 

# Structure-Adaptive Evaluation of Noise in Images for Automatic Image Quality Control

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## Abstract

The known approach to noise evaluation predominantly consists of an image differentiation and subsequent filtering. This approach requires an interactive procedure of pointing to homogeneous regions where the local variance of the processed image should be computed that is unacceptable in many on-line printing systems. The proposed model-based approach to noise estimation considers noise as stochastic-deterministic fluctuations of image intensity with respect to the assumed polynomial intensity function with added noise. The original image is restored from the printed image by using a robust filtering procedure based on the assumed polynomial regression model. The difference between the original image and the scanned image during the printing process is then analyzed in order to detect the significant values of the residuals which represent the printing defects or noise.

## Introduction

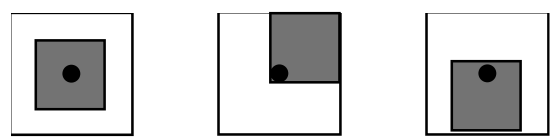
The noise level in printed images is one of the basic characteristics during evaluation of the print quality. Here, the noise is considered in a broad sense, namely as stochastic or mixed (both stochastic and deterministic) unwanted fluctuations of image intensity (luminance and color components) over the image plane. This concept, besides the white independent noise includes graininess, banding, edge raggedness and other artifacts. It is supposed that these fluctuations are insignificant in magnitude as compared to the relevant intensity changes or they have relatively short duration on the image plane.

The known approach to noise evaluation predominantly consists of image differentiation and subsequent filtering [1]. This approach requires an interactive procedure of pointing to homogeneous image regions where the local variance of the processed image should be computed that is unacceptable in many on-line printing systems [2].

The proposed approach is based on a non-homogeneous polynomial regression model of images which includes the noise variance as one of the unknown parameters to be estimated. Besides, the developed image model is also consisted of domain model of local objects and image details which are described by the so-called structuring regions. In order to model different distributions of stochastic noise, it is approximated by the mixed noise model consisting of white Gaussian noise and outliers from the Gaussian distribution.

The noise estimation procedure is based on the selection of the most probable structuring region from all possible structuring regions inside a sliding window and estimation of the model parameters over the pixels belonging to this region. Thus, the selected structuring region matches the local polynomial intensity model with mixed noise. The parameters to be estimated include the polynomial regression coefficients, local contrast, and the noise variance. In order to measure different kinds of noise, especially the edge raggedness and banding, the method of adaptation to edge structures is proposed as well.

This method has been tested on real scanned images with added noise as well as on real scanned images with print defects. The results are better as compared with the known approach of differentiation which is a content-dependent technique and yielded an exaggerated estimation of the noise variance.



*(a) (b) (c)*

*Figure 1. An illustration to the formation of two out of eight edge structuring regions (b) and (c) by the structuring element (a).*

## Polynomial Regression Modeling of Printed Images

The underlying model of printed and scanned images is composed of two parts: original image model and model of image distortions. Since we are modeling an image as a function of two variables which are the pixel coordinates, we model separately the domain as the image plane and the intensity function as a surface in three-dimensional space. The domain modeling is necessary to represent local objects in images as well as edge structures of the local objects in order to have structure-adaptive procedures for filtering and noise estimation. The first model, the domain model, is deterministic and is based on notions and operations of mathematical morphology [3]. The basic concept of this model is a complete set of the so-called *structuring regions* $\{V_k(i,j)\}$, consisting of edge structuring regions and one symmetric structuring region relatively to a current pixel $g(i,j)$ (see Fig. 1). Every pixel on the image plane belongs at least to one of all these structuring regions. The second model, i.e. the model of the intensity function, is a stochastic one in a broad sense and uses a polynomial regression representation of intensity.

The polynomial regression model states that the intensity function $g(i,j)$, where $(i,j)$ are the pixel coordinates as the non-random explanatory variables of the regression, can be represented as a polynomial function of order $q$ within a neighborhood $D(u,v)$ relatively to a current point $(u,v)$ plus independent noise $n(i,j)$ with a Gaussian distribution $\mathbf{N}(0,1)$. For example, in the two-dimensional case it can be written as

$$g(i,j) = \sigma \cdot n(i,j) + \sum_{r+s \le q} \theta_{r,s} \cdot i^r j^s \,,$$

$$for \;\; \forall (i,j) \in D(u,v)\,, \tag{1}$$

where $D(u,v)$ might be a homogeneous asymmetric region or the structuring region as a subset of this homogeneous region including current point $(u,v)$, $\theta_{r,s}$ is the $(r,s)$ regression coefficient (parameter), $n(i,j)$ is the white noise having zero mean and unit variance, $\sigma$ is the noise scale parameter. The first term of the right part in Eq. (1) is treated as residuals of the polynomial regression model. The regression coefficients $\{\theta_{r,s}\}$ are considered together with the scale parameter $\sigma$ as the model parameter vector $\theta=[\theta_1, ..., \theta_t, \sigma]$ to be estimated. Usually, noise $n(i,j)$ contains a relatively small fraction of outliers $\varepsilon$ that can be modeled as Gaussian noise with a stationary standard deviation $\sigma$ over a region of interest mixed with impulsive noise with a known distribution. The regression coefficients are changing from point to point, thus being non-stationary values and representing the non-homogeneous background. The combination of Gaussian noise with outliers is a quite general additive noise modeling because by combining the value of $\sigma$ with different values of the outlier fraction $\varepsilon$, different practical cases of noise distribution can be satisfactory approximated. The intensity of the outliers as possible print defects is described by their local contrast relatively to the background. The regression parameters, the local contrast, as well as the variance of the Gaussian residuals are estimated by using robust estimation procedures developed for this special purpose in order to diminish the influence of outliers.

## Detection of Print Defects

The automatic estimation of noise level or detection of print defects like the banding, edge raggedness, mottles and graininess is based on the intensity estimation of initial (free of defects) image, i.e. the image to be printed. It is assumed that the initial images can be represented by the described composite image model consisting of structural regions within each of them the image intensity is represented by the polynomial function. Then, the difference between the restored (estimated) image and the input image (with print noise and defects) is computed for specified regions of interest. The regions of interest can be selected automatically or pointed out manually by an operator. In the present research it is supposed that the location of the regions of interest is known and the assumed composite image model is valid within the regions of interest. For example, the region of interest can be an edge fragment in order to measure the noise level and edge raggedness. Another example of the regions of interest is the image areas containing just the printed text areas without figures. For direct detection of print defects, the obtained difference image is subjected to a thresholding operation with a constant or floating threshold. The threshold is set on the appropriate level for discrimination of the print defect component from the additive noise component. The resulting binary image containing presumably the print defects or just the noisy pixels is analyzed in detail for noise level estimation and measurements of print quality.

In order to detect print defect of different size and location, the principle of multi-resolution image representation has been used. The additive noise component is extracted and estimated with respect to the variance on the initial resolution level. The print defects of different size are analyzed on lower resolution levels.

## Robust Estimation of the Regression Coefficients and Noise Level

The restoration of the initial image from the noisy and defective image is made in two stages. The first stage consists of a robust estimation of the regression coefficients in order get rid of outlier influence which can be interpreted as print defects. The final intensity estimate including the noise variance estimation is made at the second stage by using the concept of structuring regions described in Sec. 2.

Let us assume that noise (as the model of the polynomial residuals) $n(i,j)$ has a mixed distribution, e.g. the Gaussian distribution for most pixels and impulsive independent noise with a point contamination probability $\varepsilon$. In general case, the distribution of the magnitude of impulsive noise is not known, but its magnitude is significantly greater than the rest of points. Since the most of points are free from outliers and have Gaussian distribution, the conditional minimization of the sum of squares is chosen as a partial estimate of the regression parameters because it coincides with the maximum likelihood (ML) approach in this case. So, the regression coefficients are computed by the least squares method as the solution of the system of linear equations involving elements of selected sub-samples. For a low-degree regression (up to the second order), the explicit conventional equations for the coefficients are known. The final estimate of the parameter vector $\theta=[\theta_1, \ldots, \theta_t, \sigma]$ is calculated as the maximum a posteriori probability (MAP) estimate over all optimal partial estimates $\{\theta_k\}$. It is assumed that the total number of outliers in a selected region for partial estimation will be not greater than $(N-1)/2$, where $N$ (odd) is the number of all pixels in a subset. The value of the vector $\theta_k$ is selected as the best estimate by the ML principle of the regression coefficients over all possible sub-samples which can be without $k$ outlier pixels at the same time (the sub-sample size is equal to $N$-$k$).

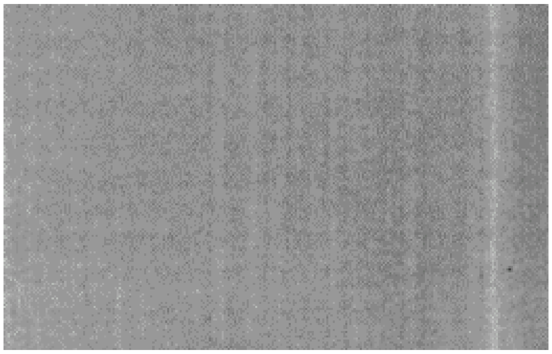


*Figure 2. A region of interest on a printed image containing noise and print defects (banding) in the right part.*

Assuming that under the proposed structural model every pixel belongs at least to one structuring region out of all L structuring regions $\{V_k(i,j)\}$, it is advisable to evaluate its value based mostly on the pixel values from this region. In other words, the current pixel value should be estimated from the population with the same distribution except for a small percentage of outliers. This follows from the image model as being composed of regions with different regression coefficients which are stationary over these regions. Based on the underlying model, we will evaluate a pixel value over one appropriate structuring region from several possible. These structuring regions are derived by using Eq. (3) in Section 2.

The most probable structuring region $V_l(i,j)$ for pixel estimation is determined by using the Bayes rule, that corresponds to the optimal selection by the maximum *a posteriori* probability as follows [4]:

$$l = \arg\max_{1 \le k \le L} \{P(k) \cdot P(y/k)\}, \qquad (2)$$

where *P(k)* is the *a priori* probability for the *k-th* structuring region; *P(y/k)* is the conditional probability for a feature *y*, and *k* takes values over all possible L structuring regions $\{V_k(i,j)\}$ (e.g., L is equal to N=9 for the case of equal in size and identical in shape structuring regions with N=3x3 points in Fig. 1). The feature *y* is a local statistic determined within a processing window and may be also a vector of features in order to possess good discriminating properties. In practice, the selection of the most probable structuring region by Eq. (4) is made in two steps. In the first step, the most probable edge structuring region is determined by using the normalized contrast with respect to each of the structuring regions as the feature y. Then, in the second stage, one of the two remaining structuring regions (edge structuring region and symmetric structuring region) is selected based only on the local variance as the discriminating feature y.

The step of final optimal estimation of image intensity *f(u,v)* is also present which coincides with a simple polynomial calculation of intensity in the current point *(u,v)* of the optimal structuring region:

$$f(u,v) = \sum_{(r+s)\le q} \theta_l(r,s) \cdot u^r v^s, \qquad (3)$$

where $\{\theta_l(r,s)\}$ is the sequence of regression coefficients estimated over the structuring region with number *l* including the current point *(u,v)*.

## Experimental Results and Conclusions

The proposed technique for defect detection and noise level estimation has been tested on different real printed images as well as on images with synthetic simulated noise and defects. The real scanned images have been obtained from a conventional laser printer and scanner at 300 dpi. One example of the region of interest with a homogeneous background is shown in Fig. 1. For the computational reason, the structuring regions in all experiments are the respective shifted versions of one structuring element (window) consisting of N points (in our example, 3x3 points). The theoretical considerations mentioned in the previous sections have been confirmed during the experiments. The application of the proposed approach to simulated noisy images yielded more accurate results as compared to the known differentiation approach [1]. The process of print defect detection and noise estimation is illustrated in Fig. 2 by the difference image (original and restored by the robust estimation method) containing noise and printing defects. The dependence of the estimated noise variance on the intensity levels for the test stripe image is shown in Fig. 3. The measured print noise has greater variance for the regions of interest with greater intensity mean values.

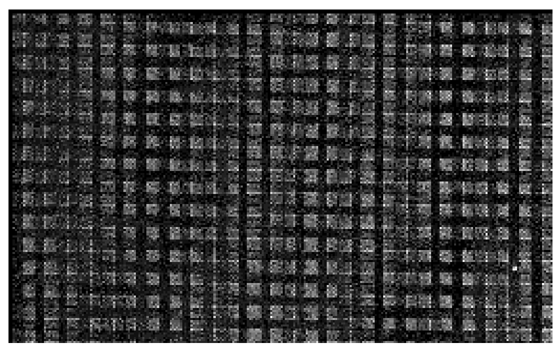


*Figure 3. The difference image corresponding to the region of interest in Fig. 2. The initial intensity has been scaled in order to see the noise structure.*

In can be clearly seen from the Fig. 4 that the multi-resolution approach allows to extract defects which are not visible at the initial resolution level. The developed method of noise estimation besides the accurate calculation of the noise variance allows to detect other print defects such as banding, edge raggedness and mottles. Further image analysis and measurements provide complete structure of print defects as well as their various properties. The whole process of noise estimation and defect detection is automatic provided the regions of interest are supplied in advance.

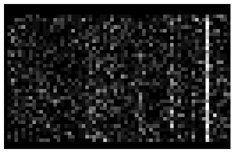


*Figure 4. The difference image at lower resolution level corresponding to the region of interest in Fig. 2.*

**Table 1. Estimated Noise Variance as Dependent on the Mean Gray Level for Different Regions of Interest**

| Percentage of gray | Noise variance |
|---|---|
| 100% | 6.02 |
| 90% | 40.58 |
| 80% | 89.68 |
| 70% | 138.68 |
| 60% | 169.91 |
| 50% | 215.11 |
| 40% | 298.11 |
| 30% | 428.31 |

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## Biography

Roman M. Palenichka graduated in applied mathematics from Polytechnic Institute of Lviv (Ukraine) in 1979. He received this Ph.D. degree in computer science from the Glushkov Institute of Cybernetics (Kyiv) in 1986. Since 1979 he works at the Institute of Physics and Mechanics of the Ukrainian National Academy of Sciences and currently he is a head of laboratory for Signal Processing and Pattern Recognition. From 1990 Dr. Palenichka was also an associate professor at the Department of Applied Mathematics of Lviv University. His research interests include computer graphics, non-linear image processing, computer vision and parallel computer architectures for image processing in real time. He published more than 34 papers and is co-author of three books including the Dictionary of Computer Graphics and Image Analysis.

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