LOCAL BLUR ASSESSMENT IN NATURAL IMAGES

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Keywords: Local Blur Detection, No-reference Blur Metric, Wavelet Analysis.

Abstract: This paper presents a local no-reference blur assessment method in natural macro-like images. The purpose is to decide the blurriness of the object of interest. In our case, it represents the first step for a plant recognition system. Blur detection works on small non-overlapping blocks using wavelet decomposition and edge classification. At the block level the number of edges is less than on global images. A new set of rules is obtained by a supervised decision tree algorithm trained on a manually labelled base of 1500 blurred/un-blurred images. Our purpose is to achieve a qualitative decision of the blurriness/sharpness of the object of interest making it the first step towards a segmentation process. Experimental results show this method outperforms two other methods found in literature, even if applied on a block basis. Together with a pre-segmentation step, the method allows to decide if the object of interest (leaf, flower) is sharp in order to extract precise botanical key identification features (e. g. leaf border).

1 INTRODUCTION

Quality assessment in terms of digital images plays an important role in various fields, such as image indexing, segmentation, recognition, etc. Image quality has received special interest during the last two decades and a vast number of quality evaluation indexes have been proposed. Based on the existence of ground-truth images, these metrics may be divided into two major classes: full-reference (FR) and no-reference (NR). However, a third class has been recently introduced that lies between the two, namely reduced-reference (RR). This paper deals with no-reference image quality assessment designed for blur distortions in macro-like photos of plants (leaves, flowers) taken in natural scenes. It serves as the first step towards a pattern recognition algorithm for plant identification.

One of the most encountered and disturbing distortion is blur. Blur can affect the entire image, or parts of it.

Macro mode allows the photographer to take images from close-up. The focus is on capturing one object, which should be sharp, while the background remains in blur. Users can shoot a plant image from close-up in order to recognize its specie. Natural macro-like images are a combination of edges, texture details and flat regions, where the color transitions are almost unnoticeable. This last aspect limits the use of global quality indexes due to a false estimation as blur. Figure 1 presents sample images of leaves containing encountered drawbacks: the object size, which can be small in comparison with the blurred background (sometimes taking up to 50% – 70% of the image size) that will mislabel the image as blurred, or, the background that may contain the same objects as the one of interest.

Figure 1: Sample blurred images from our database.

The goal is to develop a fast algorithm that finds whether the intended object is sharp or not. Although there are various algorithms proposed for a global quality assessment, one quality index

This work has been supported by the French National Agency for Research with the reference ANR-10-CORD-005 (REVES project).

Suta L., Scuturici M., Miguet S., Tougne L. and Vaida M..
LOCAL BLUR ASSESSMENT IN NATURAL IMAGES.
DOI: 10.5220/0003854001230128
In *Proceedings of the International Conference on Computer Vision Theory and Applications* (VISAPP-2012), pages 123-128
ISBN: 978-989-8565-03-7

estimated on the entire image is not enough to get a reliable decision in this case.

In this paper we propose a localized blur assessment algorithm for natural images inspired by the previous work of (Tong et al., 2004). Our aim is to detect the blurred regions that affect the object of interest, in our case the plant.

The paper is organized as follows: Section 2 describes the existing algorithms for blur assessment. Section 3 presents the proposed local blur assessment in natural images. Experimental results are shown in Section 4 followed by conclusions and future work in Section 5.

2 RELATED WORK

Blur is a caused by an imperfect image formation process. There are four types of blur: out-of-focus, camera shake, object motion and atmospheric blur (fog, rain, etc.). In this section, we restrained our research towards objective no-reference blur metrics, since we do not dispose of the reference image.

Objective no-reference blur detection methods address two types of evaluation introducing global and local metrics, respectively. Global assessment reveals blur extent coefficients, blur classification and restoration possibilities. However, methods work successfully over landscape images, these indexes have limitations when applied to macro-like photos. Local metrics are often combined with the pre-use of a global evaluation or a block division of the original image. It is more intuitive, as avoids mistakenly focusing on the blurry background.

Multiple approaches to blur detection are based on edge detection (Tong et al., 2004), (Chen and Bovik, 2011), (Narvekar and Karam, 2011)]. (Tong et al., 2004) propose a blur detection scheme built on the Haar wavelet transform and edge detection. The algorithm is based on the estimation of edge sharpness and the computation of the blur extent based on a discrimination of sharp edges. The results show a global assessment of blurred landscape images. For macro-type images, the algorithm fails. (Moorthy and Bovik, 2010) and (Chen and Bovik, 2011) investigate a blur metric using wavelets for natural scenes. The first approach represents a blind assessment based on a probabilistic support vector machine (SVM) and a support vector regression (SVR) in order to map the image statistics in one global value. The second approach consists of three steps. At first, the SVM is applied to get a coarse quality assessment. It is followed by a multi-resolution analysis to refine the blur metric and the last step consists of the prediction of the blur metric. In (Narvekar and Karam, 2011), a no-reference blur metric method is described based on the human perception and edge analysis. It is a probabilistic method applied on each edge in an image arriving to a global assessment of Gaussian and JPEG2000 blur types, respectively.

The estimation of the blur kernel is commonly used to detect and classify blurred images (Joshi et al., 2008), (Hsu and Chen, 2008). Linear blur in digital images is described using a “blur kernel” or the point-spread-function (PSF). The drawback is that linear blur does not include all blur types (e. g. out-of-focus blur). In (Joshi et al., 2008), a blur detection algorithm for spatially-varying blur functions is presented, in particular the estimation of point-spread function (PSF). The method handles defocus blur, camera motion and intrinsic image formation. The method is completely automatic and scene-independent. (Hsu and Chen, 2008), propose a blurred image detection and classification algorithm based on the estimation of point spread function and the use of support vector machine (SVM). The blur extent is computed using the image gradient model. Next, images are classified into globally or locally blurred images using the point spread function. Furthermore, globally blurred images are sorted into camera shake or out-of-focus, while on locally blurred images a segmentation algorithm is performed to detect the blurred regions and classify them into depth-of-field or moving object type, respectively. The use of SVM increases computational costs and complexity.

A region-based blur detection approach has been conducted by (Lim et al., 2005). Images are divided into non-overlapping blocks where local measures are computed through image analysis. Based on the figure-of-merits, the estimated parameters are brightness, color, median sharpness, density of sharp blocks and composition. The success rate is 90%, while the algorithm produces 10% of false alarms.

Global detection works well over landscape images where blur is usually linear. Complex blur kernels are difficult to estimate using only global quality metrics. Determining a probability of rather sharp/blurry image is not enough to decide whether the image may or may not be used in further processing steps. Localization of blurred regions are more adequate to solve problems related to objects of interest, which will consist the input for segmentation algorithms, feature extraction or recognition. The low computational cost of the Haar wavelet analysis suits the scope of implementation on smartphones.

3 METHODOLOGY

Multi-resolution analysis has been proven to provide reliable results in blur assessment tasks. The spatial-spectral properties may identify important changes in the high-frequency coefficients that correspond to the edges in the digital photo. According to (Tong et al., 2004), there are four types of edges found in digital images: Dirac-Structure, Roof-Structure Astep-Structure and Gstep-Structure, respectively.

Previous work of Tong provides a direct method for blur assessment without the description of the blur kernel. The method shows good results for landscape images. Applied to macro-like photos, it reliably detects camera-shake blur or out-of-focus if the entire image is affected. The drawback remains for partially blurred images exhibiting object motion blur or blurred background.

Out-of-focus blur introduces a separation between two image planes, the background and the foreground, leading to the following situations where a global detection method is not reliable:

- The background is blurred and the foreground is sharp. The size of the sharp foreground may be too small with respect to the size of the image.
- The foreground is blurred and the background is sharp.

Another drawback of the existing global methods appears when the size of the sharp foreground is too big and presents uniform color zones. Figure 1 shows examples for the above mentioned cases.

3.1 Proposed Method

We propose a local blur detection technique using three-level multi-resolution analysis designed for macro-like photos. Figure 2 presents the computational block diagram for the proposed method.

3.1.1 Block Selection

One user-taken plant image, I, is divided into smaller non-overlapping image blocks, I_b. The choice of block dimension is an essential step as it directly affects the accuracy. As the wavelet decomposition is dyadic, the best adapted block size is 2^n.

The pre-segmented model, I_s, allows us to find the approximate localization of the rough contour of the object (Region of Interest, ROI). Its computation uses a 2-component Gaussian mixture model and the Mahalanobis distance, (Cerutti et al., 2011).

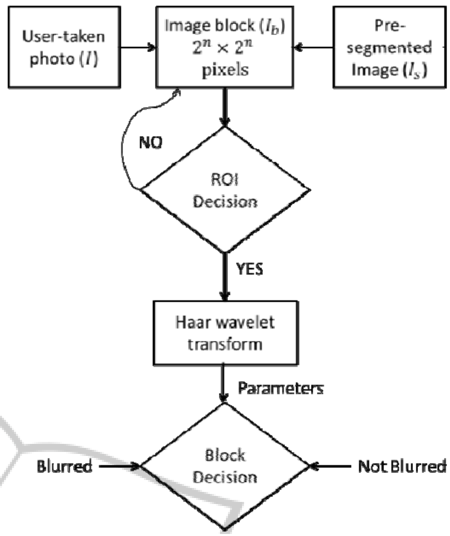

Figure 2: Computational block diagram for the proposed method.

Figure 3: The distance map (left – original image, middle - 2-Gaussians color map, right – pre-segmented model).

Figure 3 illustrates the obtained distance map based on which the appropriate pre-segmented model is selected.

I_s is divided into blocks with the same size as previously applied on I to have a perfect correspondence between the two inputs.

The following operations are executed on I_b. Firstly, a decision on the existence of an object contour is computed. To avoid blocks with ambiguous information, as containing only an insignificant amount of the object, two thresholds have been set over the total number of black and white pixels respectively, found in the model block. If the values are under the accepted thresholds, I_b is rejected from further processing steps.

3.1.2 Local Blur Detection

Each valid block is decomposed by the wavelet transform, resulting in three sets of detail coefficients on every decomposition level.

Edge type detection and analysis is performed as in (Tong et al., 2004), obtaining the statistical parameters for each edge type. The obtained detail coefficients are used to calculate the energy map as in (1):

$$E_{map_i}(p,q) = \sqrt{\int dc_i^2 \, dt} \;, i = 1,2,3 \qquad (1)$$

where dc suggests the detail coefficients for each decomposition level given by i.

Based on (1) and using the table given in (Tong et al., 2004), we can identify and compute the total number for each of the four edge types.

Contrary to the method of Tong, the decision thresholds are completely omitted due to the low edge information and uniform color regions in macro photos. We computed a new set of decision rules with supervised learning method using a decision-tree based on the C4.5 algorithm. 1504 block images have been manually labeled into two categories, as follows: "blurred" and "unblurred". Together with the color features, these were involved in the training of the decision tree. The most relevant decision rules for I_b, obtained using the method C4.5, are presented in Figure 4.

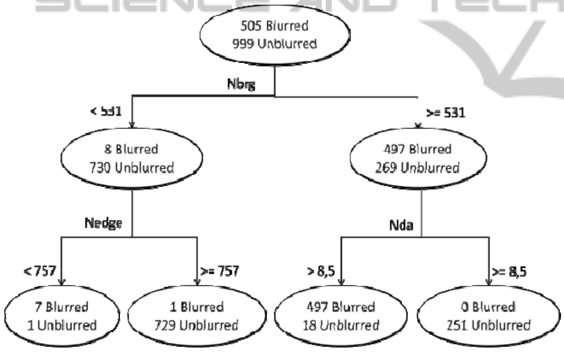

Figure 4: Decision tree presenting the set of rules.

where *Nedge* represents the total number of edges, *Nda* is the number of Dirac and A-Step classified edges, and *Nbrg* describes the number of blurred Roof-Step and G-Step edges.

The error rate in cross-validation is 0.01. Table 1 shows the confusion matrix in cross-validation.

Table 1: Confusion matrix on trained data set.

Groundtruth / Decision	Blurred	Sharp	Total
Blurred	495	10	505
Sharp	5	994	999
Total	500	1004	1504

The rules given by the supervised learning have been involved in the threshold and decision step. Based on the set of rules, I_b is labeled as blurred or not blurred, respectively. Figure 5 shows the block separation and labelling as *"B"* for blurred and *"OK"* for un-blurred image blocks. Two macro images were analysed exhibiting sharp and blurred foreground, respectively, where global metrics give "blurred" decision.

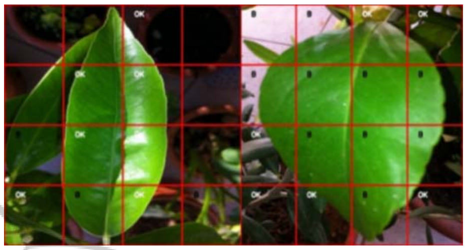

Figure 5: Blurred blocks labeling based on the set of rules (left – sharp foreground; right – blurred foreground).

We can compute a global blur metric based on the existent number of blurred blocks given by (2).

$$BlurCoef = \frac{N_{blurred}}{N_{total}} \qquad (2)$$

where $N_{blurred}$ represents the number of blurred blocks and N_{total} represents the total number of blocks of the image.

4 EXPERIMENTAL RESULTS

Tests were performed on two databases: LIVE database (174 images), (Sheikh, Wang, Cormack, and Bovik), and our ReVeS databases (94 images). ReVeS images consist of a collection of unprofessional user-taken photos using a smartphone camera. Each photo represents one or more parts of a plant in its natural habitat. 1504 non-overlapping block images were manually labeled into two categories: blurred and non-blurred.

On the previously described databases we performed our method and the objective evaluation using the cumulative probability blur detection, CPBD (Narvekar and Karam, 2011), and blind image quality index, BIQI (Moorthy and Bovik, 2010). These methods offer global metrics. For comparison, we computed the global blur parameter for each photo given by (2).

Table 2 presents test results obtained on the analyzed databases for each algorithm. The last column in Table 2 presents the Spearman rank order correlation coefficient (SROCC) between the blur coefficient of the CPBD algorithm and our blur coefficient. We can observe a moderately strong positive correlation of 0.74 between our results and the CPBD for the test performed on entire images. On the contrary, tests conducted over ReVeS database show a negative correlation which is explained by a high quantity of images with out-of-focus blur (small sharp object surrounded by a blurred background) or images containing motion blur which is not detected by the CPBD algorithm.

Table 2 : Test results on different databases.

DB	DB size	Algorithm	SROCC
LIVE	174	CPBD	0.74
LIVE	174	BIQI	0.87
ReVeS	94	CPBD	-0.85
ReVeS	94	BIQI	0.73

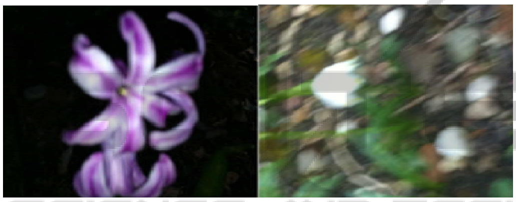

Figure 6: ReVeS database images (left – Out-of-focus blur; right – camera-shake blur).

Figure 6 highlights common problems encountered in macro-like images taken by users with smartphone cameras. There are two frequent blur types that degrades the image quality, out-of-focus blur affecting the object of interest and camera-shake blur, respectively. An objective evaluation using the CPBD metric predicts rather sharpness on both images. The computed values are 0.85 and 0.77, where the maximum of 1.00 stands for “sharp image”. However, our proposed method successfully detects the degradations with a blur estimation of 0.99 and 0.98, where the maximum of 1.00 designs a “blurred image”.

The local assessment has been performed on non-overlapping image blocks. The images from ReVeS database have been divided into blocks as described in the previous section and stored as JPG images with the size of $2^n \times 2^n$. Tests revealed that in order to be able to identify all four edge types on the three decomposition levels, the minimum block size must be $2^7 \times 2^7$. Table 3 shows the influence of size on the edge detection.

Table 3: Influence of block size on edge detection.

Block Size	Detected Edge Types
16×16	No edges
32×32	Non-discernible edge types
64×64	Ambiguous parameters
128×128	OK

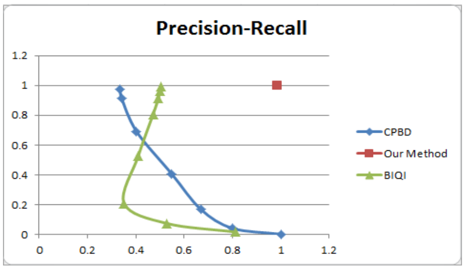

Figure 7: Graphical representation of precision-recall over the manually labeled image blocks from ReVeS database.

Figure 7 presents the precision and recall (ROC curve) for the three algorithms applied on the image blocks generated from the ReVeS database. The red point represents the precision/recall of our algorithm. The result of our algorithm is a qualitative decision (*blurred/unblurred*) given by the decision tree presented in Figure 4. For the two other methods, in order to compare them with our method, we vary the threshold allowing a decision as *blurred/unblurred* according to the coefficients calculated in their algorithms – in order to take the best value for this threshold. We vary the threshold by a 0.1 step. The ideal point in the ROC curve is (1,1): precision = 1 and recall = 1. Our algorithm gives the best results (0.984, 0.998), even for the best threshold values for each of the CPBD and BIQI algorithms.

As our interest is the contour of a shape, we use the pre-segmented model to find the approximate region of analysis. Figure 8 illustrates results obtained by our method. Note that missing blocks over the leaf object are due to the thresholds imposed on the pre-segmented model for the amount of black and white pixels distribution.

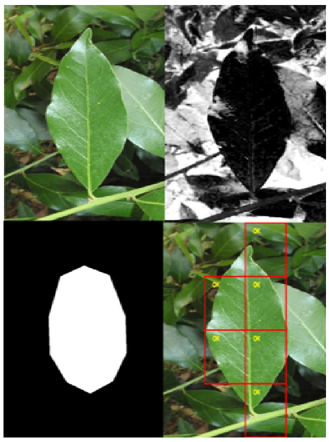

Figure 8: Test result using the proposed method (first row from left to right – original image and the distance map; second row from left to right – pre-segmented model and algorithm output).

5 CONCLUSIONS

In this paper we presented a no-reference local blur assessment method for macro-like images. Contrary to other blur detection methods, the proposed algorithm can localize blurred regions over the image and with the computed model, the estimation can be done over the region of interest.

The proposed method uses wavelet analysis for edge detection and classification. The obtained parameters are adjusted by using a supervised decision tree algorithm trained on a manually labeled base of 1504 blurred/un-blurred images

According to the difficulty of achieving a qualitative blur decision based on a single quantitative value, the set of rules given by the decision tree let us partition an image into blurred and sharp regions while the pre-segmentation model localizes the rough position of the object of interest. The use of the pre-segmented model also reduces the computational costs.

Future work includes studying the possibility of a separation between foreground and background using the proposed algorithm. The REVES project had proposed to include the quality detection as a first step of a complete processing chain. These first results suggest that segmentation and quality assessment should rather cooperate: the segmentation can help blur detection, the blur estimation process can also help the identification of different planes in the scene.

ACKNOWLEDGEMENTS

This work has been supported by the French National Agency for Research with the reference ANR-10-CORD-005 (REVES project) and co-financed from SIDOC - POSDRU/88/1.5/S/60078 project.

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