textures (e.g. some low resolution foliage textures) are statistically indistinguishable from noise. Consequently, such textures are often misclassified and treated as noisy smooth areas. This results in a significantly higher, image dependent noise estimate. On the other hand, noisy areas are occasionally misrecognized as high signal activity areas. In both cases, the result is a poor performance of imaging algorithms. For example, in the former case of an overestimated noise level, image enhancement using noise dependent threshold might apply a more aggressive denoising and yield a blurry image. In the latter case, image enhancement might apply sharpening to noisy areas, thus magnifying the noise. Most state-of-art noise estimation methods (e.g. [1],[2], and references therein) preprocess an image to reduce the influence of image features, but still suffer from residual structures. Many methods in literature assume white Gaussian noise either explicitly or implicitly. Additionally, often algorithms depend on heuristically or empirically chosen parameters. The method proposed in this paper solves noise and signal activity estimation problems in a systematic, statistically sound way.

2. LOCAL NOISE AND SIGNAL ACTIVITY ESTIMATION

2.1. Statistical noise estimation

In this section, we describe briefly the intuition and the main ideas of the proposed statistical noise estimation (detailed in [3]). To estimate the noise variance, we first divide the image into non-overlapping blocks. Note that, whereas the underlying variance for featureless blocks is the variance $\hat{\sigma}_n^2$, of noise *n*, the underlying variance of the other blocks is larger, namely the noise variance plus some bias due to the local features. Therefore, ordering the sample (block) variances on a scale, results in a separation between featureless blocks on the low end of the scale and other blocks above them. Within the low part of the sample variance scale, the addition to the variance due to image features may be very small, if any. Thus, although in some cases it is impossible to tell locally, whether a given pattern is noise or texture, global analysis of variances can easily make this distinction.

The proposed noise estimate uses a set of T (usually up to 30) image blocks with *lowest* sample variances. In [3] we show that with high probability these are blocks from featureless areas. To take into account rare cases wherein some of these blocks are from texture regions, we test the block set for 'irregular' behavior using e.g. F-test statistics

[3], and trim it appropriately. This yields a subset of $1 \le T \le 30$ blocks. Further influence of image features within this subset is minimized by using the median absolute deviation from a mean as a measure of the noise energy in a block. The proposed noise estimate is:

$$\hat{\sigma}_n^2 = C_{T,K,N} \cdot w\left(\{s_t^2\}_{t=1}^{T}\right), \qquad (1)$$

where w is some statistic, e.g. a weighted average, of a set s_t, $t = 1,\ldots,T$ of the lowest block noise measures, and $C_{T,K,N}$ is the *bias* constant that is dependent, in general, on the block size K, on T, on the choice of w and on sample size N. An important contribution of this noise estimate is that it is based on a function of a set of lowest order statistics; this ensures the resilience to image textures. Its accuracy is due to a statistical estimation of the bias constant $C_{T,K,N}$. The main idea here is that by the Central Limit Theorem, the noise can have arbitrary distribution, but for sufficiently large K, its sample variance has a nearly Normal distribution. Therefore, we derive $C_{T,K,N}$ based on known tables relating ordered statistics for Normal variables. In [3], we analyze the statistical properties of the proposed estimate (1) and show that it is accurate for general noise distributions (including Gaussian).

2.2. Spatially varying noise

In many cases of practical interest the noise is not spatially stationary over the image. Accurate estimation of local noise level is a difficult problem. On one hand, the local noise estimate should not be influenced by distant data samples. On the other hand, in order to have a reliable estimate we need to use sufficient data samples. In order to cope with these difficulties we use prior knowledge of the noise mechanism, and cluster blocks having similar noise factors for common estimation, separately for each such cluster.

For example, one reasonable choice of the noise factor is the mean local lightness. The luminance dependence of noise in raw (sensor) data can be modeled based on the sensor physics (see for example [4], [5]). However, accurate modeling of the image noise at a device output is usually impossible because of various image processing steps such as local and global contrast enhancements, various non-linear transformations, and compression. Nevertheless, even in processed images, noise reveals strong dependence on lightness [5]. Figure 1 shows an example of luminance dependent noise standard deviation (STD) measured in 8 different lightness intervals in the image of Figure 3, left. Note the increased noise level in the lower lightness values.

A block-diagram of the proposed method for the case of luminance dependent noise is depicted in Figure 2. First, the lightness range is adaptively segmented into M (typically up to 10) intervals. Then, the statistical noise estimation from the Section 2.1 is applied separately to each interval. The M resulting noise variance values are tested for the presence of outliers; after the outliers are removed, the remaining noise variance values are interpolated to a *noise function* $\hat{\sigma}_n^2(L)$ of the lightness L (usually, $L=0,1,2,\ldots,255$). Note that although we assume some smoothness of $\hat{\sigma}_n^2(L)$, we do not fit any parametric model of noise generation to the measured data. Finally, the function $\hat{\sigma}_n^2(L)$ is translated into a pixel-wise *noise variance map* $\hat{\sigma}_n^2(j,k)$, based on mean local lightness. Figure 3, middle depicts corresponding noise STD map.

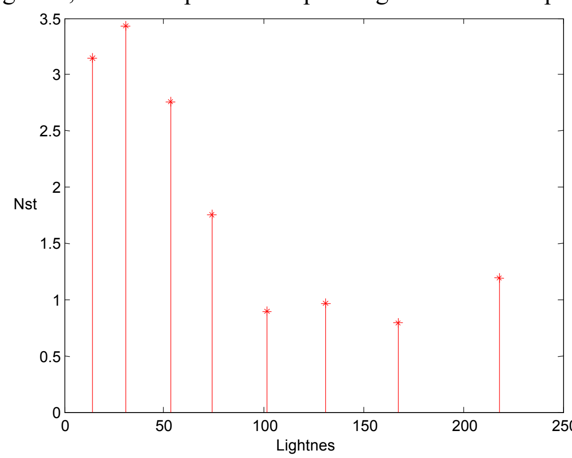

Figure 1. Luminance dependent noise STD measured in 8 different lightness intervals in the image of Figure 3, left.

2.3. Spatially varying signal activity estimation

The proposed local noise estimate allows one to detect image features more reliably. We measure the local feature content *with respect to the local noise* level $\hat{\sigma}_n^2(j,k)$, and calculate the signal activity map as:

$$f(j,k) = \sum_{i:|c_i|>\alpha\hat{\sigma}_n(j,k)} |c_i(j,k)|^p \; \Big/ \; \sum_i |c_i(j,k)|^p, \qquad (2)$$

where, in general, c_i can be coefficients of an image representation in some dictionary of functions (e.g., the Wavelet, the Discrete Cosine, etc.). In a simple and efficient setting, the coefficients c_i are calculated as the local directional derivatives, or the differences between a

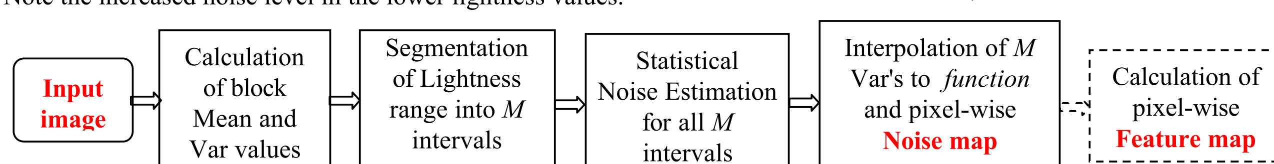

Figure 2. Block-diagram of the proposed noise and feature estimation method in the case of luminance dependent noise.

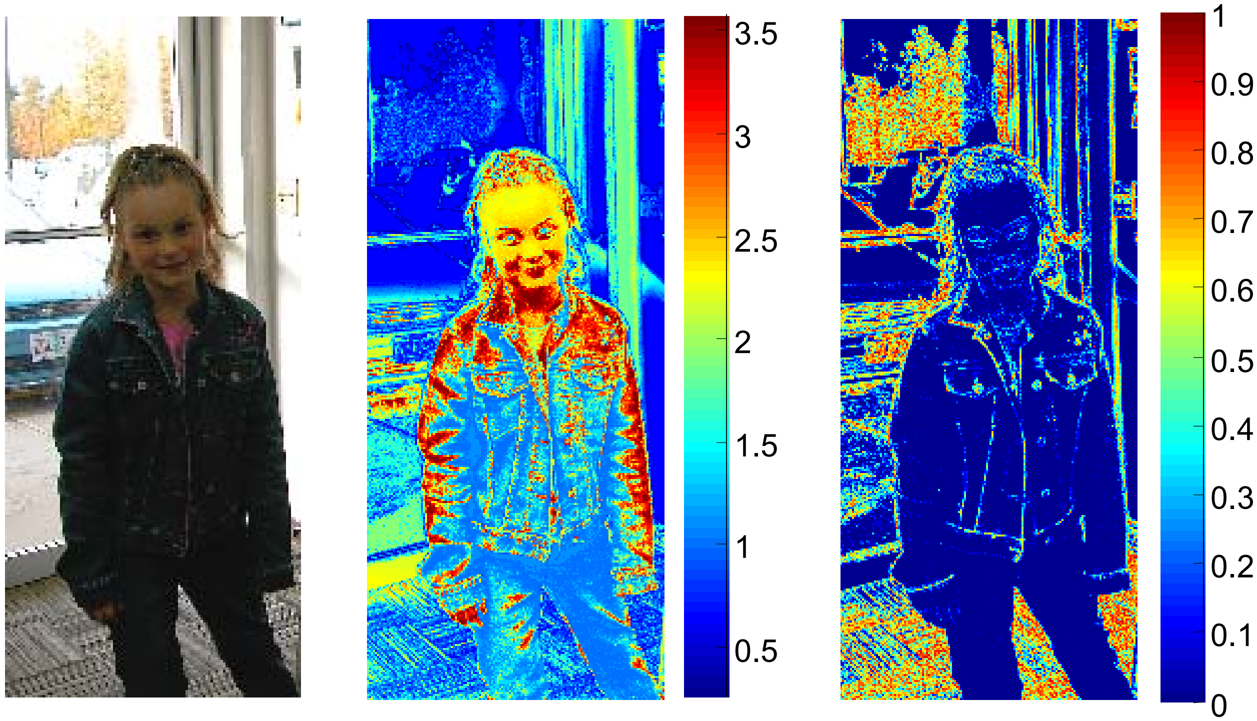

Figure 3. The original image (left), noise standard deviation map (middle), and signal activity map (right).

pixel and its neighbors:

$$c_{i=(u,v)}(j,k) = I(j,k) - I(j-u,k-v), \quad u = 1...U, v = 1...V,$$

where $I(j,k)$ is an image intensity value in the pixel (j,k).

For p = 1 or p =2, $f(j,k)$ depends on the signal activity strength (contrast), thus emphasizing strong image features (e.g., strong edges). For p = 0, $f(j,k)$ is virtually independent of image feature contrast, and emphasizes weak image features (e.g., textures). Note, that in (2) the 'feature threshold' $\alpha\hat{\sigma}_n(j,k)$ is dependent on the spatially varying noise estimate from the Section 2.2; therefore, in general, this threshold is different for each pixel.

An example of such pixel-wise signal activity map, where the coefficients c_i are calculated as local pixel differences, and p = 0, is presented in Figure 3, right. The middle image in Figure 3 indicates that the noise STD varies from 0.3 to 3.5 gray levels. Signal activity values close to 1 in the right image, reflect high signal activity. Let us compare two areas in the picture: texture in the trees and noise on the face and neck. Actual measured variance in the trees area was lower than the one measured on the face. Yet, these weak textures are correctly detected as activity areas, while the strong noise on the face is detected as a feature-free, noisy area.

3. APPLYING NOISE AND SIGNAL ACTIVITY MAPS TO VARIOUS APPLICATIONS

Depending on the application, noise and signal activity maps can be combined in various ways. We show here two examples of applications that benefit from these maps. The importance of the reliable noise and signal activity estimation for image enhancement tasks was briefly discussed in the introduction. In image enhancement, the noise map provides correct values for a local threshold, separating the noise patterns from the intrinsic image features. In addition, the signal activity map guides the image *sharpening* filter. Therefore, the combination of these two maps allows one to better denoise smooth areas, while enhancing intrinsic image features without magnifying the noise. In particular, we use noise and signal activity maps for image enhancement based on non-linear denoising-sharpening filters (e.g. Bilateral filter [6]) as follows. The threshold, separating noise and image features, is set to be proportional to the ratio:

$$th(j,k) \sim \hat{\sigma}_n(j,k) / \left(f(j,k) + \varepsilon \right)$$

thus, taking into account the *masking effect*. This threshold defines the faith of each pixel; roughly speaking, noisy pixels will be averaged with their neighbors, while the local contrast of 'signal' pixels will be magnified. This improves denoising in smooth regions and sharpening of details in feature containing areas.

Another type of imaging applications that can use the proposed method is automatic image defect detection. A significant problem with automated techniques for various defect detection tasks, namely print defect detection, dust and scratch detection and removal in scanned images and others, is that such techniques often fail to adequately distinguish actual image features, such as line segments

Figure 4. Original image (left); enhanced with a non-linear denoising-sharpening filter driven by manually chosen threshold (middle); enhanced with the above filter driven by noise and feature maps of the proposed method (right).

and various textures, from true defects, such as scratches or other artifacts. This results in a poor trade-off between missing defects and false-alarms, especially for applications targeted at low contrast defects. In order to overcome this problem we set the defect detection threshold to be proportional to a local activity:

$$th_{\text{detect}}(j,k) \sim f(j,k) .$$

This allows better detection in feature-free areas, and, at the same time, lower false alarms in feature containing areas.

4. RESULTS

Statistically good behavior of the noise estimate from section 2.1 was proved in [3] by theoretical and experimental study. In one of the experiments, white Gaussian noise of various STD's was added to 130 natural images. Noise STD was estimated for the artificially noised images, and compared to the added noise, after the intrinsic noise estimated from the original images was subtracted. The worst-case estimation error of the competing methods ([1],[2]) was *260%*; the one of the proposed estimator was *7.3 %*. In another experiment, we cropped manually a few featureless image areas, and applied the proposed and competing methods to estimate the noise from these areas. The methods yielded similar estimates. Then, the methods were applied to complete images. The competing methods consistently overestimated the noise level, while the proposed method yielded nearly the same estimates as in the 'manual' case, showing high robustness to image content.

The performance of the proposed local noise and signal activity estimation was further extensively tested in various experiments on natural images having various formats including JPEG [3]. Figure 4 depicts an example of general image enhancement implemented in a non-linear denoising-sharpening filter. Here we compare the proposed method against the same filter with a fixed noise threshold chosen manually to optimize the trade-off between noise removal and image feature preservation. The enhanced image of the proposed method looks more natural, is sharper and has less residual artifacts. Similarly, image enhancement based on the proposed method was tested on the set of 130 images and compared favorably to results of competing methods (e.g. [7]).

5. CONCLUSIONS

In this paper, we proposed noise and signal activity estimation method that discriminates noise from signal based on local and global properties of the image. The obtained pixel-wise maps of the noise variance and of the signal activity guide imaging algorithms such as image enhancement and print defect detection, and improve their performance.

6. REFERENCES

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