BIASED IMAGE CORRECTION BASED ON EMPIRICAL MODE DECOMPOSITION

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ABSTRACT

The automated analysis of images is an active field of research in image processing and pattern recognition. In many applications, the first issue is to face illuminations artifacts that can appear due to bad imaging conditions. These artifacts often have direct consequences on the efficiency of the image analysis algorithms but also on the quantitative measures. This paper presents a fully automated nonuniformity correction based on empirical mode decomposition. The performances are outlined using both synthetic and real data.

Index Terms— Image analysis, image enhancement, image restoration, biomedical image processing, biomedical microscopy.

1. INTRODUCTION

In many applications (magnetic resonance, confocal microscopy, radar, ultrasound, etc...) images are subjected to illuminations artifacts. These biases, or shading, can strongly corrupt low level image analysis (such as segmentation, intensity evaluation) or higher level computations (features detection or any kind of *ad-hoc* descriptors extraction) [1]. To overcome this drawback many methods have already been proposed in literature. A reader can refer to [2] for a comparative evaluation of the most common intensity inhomogeneities correction techniques. These methods can be classified into two families: parametric and non parametric. In this paper, we propose a non parametric method based on Empirical Mode Decomposition (EMD) surface modeling.

In section 2, we formulate the problem of bias in image processing. Section 3 of this paper presents our technique for image bias correction based on empirical mode decomposition. In Section 4, we validate our algorithm on simulated and biological images.

2. BIAS IMAGE CORRECTION

Shading phenomenon is often defined as a smooth intensity variation, leading to a nonuniform illumination of the image. Based on this definition, we assume that the corrupted images can be seen as a non-stationary process.

In signal processing, according to the traditional definition, a time series, $X(t)$, is stationary in the wide sense, if, for all t,

$$\begin{cases} E(|X(t)^2|) < \infty \\ E((X(t)) = m, \\ C(X(t_1), X(t_2)) = C(X(t_1+\tau), X(t_2+\tau)), \end{cases} \quad (1)$$

in which $E(.)$ is the expected value and $C(.)$ is the covariance function.

In our context, we consider that each pixel $I(x, y)$ of an image I is a combination of its real intensity $I_0(x, y)$, an illumination bias artifact $b(x, y)$, and an additive white Gaussian noise $\epsilon \equiv N(0, \sigma^2_{noise})$ [3], where (x, y) is the spatial location of a specific point within an image of size $X \times Y$. The relation is given by:

$$I = I_0 b + \epsilon. \quad (2)$$

It is necessary to find a method which is able to discriminate the variation of the expected value during the time. According to equation (2), to correct each picture, we divide the observed signal I by the estimated bias $\hat{b}$. Equation (2) thus becomes:

$$\frac{I}{\hat{b}} = \frac{I_0 b}{\hat{b}} + \frac{\epsilon}{\hat{b}}.$$

We systematically apply a Gaussian filtering to the image prior to estimating the bias. Hence, $\epsilon << \hat{b}$ can be omitted and we obtain:

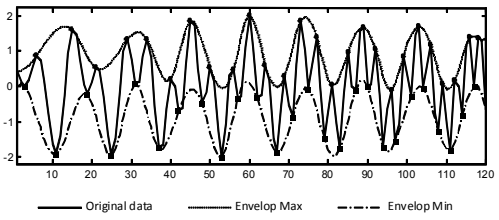
$$\hat{I_0} = \frac{I}{\hat{b}} \approx \frac{I_0 b}{\hat{b}} \approx I_0, \quad (3)$$

where $\hat{I_0}$ is the corrected image.

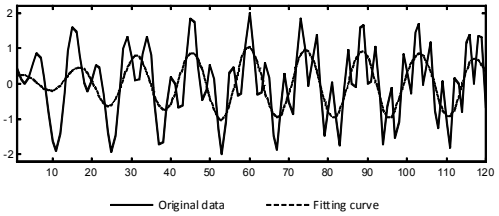
3. EMPIRICAL MODE DECOMPOSITION

3.1. 1D overview

In a recent work, Huang *et al.* [5] proposed a new method to analyze some nonlinear and non-stationary process called Empirical Mode Decomposition (EMD).



(a)



(b)

Fig. 1. EMD process on a 1D signal [4]. Top: The original signal between the interpolated envelop E_{max} and the interpolated envelop E_{min}. Bottom: the original signal and the residue.

It is based on the localization of the different maxima and minima which contain the signal. If we take a simple example like a pure sinus signal, it is obvious to see that the frequency of the signal is the result of two consecutive maxima or minima and the variation of the mean is also subjacent to the value of these extrema.

The principle of this basis construction is based on the physical time scales that characterize the oscillations of the phenomena. EMD provides an adaptive and locally decomposition method. The signal is decomposed into a redundant set of signals denoted IMF for intrinsic mode functions and a residue (see Fig.1). Authors in [6] propose a first mathematic approach of the IMF. Adding all the IMFs together with the residue reconstructs the original signal without information loss or distortion. The empirical mode frequency called *empiquency* is obtained by considering the successive extrema points of the function. The EMD algorithm is:

- find all the local minima and all the local maxima in the image,
- make a spline interpolation of the local maxima, that will be defined as the upper envelope denoted $E_{max}(t)$,
- make a spline interpolation of the local minima, that will be defined as the lower envelope denoted $E_{min}(t)$,
- calculate the mean of the upper envelope and the lower envelope,

$$M(t) = \frac{1}{2}(E_{max}(t) - E_{min}(t)),$$

- subtract the mean signal $M(t)$ from the input signal $X(t)$,

$$H(t) = X(t) - M(t).$$

This algorithm is iterative, and we consider the mean signal $M(t)$ as the input signal.
We obtain a representation of $X(t)$ of the form:

$$X(t) = M_K(t) + \sum_{k=1}^{K} H_k(t).$$

This method is principally used in the signal processing field. We propose here to extend this approach for image bias estimation.

3.2. 2D extension

To our knowledge, most of the applications using EMD are in 1D [4]. Nevertheless, the EMD can be implemented in two dimensions via, for example, the thin-plate spline [7]. After the extraction of local maxima we proceed to an interpolation by a radial basis function (RBF). The RBF is an interpolation method that finds a minimally bent smooth surface that passes through all given points.
We want to estimate the function s, with $s(x_i, y_i) = z_i, \forall i \in (1, n)$.

$$s(x,y) = p_1(x,y) + \sum_{i=1}^{n} \lambda_i . \Phi\Big(\Big| \begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} x_i \\ y_i \end{pmatrix} \Big| \Big),$$

with p_1 a polynomial of degree 1, $p_1(x,y) = c_0 + c_1 x + c_2 y$, λ_i is a real-valued weight, $\Phi(.)$ a basis function, $|.|$ denotes the Euclidean norm and x_i, y_i the points known. To obtain the surface interpolation, we have to solve:

$$\begin{pmatrix} A & Q \\ Q^T & 0 \end{pmatrix} \cdot \begin{pmatrix} \lambda \\ c \end{pmatrix} = \begin{pmatrix} z \\ 0 \end{pmatrix},$$

with $A = a(ij) = \Phi\Big(\Big| \begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} x_i \\ y_i \end{pmatrix} \Big| \Big)$, and:

$$\begin{cases} c = (c_1, c_2, c_3)^T, \\ p_1 = c_0 + c_1 x + c_2 y, \\ z = (z_1, z_2 \dots z_n), \\ \lambda = (\lambda_1 \dots \lambda_n)^T, \end{cases} \text{ and } Q = \begin{pmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ . & . & . \\ . & . & . \\ 1 & x_n & y_n \end{pmatrix}.$$

In our case, we choose $\Phi(r) = r^2 \log(r)$ leads to a thin-plate spline interpolation. Then, once we know values for λ_i and c_1, c_2, c_3, we can interpolate z for any arbitrary points (x, y).

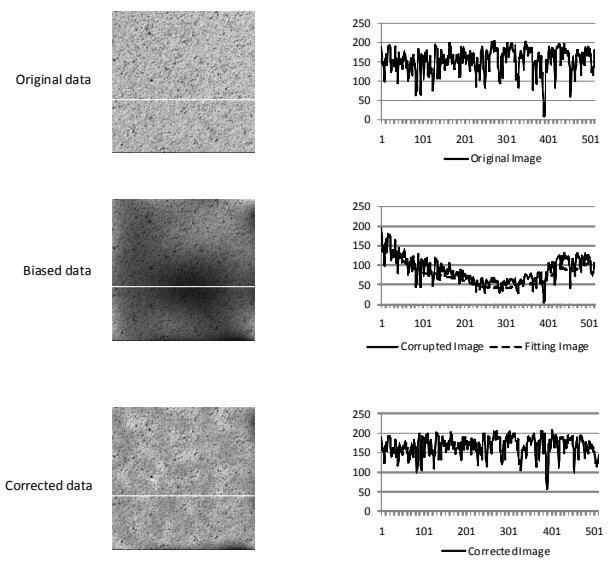


Fig. 2. From top to bottom: Original texture (sand) and one associated intensity profile. Biased texture and corresponding profile where we can see the trend of the image, and the trend estimated by our method. Corrected texture and corresponding profile

4. VALIDATIONS

In this section we apply our correction scheme on artificially biased texture and real microscopic cells corrupted images.

4.1. Simulated bias images

In order to validate our algorithm, we are looking for some images that verify the assumption of stationarity: mean, variance and autocorrelation structure should not change over time as defined in Eq.(1). Textures are defined like stochastic and stationary images. In our purpose, we choose deterministic textures from the Brodatz[1] database and we generate smooth bias images issued from low order Legendre orthogonal polynomial functions. This bias is multiplied by texture images. The resulting image becomes non stationary.

Figure 2 illustrates how a bias modifies the original image and leads to a non stationary image with a smooth trend. We recover the trend present in the biased image by our method as described in Eq.(2).

We apply this correction framework on different textures. To evaluate the result, we calculate the Euclidean distance between original, I_0, and biased, I, data and then between original and the corrected data $\hat{I}_0$ as describe in Eq.(3).

Table 1 displays the results of this evaluation. For each texture, we improve the L_2 distance between original and corrected images. In order to verify Eq. (1), we calculate the variance of a sliding mean over the whole image. Our results seems to be related to the stationarity of the original data. However, the last criterion for the stationarity (covariance) is not necessary increase.

[1] http://www.ux.uis.no/tranden/brodatz.html

	$L_2(I_0, I)$	$L_2\ (I_0,\hat{I}_0)$	$\sigma_\mu(I_0)$	$\sigma_\mu(I)$	$\sigma_\mu(\hat{I}_0)$
sand	0.095	0.029	2.48	37.28	6.90
wood	0.055	0.038	3.99	25.02	15.06
grass	0.043	0.033	6.9	17.04	13.09

Table 1. Euclidean distance and variance of the mean for three different textures. Correction process always improves these criteria.

4.2. An application to cellular imaging

Nowadays, new microscope imaging platform provides a very large amount of pictures and requires more quantitative process than before. To perform this, it is important to add a robust correction pre-processing. In the biological microscope image processing field, it is typical to deal with biased images (in our case due to bad auto-focusing and dichroic mirror deformation) and thus, it is helpful to develop an accurate restoration algorithm. Figures 3 & 5 display typical cell images and reveal that this kind of images can be considered as texture, as defined in the previous section. We propose here to perform EMD bias correction on fluorescence microscope cell images and thus to validate the relevance of this algorithm for these particular images.

Figure 3 presents a typical biased present in microscope images. We choose an intensity profile in a highly corrupted area of the picture to confirm the improvement of the correction. Moreover, figure 5 points out a visual improvement of a global segmentation process.

We also make a qualitative validation with a higher level process describes in [1]. Figure 4 shows that this feature detection framework is enhanced by the pre-processing step we propose.

5. CONCLUSION

Most sensors produce illumination artifacts on images and lead to poor analysis results. The formulation of the bias is commonly accepted to be a multiplicative term. In this paper we have established a first approach of the capabilities of the empirical mode decomposition to approximate the bias either on synthetic or natural images. An experiment on textures allows us to obtain a quantitative validation. We also apply our algorithm on confocal microscopic images and evaluate it with low and high level criteria. The first one is a global segmentation and the second one is a detection of feature points. In both cases, we significantly improve the results. We are actually working on a comparative evaluation of our technique

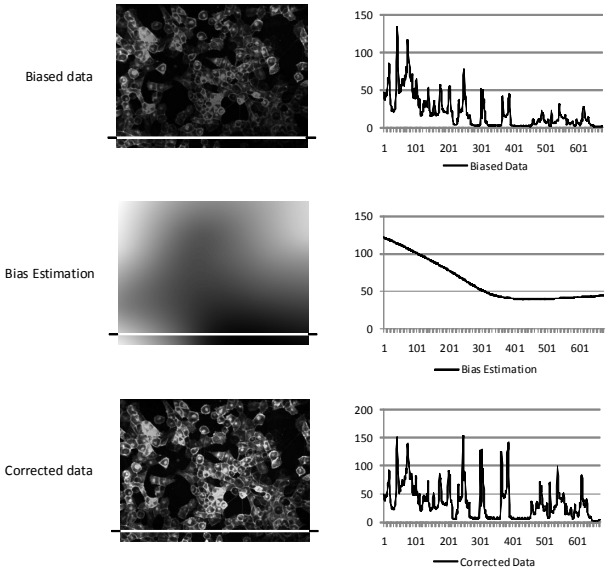


Fig. 3. From top to bottom: microscope cells biased image and associated intensity profile. EMD bias estimated and corresponding profile. Corrected image and its profile. It is important to notice that the corrected image has been multiply by a factor for visualization convenience.

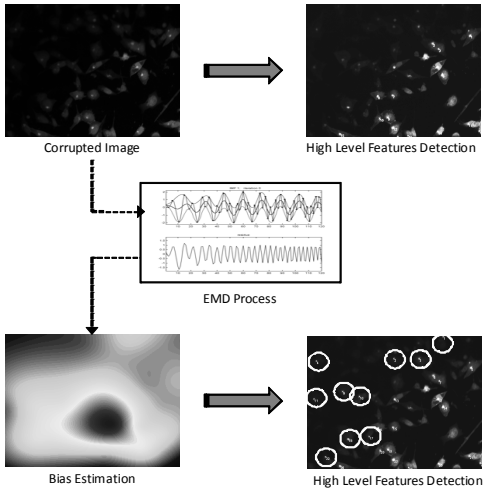


Fig. 4. Scheme of the detection process. We improve the segmentation and so the detection of point.

to the most commonly used in the literature.

6. ACKNOWLEDGMENT

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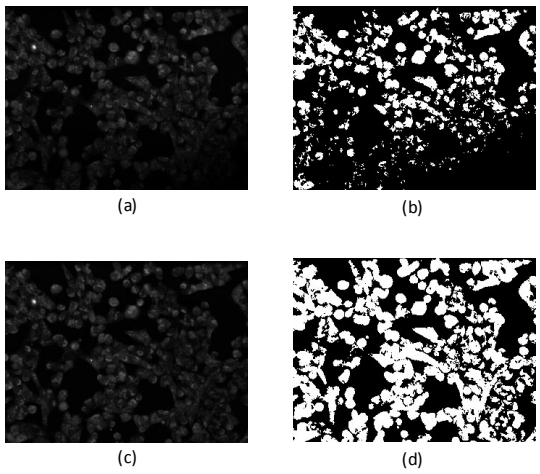

Fig. 5. From top to bottom: microscope cells biased image and the result of a K-mean segmentation. Corrected image and the result of a K-mean segmentation.

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