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Monte Carlo based reduction of image resolution in view of no-reference image quality assessment

***Abstract**. In the paper a fast algorithm of image downsampling is presented which is based on the estimation of mean local luminance using the Monte Carlo method assuming the division of an image into smaller non-overlapping blocks. Due to modifications proposed in the paper, one can obtain similar results than for classical methods compared using recently proposed no-reference image quality metrics. Nevertheless, further optimization requires the development of no-reference image quality metrics with higher accordance to human perception of typical distortions.*

Streszczenie.** W artykule zaprezentowano szybki algorytm redukcji rozdzielczości obrazu oparty na estymacji średniej jasności w bloku z użyciem metody Monte Carlo. Dzięki zaproponowanym modyfikacjom możliwe jest uzyskanie rezultatów podobnych do klasycznych metod, porównywanych z wykorzystaniem metod "ślepej" oceny jakości obrazów opracowanych w ostatnich latach. Dalsza optymalizacja wymaga jednakże opracowania "ślepych" wskaźników jakości obrazu charakteryzujących się wyższą korelacją z percepcją typowych zniekształceń obrazu przez człowieka.* ***Redukcja rozdzielczości obrazów bazująca na metodzie Monte Carlo w aspekcie „ślepej" oceny jakości obrazu

Keywords: image downsampling, Monte Carlo method, blind image quality assessment.
Słowa kluczowe: redukcja rozdzielczości obrazów, metoda Monte Carlo, „ślepa" ocena jakości obrazu.

Introduction

Reduction of image resolution is one of the main operations related to preprocessing of digital images which is implemented in most image processing applications. The image downsampling task is one of the relevant stages also in many image recognition and classification systems e.g. related to face recognition [1] independently of the reduction of features set dimensionality e.g. using various modifications of the Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) methods [2].

One of the commonly applied methods for accelerating the procedures of vision based navigation of mobile robots, automatic motion tracking devices etc., is using the simplified processing of the reduced resolution input images. The simplest method allowing to obtain such low resolution images is just using the low resolution cameras although, due to the technological advances, more and more often only high resolution cameras are available so it is necessary to reduce the image resolution for such purposes. Application of software solution extends the range of applications into hybrid solutions in which part of the algorithm works on the basis of full resolution image and another part utilizes the reduced resolution one [3].

One of the simplest methods is just omitting some pixels e.g. using only each second row and each second column. This method is fast but may cause some artefacts, especially for colour images, so there is a risk of drastic changes of image contents. Another popular method based on averaging of neighbouring pixels requires more operations and may cause blurring. Both of those basic methods have been displaced by more effective nearest neighbour interpolation and bilinear interpolation. Nevertheless both of them still require the analysis of all pixels of the image with additional interpolation operations. A more advanced method, leading to better results at the cost of more calculations, is the bicubic interpolation.

A different approach to change of image resolution is based on the frequency domain processing. Some other more complicated algorithms utilize wavelet decomposition. Unfortunately, the computational cost of both those approaches is much too high for the above mentioned scope of applications and therefore they are not analysed in the paper.

The idea of image simplification using the Monte Carlo approach

Change of the image resolution can be obtained using the division of the image into non-overlapping blocks of size $r \times r$ pixels. For each block the average values of the pixels' intensity can be calculated and used as the resulting intensity value for the single pixel of the reduced resolution image (replacing the whole block). Such an approach is identical to the method based on averaging the neighbouring pixels but limited to the block of $r \times r$ pixels. In order to significantly speed up the algorithm a statistical experiment carried out by the Monte Carlo method can be used which consists of three main steps:

- reshaping the block of $r \times r$ pixels to one-dimensional vector W of r^2 pixels,
- random choice of n pixels from the vector W,
- drawn pixels are stored in the new vector V of length n.

The vector V becomes a simplified representation of the image block of $r \times r$ pixels. Reshaping the block into one-dimensional vector allows using a single pseudo-random numbers generator of uniform distribution, significantly simplifying the practical implementation of the algorithm. Since the vector V can be considered as a simplified representation of the block, as mentioned above, the average values of its values can also be determined as the estimated values of the average intensity of pixels located within the entire $r \times r$ pixels block. The idea of the method is illustrated in Fig. 1.

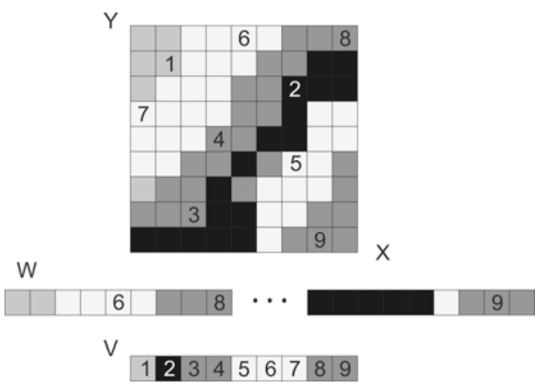

Fig.1. Illustration of the idea of the algorithm for a single block

Practical verification and extensions of the method

In the first stage of experiments the estimated time of execution of the algorithm has been compared with classical algorithms. Even considering the necessity of randomly drawing the samples, the reduction of the computation time for the proposed solution based on the Monte Carlo method can be observed. Due to the reduction of the amount of analysed data, the benefits increase together with the size of the block (value of the r parameter) and decrease of the number of drawn pixels (parameter n). Since the slowest method has been the bilinear interpolation for $r=8$ (bicubic interpolation has not been considered at this stage), it has been chosen as the reference and the execution time for the other procedures has been normalized. The comparison of obtained results for typical images is shown in Table 1.

Table 1. Normalized computation time obtained for various algorithms of decreasing the image resolution

Method	Block $r=8$	Block $r=32$
Averaging all pixels	0.86	0.90
Monte Carlo average $n=10$	0.72	0.68
Monte Carlo average $n=3$	0.70	0.65
Nearest neighbour	0.80	0.75
Bilinear interpolation	1.00	0.95

Due to the application of the Monte Carlo method noticeable reduction of the calculation time can be achieved but another relevant issue is the quality of resulting images which are the input data for some other algorithms. Since the verification of the method should be conducted for the representative images containing some details which should be visible also for downsized images, the experiments have been conducted on the natural scene images (photographs) containing some portions of text which should be readable after the processing.

The detailed comparison of results obtained for various methods has been done for intentionally chosen image "India" of resolution 2816×1872 pixels which is difficult for downsizing due to the presence of details. The obtained results are shown in Fig. 2 where the disadvantages of nearest neighbour method are clearly visible. Nevertheless, the other methods differ from each other mainly by the amount of introduced blur distortions.

Considering the fact that the blurring of images is typically introduced by the averaging of neighbouring pixels a modification of the proposed approach has been done which is based on replacing the average intensity value estimated for its block by the median intensity value of the randomly drawn pixels for the block slightly increasing the computational complexity. Nevertheless, the execution time is still comparable to nearest neighbour method and significantly shorter than achieved for bilinear interpolation.

The results obtained for this approach in comparison to the Monte Carlo averaging are shown in Figures 3 and 4.

Application of no-reference image image quality metrics

Analysing the results shown in Figures 4 and 5, an important issue can be noticed related to the choice of the number of drawn pixels, influencing the quality of the resulting image (obviously higher quality is obtained using more drawn points).

Nevertheless, in order to develop any optimization procedure or even any other algorithm for the automatic choice of the number of randomly chosen pixels, necessary for an acceptable quality of the downsampled image, a method of automatic quality assessment of obtained images is necessary.

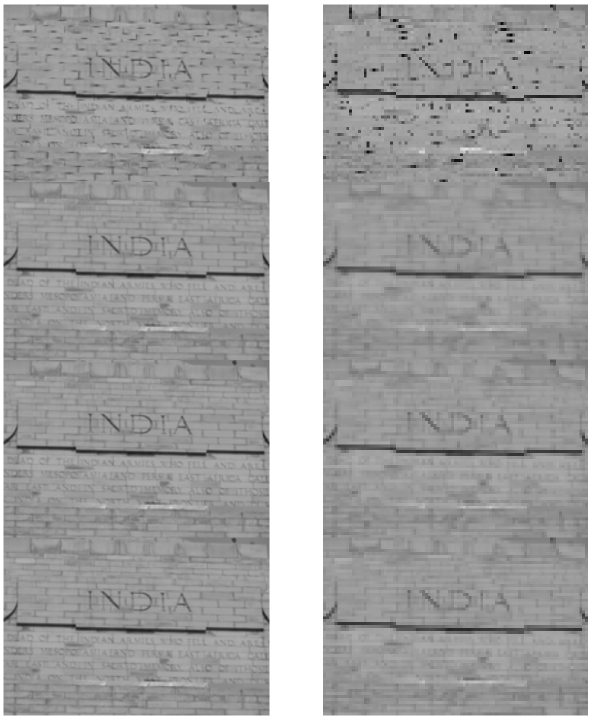

Fig.2. Zoomed results obtained for various algorithms of image downsizing using $r=8$ (left) and $r=32$ (right) – from top to bottom: nearest neighbour, bilinear interpolation, bicubic interpolation and averaging all pixels

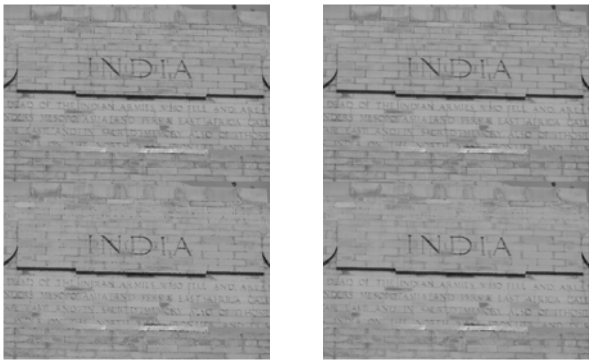

Fig.3. Zoomed results obtained for the Monte Carlo averaging (top row) and median based (bottom row) algorithms for $r=8$ using $n=7$ (left) and $n=25$ drawn samples (right)

Fig.4. Zoomed results obtained for the Monte Carlo averaging (top row) and median based (bottom row) algorithms for $r=32$ using $n=9$ (left) and $n=50$ drawn samples (right)

Unfortunately, most of the full-reference image quality assessment methods, including recently developed combined metrics [4, 5, 6], despite their universality and relatively high correlation with subjective perception of various distortions, cannot be applied for this purpose. The reason is related to their main limitation caused by the necessity of using the reference image which should have the same resolution as the assessed image. In the case of changed resolution, the use of the reference image would require the same operations as for the assessed image, introducing the same type of distortions so that the processed image cannot be considered as the reference one any more. In such case the only possibility is the application of no-reference ("blind") metrics which do not use any information about the reference (pristine) images.

In the paper two of the recently proposed no-reference image quality metrics have been used. The first one, known as Blind Image Quality Index (BIQI) [7, 8] utilizes the approach based on wavelets and distortion classification using the Support Vector Machines (SVM). It has been trained on the commonly used LIVE Image Quality Assessment Database [9] containing 779 images corrupted with five types of distortions (JPEG and JPEG2000 compression, Gaussian blur, white noise and simulated transmission over fast fading Rayleigh channel) together with their subjective quality scores expressed as Differential Mean Opinion Scores (DMOS). The second metric is known as Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE) [10, 11] and measures image naturalness based on deviations from a natural image model.

Table 2. Obtained results of the BIQI and BRISQUE metrics for various methods of resolution decreasing for $r=8$

Algorithm	BIQI	BRISQUE
Nearest neighbour	18.5935	46.5219
Bilinear interpolation	19.7979	41.4744
Bicubic interpolation	17.9107	37.0926
Average from whole block	19.3777	44.7897
Median from whole block	12.3567	40.7050
Monte Carlo average $n=7$	27.4167	42.4524
Monte Carlo median $n=7$	20.7087	44.2523
Monte Carlo average $n=10$	27.3706	40.6865
Monte Carlo median $n=10$	19.1410	44.1352
Monte Carlo average $n=25$	26.9397	40.9574
Monte Carlo median $n=25$	14.0576	39.1828

Table 3. Obtained results of the BIQI and BRISQUE metrics for various methods of resolution decreasing for $r=16$

Algorithm	BIQI	BRISQUE
Nearest neighbour	24.6057	56.4603
Bilinear interpolation	50.4509	34.5509
Bicubic interpolation	43.6535	30.1624
Average from whole block	47.0970	45.1230
Median from whole block	23.6875	45.9334
Monte Carlo average $n=15$	29.2500	41.6051
Monte Carlo median $n=15$	34.5779	44.1842
Monte Carlo average $n=35$	31.9291	38.7761
Monte Carlo median $n=35$	33.7762	43.8215

Table 4. Obtained results of the BIQI and BRISQUE metrics for various methods of resolution decreasing for $r=32$

Algorithm	BIQI	BRISQUE
Nearest neighbour	35.8201	59.4500
Bilinear interpolation	60.6705	40.5778
Bicubic interpolation	55.2831	40.2584
Average from whole block	65.4143	45.7936
Median from whole block	23.1252	39.2951
Monte Carlo average $n=9$	65.3342	51.5029
Monte Carlo median $n=9$	43.9911	48.6626
Monte Carlo average $n=20$	66.3259	45.8161
Monte Carlo median $n=20$	27.3387	45.2382
Monte Carlo average $n=50$	63.5892	47.9300
Monte Carlo median $n=50$	23.9902	35.9848

The results obtained for both metrics are presented in Tables 2 – 4. It is worth to mention that both those metrics are normalized so that 0 indicates the best quality and 100 the worst.

Conclusions and future work

Analysing the results of the no-reference image quality assessment, relatively good quality of the resulting images can be observed not only for bicubic interpolation but also for the median based algorithm and its Monte Carlo version. Nevertheless, in the latter case the results depend on the size of the block and the number of randomly chosen pixels.

Nevertheless, observing the resulting images presented in Figures 3 – 5, some other conclusions can be made since the perceived quality of them differs from the values of no-reference metrics. For example, the Monte Carlo averaging and Monte Carlo median algorithms for the blocks of 32×32 pixels and $n=50$ samples lead to results corrupted by different types of contamination which are very hard for a reliable comparison using the BIQI and BRISQUE metrics.

Concluding the results of the experiments it should be noticed that further optimization of the Monte Carlo based algorithms would require the use of some other methods of no-reference image quality assessment which should be better correlated with human perception of distortions typical for image downsizing.

Since currently known state-of-the-art metrics are not necessarily oriented towards the assessment of such types of distortions, there may be a need to develop some new "blind" image quality assessment methods for this purpose.

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