Blind Noise Level Detection

Anna Tomaszewska

West Pomeranian University of Technology in Szczecin,
Faculty of Computer Science,
Żołnierska 49, 71-210, Szczecin, Poland
atomaszewska@wi.zut.edu.pl

Abstract. In this paper we present a new fully automatic algorithm for blind noise level evaluation based on natural image statistics (NIS). Natural images are unprocessed reproductions of a natural scene observed by a human. During its evolution, the Human Visual System has been adjusted to the information encoded in natural images, making images interpreted best by a human when they fit NIS. The main requirement of such statistics is their striking regularity. Unfortunately, most computer images suffer from various artifacts, such as noise, that distort this regularity. Our contribution is applying the statistical behaviors for noise level evaluation. As most denoising algorithms require the user to specify the noise level automatization of the process makes it more usable and user independent. We compare the quality of our results to other algorithms.

Keywords: noise level detection, data restoration, computer graphics.

1 Introduction

The analysis of computer images from the basis for many fields of knowledge. Images are mainly used in applications such as nanotechnology, face identification, medical data visualization, simulations of physical processes and criminology. Currently, intensive research is being conducted on increasing the dynamics of LCD monitors, improving sensor performance in digital cameras and increasing the resolution of devices. However, huge limitations still exist in high quality image acquisition. Not only do images lack focus and sufficient resolution, but they also curry distortion in the form of noise in the acquired image.

Different approaches to image denoising exist, and specifying the noise level is meaningful in most of the methods. Most frequently, computer vision algorithms require the parameters to be adjusted according to the image noise level, making it an important quantity to estimate. Very often however, however, it rests with the user to evaluate the noise level perceptually. This is problematic as it decreases algorithm effectiveness as well as the application opportunities.

One of the approaches adopted to solve the problem is natural image statistics (NIS), defined as the characteristics of unprocessed images found in nature. The Human Visual System (HVS) during its evolution has been adjusted to the information encoded in natural images, therefore the human eye is well adapted

A. Campilho and M. Kamel (Eds.): ICIAR 2012, Part I, LNCS 7324, pp. 107–114, 2012.

to natural scene appearances. Owing to this it is possible to recognize and interpret signals with characteristics that follow such statistics. The adjustment of the characteristics of an arbitrary image to the shape of natural statistics allows the transformation of such an image into a form that is well interpreted by HVS. However, the image artifacts can destroy such a structure. This fact can therefore be used to remove distortion, especially if there is a definable dependence between the distortion and the statistic shape. The situation appears exactly in the case when the image is distorted by noise. The specified noise level changes the statistic shape in a repeatable manner.

In the paper we present a new approach for the noise level evaluation based on NIS. We analyze statistics to understand how their properties depend on the level of noise. Our approach is based on higher order statistics computed in the wavelet domain. While selecting the noise model, it was decided we choose the Gaussian noise commonly used in different analyses. Owing to that choice an opportunity arose to compare our approach with the existing methods of denoising. As most of denoising algorithms require the user to specify the noise level, this new approach may be adopted as a module in any denoising method that requires defining the level of noise as an input parameter.

In section 2 we overview previous work. Natural image statistics and noise level evaluation based on these are explained in Section 3. Presentation of the method results is in Sect. 4 The paper is concluded in Sect. 5.

2 Previous Work

Apart from the blur, noise is the second main limitation in image accuracy. There exist many approaches for image denoising. All methods depend on a filtering parameter measuring the degree of filtering applied to the image. For most methods, the parameter depends on the estimation of the noise variance. We begin from the Gaussian smoothness model, through iterated total variation refinements [7], Yaroslavsky neighborhood filters [8], fixed ISO setting for the affine noise model [9],exploiting the SNR advantage of high ISO settings [10], translation invariant wavelet thresholding [11], or a simple and performing variant of the wavelet thresholding [12] where the most frequently adopted are hard and soft thresholding. The idea of the algorithms consists of removal of signal values under the threshold or in the defined band. A probability of artifacts occurring after wave transformation and resulting from the lack of information in thresholding spaces is a disadvantage of hard thresholding. The blur of results and loss of details are side effects of soft thresholding. There also exists a group of algorithms based on the regular structure of image characteristics encoded in the Human Visual System [2]. This method describes which geometrical features or details are preserved or eliminated by the denoising process. In order to preserve as many features of the original image as possible, the method should look like white noise as much as possible [13]. Estimation of an upper bound on the noise level from a single image based on a prior piecewise smooth image model and measured CCD camera response functions was proposed in [4]. They used the relation between noise level changes with respect to brightness on a Bayesian MAP to infer the noise level function from a single image. The other technique, NormalShrink, computed in a wavelet domain based on Gaussian distribution was proposed in [5]. This algorithm uses the features of soft thresholding. Noise variance evaluation is based on the median of subband coefficients, and their standard deviation. Features of characteristics encoded in natural image statistics for noise level evaluation and noise signal separation from original one were suggested in blsgsm algorithm [6]. This method uses the covariance of neighboring scales computed in a wavelet domain for the noise level evaluation. The results are very promising, however the approach is quite complex. In this paper we propose the approach MNE (Marginal Noise level Evaluation model) based also on characteristics of unprocessed images (natural image statistics). In contrary to the previous algorithms it characterizes with simplicity (low cost of calculations) and comparable efficiency.

3 Blind Level of Noise Detection

The set of all possible image groups is huge, however, not all of them are identified in the same way by the HVS, which enables distinguishing the context of the images based on key features coded in their statistics. In the case of an image distorted by noise, the process of detecting the original signal might be referred to as searching for the highest probability defining the signal which is closest to the image not distorted by noise. Image statistics can model information in natural images, therefore it can help in separation of the original signal from noise. Defining a set of key image features and their changes with reference to the level of noise, might be adopted to define a model of noise level detection.

3.1 Natural Images Statistics

Natural image statistics can be characterized by their order. In particular, the first, second and higher order statistics can be distinguished [14]. First order statistics consider only pixel values. There is no dependency between the neighboring pixels, so this kind of statistics is described by the histogram of pixel values. They are scalable and their translation is invariant, but they do not identify natural images. We can easily generate some noise and fit it in any histogram. Second order statistics consider the mutual relation of two pixels in an image. Such an approach is more powerful as pixels depend on each other in some way. It can be expressed as autocorrelation where we look at pixel intensities in two different positions that describe a vector. The autocorrelation can also be expressed in the Fourier domain as a power spectrum. Here, the distance between pixels can be described as the frequency and the difference in intensities as the amplitude. There is a problem in this approach, i.e. we lose information on feature location by averaging the amplitudes on phases.

Therefore, in this project we used higher order statistics that consider relations between pixel values, characterize with edge detection, and identify information on objects that are present in the image. The statistics are measured in the wavelet domain, so both spatial and frequency information are taken into consideration. In order to present the existing relation between the level of noise and the image characteristics, basic concepts and definitions connected with the marginal model will be introduced first. The model assumes that coefficients within a subband are independent and identically distributed [2]. To calculate these statistics the image is transformed into the wavelet domain, then a subband on which the statistics are computed is chosen. Next, the wavelet coefficients are grouped into bins and resulting values (see Fig. 1) are normalized.

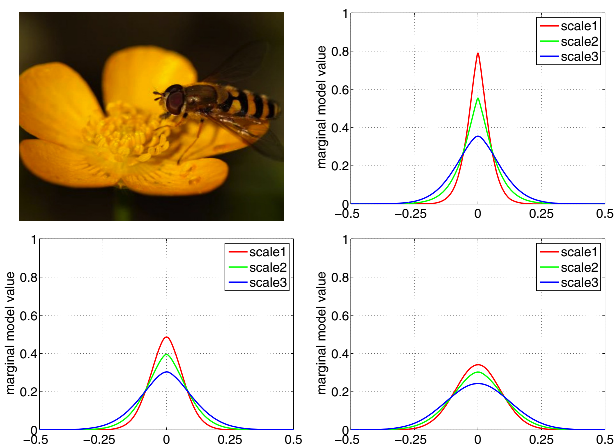

Fig. 1. Influence of the level of noise on the marginal model. Top: left original image, right: marginal model for three different scales computed for a noise level equal to 5, bottom from left: noise level equal to 10 and 15 respectively.

The distribution of wavelet coefficients is well modeled by the generalized Laplacian distribution (Eq. 1) [15]. An exponent of $p = 2$ corresponds to the Gaussian density, and $p = 1$ corresponds to the Laplacian density. In general, smaller values of p lead to density that is both more concentrated at zero and has more expansive tails. It can be observed that values of the exponent p typically lie in the range of $[0.4, 0.8]$. The factor s changes monotonically with the scale of the basic function, with correspondingly higher variance for coarser scale components [15].

$$P_c(c; s, p) = \frac{\exp\left(-|\frac{c}{s}|^p\right)}{Z(s, p)}, \tag{1}$$

where s and p are function variables and c denotes wavelet coefficient and the normalization constant is given by Equation (2).

$$Z(s, p) = 2\frac{s}{p}\Gamma\frac{1}{p}. \tag{2}$$

3.2 Algorithm

While analyzing the higher order statistics calculated for the images destructed by an increasing noise level, a distinctive, repeatable manner of character change has been noticed. The nature of this change appeared to be independent from the image context. The change in question concerned the marginal model and it is adopted in our algorithm. It has been noticed that together with an increase in the level of noise, the value of the marginal model is lower at its maximum. Additionally, the statistics for neighboring scales (level 1, 2 and 3 respectively) slowly started to overlap. Such an effect for an image example is illustrated in Figure 1. As long as the marginal statistics for neighboring scales differed to a large extent in an image with a low level of noise, the difference appeared to be less significant for statistics computed for a higher level of noise. The observed rule can be adopted in the process of detecting the level of noise.

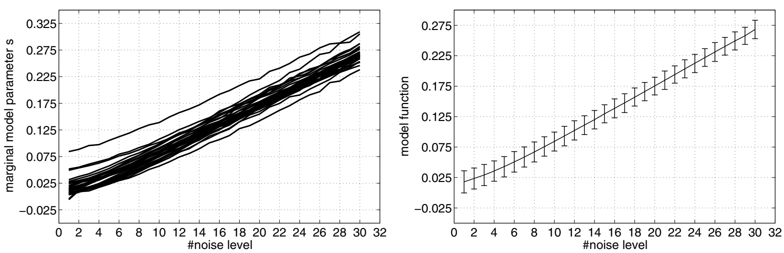

Fig. 2. Left: Relation between the marginal model parameter s calculated for the images from the LIVE database [3] and noise ranged in $< 1, 30 >$ %. Right: the averaged result with error bars computed based on standard deviation.

In this project particular attention was paid to the parameter s of the marginal model. While analyzing its behavior for the noised images, a monotonical change in the parameter was noticed for the level of noise coefficient. The value of parameter s appears to be directly proportional to the noise level (see Fig. 2 left). The dependence was tested on 30 example images from the LIVE quality database [3]. We chose this database as it contains a broad range of content type, including faces, animals, man-made objects and nature. The variety of images context seems to be sufficient for reliable investigations. Regardless of the context for the analyzed image, the character of the parameter s behavior did not alter. On the basis of the collected data, a Basic Noise Level (BNL) function was defined. It was obtained as an average of the functions of parameter s and a noise level calculated for each image separately. (see Fig. 2 right). The averaged function is well described by first degree polynomial (Eq. 3) and is proposed to restore the level of noise.

$$f(n) = p(1)s + p(2), \tag{3}$$

where n denotes the level of noise and s the parameter of the marginal model computed for the analyzed image, $p(1) = 112$ and $p(2) = 0.15$.

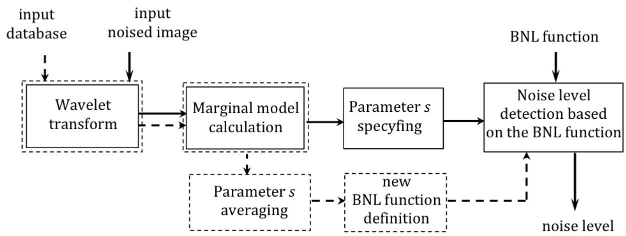

Fig. 3. The scheme of the noise detecting algorithm based on the marginal model. Dot-line blocks denote the process of BNL function acquisition. Solid-line blocks correspond to noise level detection based on a previously defined BNL function.

The universal character of the model results from taking into account images with different context. In the case of a non-standard group of images (e.g. microscopic images which are understandable only for a narrow group of experts), it is possible to generate ones own BNL function in order to gain higher accuracy (see Fig. 3). In that case, information about images of similar character (2 or 3 are sufficient) and with an insignificant noise level should be provided. Then, input image luminance must be transformed into the wavelet domain and its coefficient must be computed. Subsequently, marginal model parameters must be calculated. To provide the greatest stability of the characteristic, average coefficients from horizontal, vertical and diagonal subbands of the first level scale should be used. Next, the data must be averaged in order to obtain the BNL function.

4 Results

The approach was implemented in Matlab. To compute the universal BNL function we used images from the LIVE database [3] containing a broad range of content type, including faces, animals, man-made objects and nature. 30 images were gradually destructed with noise ranging from 1 to 30%. Then, higher order statistics were calculated for the obtained images. Creating a database on the basis of so many images is a time consuming process, however, it was prepared one time. Further calculations use a model extracted from the database. A standard deviation of 0.015 was received for the model (see Fig. 2). Accuracy of the method was noticed with about 1% which denotes one level of noise (see Fig. 4). To confirm the quality of our results we compared them with the other approaches considering the evaluation of noise level in the wavelet domain: NormalShrink [5] and Blsgsm [6] (see Fig. 4). To make a reliable comparison, the codes of the algorithms were downloaded from their authors websites. The level of noise detected on the basis of our algorithm appear to be comparable with NormalShrink and Blsgsm, despite the smaller complexity.

The model was also examined for different ranges of content type: people, nature and abstraction. As it was noticed in [1], the statistics for images of different context kept the same character, however, they are shifted with reference to each other. This results from the definition of the HVS that also enables distinguishing of the context of the images by a human based on key features coded in their statistics. Therefore, in the case of higher accuracy, it is proposed to calculate ones own basic model on the basis of images with similar content. It is quite important as there is a broad range of untypical images whose context is not obvious to everyone. The problem concerns all algorithms based on natural image statistics. Microscopic images which are understandably only for a narrow group of experts are a good example. In this case, using characteristics encoded in standard images can be affected by error. As the removal of noise from those images is a critical issue, the possibility of tuning the function parameters for non-standard features of the images is important.

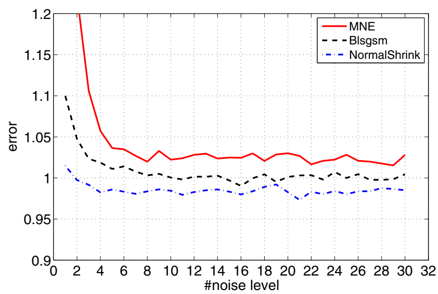

Fig. 4. Comparison of the efficiency of the algorithms for noise level detection by received error for MNE, Blsgsm and NormalShrink algorithms. The error is computed as difference between the noise level which distorted the image and the detected one.

5 Conclusions and Future Work

In this paper, the algorithm for blind level of noise detection is presented. The basis of the approach is a marginal model of Natural Images Statistics. The relation between the shape of higher order statistics and the level of noise, whose character changes in a repeatable manner, was used to compute a basic model enabling reconstruction of the level of noise for any image, with an error of about 1%. The possibility of calculating ones own BNL function was proposed in order to increase the accuracy of calculations for an untypical set of images. The results were compared to other well-known approaches and similar results were observed. The advantage of the proposed approach is its simplicity. It could be used as an input for algorithms requiring the specification of noise level by the user. It might also be used in applications of image processing to check the level of noise as their side effect.

Acknowledgements. This work was supported by the Polish Ministry of Science and Higher Education through the grant no. N N516 193537.

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