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GLOBAL BLUR ASSESSMENT AND BLURRED REGION DETECTION IN NATURAL IMAGES

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Abstract:In this paper we present a global no-reference blur metric based on a local approach of blur detection in natural macro-like images. The purpose is to study the possibility of global assessment based on thedetection of blurred regions over an analyzed image. 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 set of rules is obtained by a supervised decision tree algorithm trained on a manually labeled blurred/un-blurred image blocks which leads to a qualitative decision of the blurriness/sharpness of the regions. Experimental results show how the qualitative decision may be transformed in a global assessment.

Keywords: *global blur assessment, local blur detection, no-reference blur metric, wavelet analysis.*

I. INTRODUCTION

Image quality – in image processing can be defined as the degree of suitability for a given problem without previous assumptions regarding the receiver which can be either human or an application. The suitability determines the type of the chosen assessment method. If the ultimate users are humans, a subjective evaluation would best fit the given problem. On the other hand, in computer vision fields, such as image indexing, segmentation, recognition, etc., human interaction for quality assessment may become tedious and time-consuming. This drawback leads to the development of objective evaluation methods, which can automatically predict the suitability of an image for a given application.

Objective image qualityassessment has received special interest during the last two decades and a vast number of quality evaluation indexes have been proposed. These metrics can bebased 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.

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.

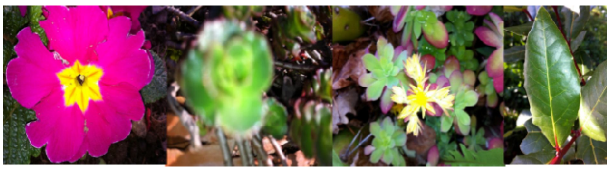

Figure 1: Sample blurred images from our database (ReVeS database). Note that either foreground/background objects may be blurred, as well as the object size may vary.

The goal is to develop a global no-reference blur metric based on a local approach of blur detection in natural macro-like images. The purpose is to study the possibility of global assessment based on the detection of blurred regions over an analyzed image. Starting with a local approach, we can identify the blurred regions. This aspect can be further explored to detect whether the object of interest is sharp.

The paper is organized as follows: Section 2 describes the existing algorithms for blur assessment. Section 3 presents the methodology and Section 4 describes the proposed blurred region detection approach and defines the global blur metric. Experimental results are shown in Section 5 followed by conclusions and future work in Section 6.

II. RELATED WORK

Blur is a caused by an imperfect image formation process. There are four types of blur: out-of-focus, camera shake,

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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[1],[2],[3], [4]. In [1]is proposed 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. [4] and [2] 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 [3], 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[5], [6]. 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 [5], 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.[6], 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[7]. 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. It can be transformed in a global blur metric to estimate the blurriness of an image. The low computational cost of the Haar wavelet analysis suits the scope of implementation on smartphones.

III. METHODOLOGY

According to[8], there are three types of edges found in digital images: Dirac-Structure, Roof-Structure and Step-Structure. In [1], Step-Structure is furthermore divided into two subcategories, Astep-Structure and Gstep-Structure, respectively. Figure 2 graphically represents the four edge types.

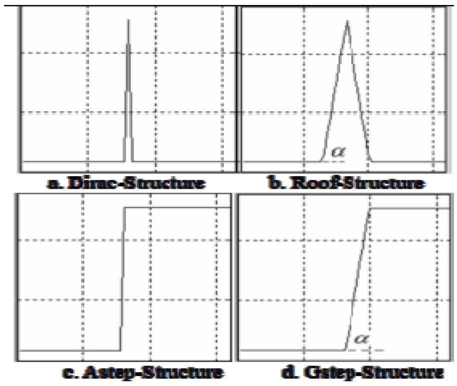

Figure 2: Graphical representation of the edge types, [1].

The influence of the blur distorsion on the above edge types and the variation of the α parameter are presented in Table 1.

Table 1: Blur effect on different types of edges

Original	After Blur	Change of α
Dirac-Structure	Roof-Structure	none
Astep-Structure	Gstep-Structure	none
Gstep-Structure	Gstep-Structure	smaller
Roof-Structure	Roof-Structure	smaller

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. An important property of Harr wavelet transform is its ability to recover the sharpness of the blurred edge: when observed at a small scale, the blurred Roof-Structure and Gstep-Structure will become thinner and thus recover their sharpness.

The detection of the edge types presented in *Figure 2* can be formalized,with respect to the Haar wavelet transform, using the following rules based on the energy property that lies in the detail coefficients, [1]. The first rule decides whether an edge is detected. Classification cannot be done unless and edge has been previously identified.

Rule1: if $\mathrm{E}_{\max1}(\mathrm{k},\mathrm{l}) > threshold$or $\mathrm{E}_{\max2}(\mathrm{k},\mathrm{l}) > threshold$or $\mathrm{E}_{\max3}(\mathrm{k},\mathrm{l}) > threshold$, then (k, l) is an edge point.

Rule2: For any edge point (k, l) , if $\mathrm{E}_{\max1}(\mathrm{k},\mathrm{l}) > \mathrm{E}_{\max2}(\mathrm{k},\mathrm{l}) > \mathrm{E}_{\max3}(\mathrm{k},\mathrm{l})$, then (k, l) is Dirac-Structure or Astep-Structure.

Rule3: For any edge point (k, l) , if$\mathrm{E}_{\max1}(\mathrm{k},\mathrm{l}) < \mathrm{E}_{\max2}(\mathrm{k},\mathrm{l}) < \mathrm{E}_{\max3}(\mathrm{k},\mathrm{l})$, then (k, l) is Roof-Structure or Gstep-Structure.

Rule4: For any edge point (k, l) , if $\mathrm{E}_{\max2}(\mathrm{k},\mathrm{l}) > \mathrm{E}_{\max1}(\mathrm{k},\mathrm{l})$ and $\mathrm{E}_{\max2}(\mathrm{k},\mathrm{l}) > \mathrm{E}_{\max3}(\mathrm{k},\mathrm{l})$, then (k, l) is Roof-Structure.

Rule5: For any Gstep-Structure or Roof-Structure edge point (k, l) , if$\mathrm{E}_{\max1}(\mathrm{k},\mathrm{l}) < threshold$, then (k, l) is more likely to be in a blurred image.

According to the human vision system and based on experimental results, the threshold may be set to 35 (the human visual system is not sensitive to intensities below 30).$\mathrm{E}_{\max\_i}$ denotes the maximum energy for each decomposition level within a sliding window.

The described methodology, [1], provides a direct method for blur assessment without the description of the blur kernel. This approach 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 utterlyaffected. 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 of the above mentioned cases.

IV. PROPOSED METHOD

We propose a local blur detection technique using three-level multi-resolution analysis designed for macro-like photos. Figure 3 presents the computational block diagram for the proposed method.

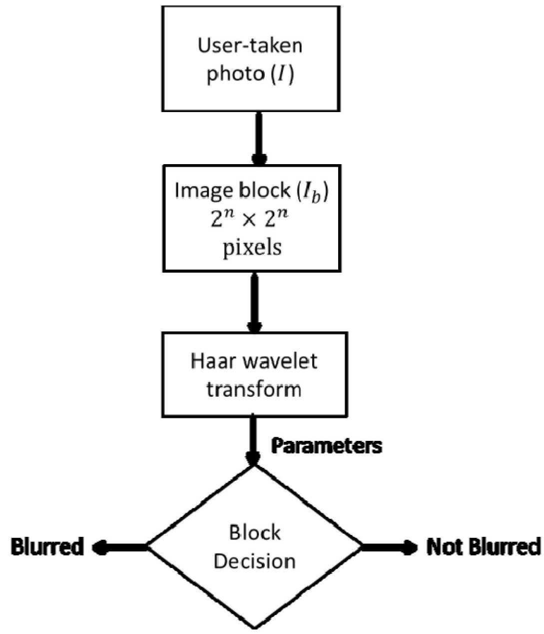

Figure 3. Computational block diagram for the proposed method.

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 of edge detection over the wavelet decomposition levels. As the wavelet decomposition is dyadic, the best adapted block size is 2^n.

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

Edge type detection and analysis is performed as in[1], using the rules described in the previous section. Edges are identified and classified in one of the four possible categories. For each category, we sum the number detected edges obtaining the statistical parameters for each edge type. Based on (1) and using the table given in [1], 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. Based on the values for each total number of edge type and the total number of edges found, the most relevant decision rules forI_b, obtained using the method C4.5, are presented in

Figure 4. These rules are being used in the following processing steps.

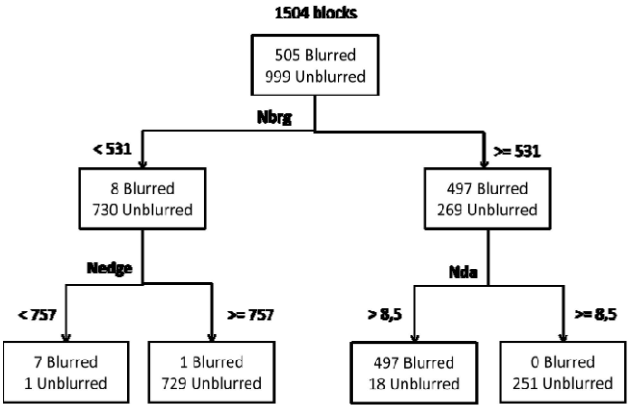

Figure 4. Decision tree presenting the set of rules.

In Figure 4*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 has decreased from 55% to 0.01% compared to the original method. Table 2 shows the confusion matrix in cross-validation.

Table 2: Confusion matrix on trained data set.

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

The new 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. In the left image, the foreground is mostly sharp, while the background is mostly blurred. The image on the right has the exact reverse properties.

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

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

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

V. EXPERIMENTAL RESULTS

In this section we intend to study the behavior of the global assessment obtained from the qualitative decision. We present comparative test results with the state-of-the art methods. Also, performance tests were conducted to demonstrate the linearity of the global blur metric and the precision-recall representations have been computed for the proposed method and the state-f-the-art approaches.

As the implementation is intended to be further used in a mobile application, we have acquired 94 images of plants using a smartphone camera in a natural environment. These compose the ReVeS database. Each image contains one or more parts of plants (e.g. leaf, flower, etc.). Images are partially or totally corrupted by blur. This may affect either the foreground or the background objects. In addition, object size may also vary with respect to the image size. These drawbacks and their impact on blur assessment have been discussed in the previous sections.

Tests were performed on two databases: LIVE database (174 images), [9], and ours, ReVeS database (94 images).

On the ReVeS database, 94 images were resized by extrapolation to the dimension of 1024×1024 and divided into 1504 non-overlapping block images and saved as JPEG format.Each block was manually labeled into one of the two categories: blurred and non-blurred. These blocks were used to train the decision tree C4.5.

In order to compare the performance of the proposed method, we conducted tests on the ReVeS and LIVE databases.We performed our method and the objective evaluation using the cumulative probability blur detection, CPBD [3], and blind image quality index, BIQI [4]. These methods offer global metrics. For comparison, we computed the global blur parameter for each photo given by (2).

First, we show the performance results of the original method over the mentioned datasets. The last column in Table 3 corresponds to the spearman's rank order correlation coefficient between the blur extent computed in [1] and the coefficients obtained with [3] and [4]respectively.

Table 3:Summary table on comparative tests performed with the original method,[1], on the presented databases.

Database	Database size	Algorithm	SROCC_1
LIVE	174	CPBD	0.76
LIVE	174	BIQI	0.78
ReVeS	94	CPBD	-0.90
ReVeS	94	BIQI	0.68

Table *4* 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 4.Summary table on comparative tests performed on the presented databases, [10].

Database	Database size	Algorithm	SROCC_2
LIVE	174	CPBD	0.74
LIVE	174	BIQI	0.87
ReVeS	94	CPBD	-0.85
ReVeS	94	BIQI	0.73

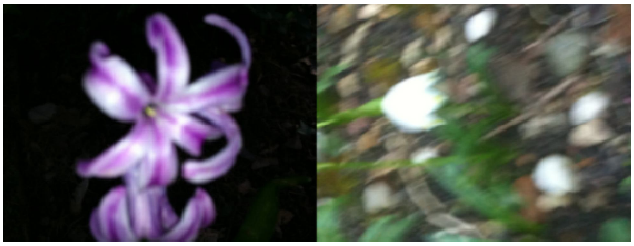

Figure 6. ReVeS database images (left – Out-of-focus blur; right – camera-shake blur).

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 0.94 and 1.00, where the maximum of 1.00 designs a "blurred image".

Figure 7: Left: Original image. Right: Artificial gaussian blur with sigma=23.

Figure 7 presents a test image over which artificial gaussian blur has been added to study the linearity of the proposed blur coefficient. In Figure 8 we present the linear dependence of the proposed blur coefficient and the increasing artificial blur.

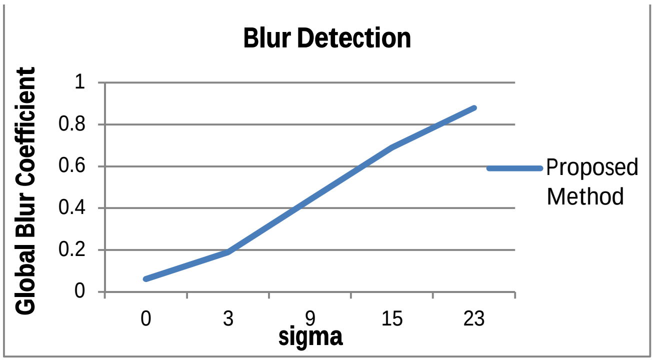

Figure 8: Linear increasing behavior of the proposed blur coefficient for increasing artificial gaussian blur presented in Figure 7. Sigma = 0 represents the blur detected in the original image.

Figure 9 presents the precision and recall (ROC curve) for the four 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.

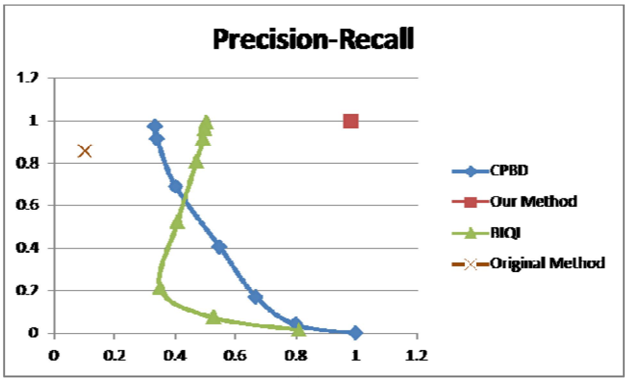

Figure 9. Graphical representation of precision-recall over the manually labeled image blocks from ReVeS database.

The brown point represents the precision/recall for the original algorithm which also gives a subjective evaluation as output. 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.

Figure 10 illustrates results obtained by our method applied on two images from our database.

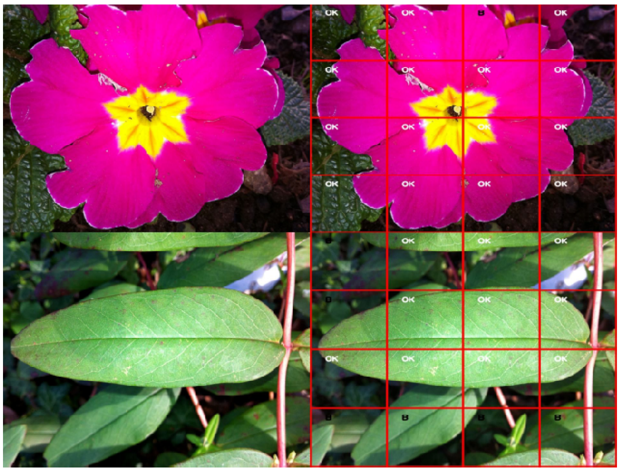

Figure 10. Test result using the proposed method (from left to right – original image and algorithm output). The first row contains a sharp image with large flat regions. The second row exhibits a sharp foreground while most of the background objects remain blurred.

VI. CONCLUSIONS

In this paper we presented a global blur assessment based on no-reference local blur detection for macro-like images. Contrary to other blur detection methods, the proposed algorithm can localize blurred regions over the image and to give a numerical metric of the blurriness of the analyzed image. We aimed to study the potential use of this metric in blur assessment.

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. The set of rules given by the decision tree let us partition an image into blurred and sharp regions. This qualitative decision can be used to the design of the global blur metric.

An improvement in computational time could imply the use of a pre-segmentation model that may roughly indicate the localization of the object of interest. This approach can be suitable to tell whether further analysis, such as segmentation of the object of interest, is possible. On the other hand, it can avoid certain false alarms due to the wavelet approach.

Future work includes studying the possibility of a separation between foreground and background using the proposed algorithm. Another interesting aspect worth to explore is the correspondent original image region at full size. A blurred block may present in the original image sharp regions which can be detected with the presented approach. This aspect in the context of plant recognition can much precisely estimate whether, for example, the contour of a leaf is distinguishable.

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