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Benchmark of Similar Blocks Search under Noisy Conditions

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Abstract

A similarity search in images has become a typical operation in many applications. A presence of noise in images greatly affects the correctness of detection of similar image blocks, resulting in a reduction of efficiency of image processing methods, e.g., non-local denoising. In this paper, we study noise immunity of various distance measures (similarity metrics). Taking into account a wide variety of information content in real life images and variations of noise type and intensity. We propose a set of test data and obtain preliminary results for several typical cases of image and noise properties. The recommendations for metrics' and threshold selection are given. Fast implementation of the proposed benchmark is realized using CUDA technology.

Introduction

Noise that is practically always present in acquired images significantly decreases image visual quality and influences subsequent image processing in a negative way [1]. In recent decades, it has become popular to exploit image self-similarity [2] to denoise images more efficiently. The operation of similar block (patch) search and their joint use is in a base of nonlocal techniques of image denoising that gained high popularity [3-5]. Note that a similar block search is used in many other applications such as fractal image compression, content-based image retrieval, classification, clustering, and pattern recognition [3]. For most of them, a similarity search should be fast. In case of intensive, non-Gaussian and/or spatially correlated noise, similar patch search should be also noise-immune and accurate [6, 7].

Although many similarity metrics (distances) have been already proposed and used in different applications, it is still unclear how to choose a proper metric for a given type of images currupted by a given noise type [6-8]. There are several reasons behind this. Preliminary studies have shown that there is no universal similarity metric [6-8]. Metrics performance depend upon many factors such as image properties (image content), noise characteristics, domain where similarity is estimated, block size, reference block used, etc. Then, one needs a special tool or a benchmark for simulating and comparing performance of the candidate similarity metrics to choose the best (optimal) of them or, at least, a quasi-optimal one.

Although a block size can be arbitrary, the commonly used size in practice is 8x8 pixels. This deals with a high computational efficiency if metric's calculation is carried out in transform domain in sequential or parallel manner [9]. Usually one has a reference patch and looks for a certain number of similar patches. The similarity metrics are expressed as distances between blocks or vectors [10], where their smaller values for given two blocks mean higher similarity. Then, for a given reference patch, a search is done for an entire image or its part by calculating distances (and, possibly, creating a distance map). Often, a threshold is used to determine (decide) are the patches similar or not.

A high level of noise in images may result in incorrect detection of similar patches due to the fact that noisy pattern in the reference patch can be matched to a similar noisy pattern in another patch, but a content of these two patches would be dissimilar (this often happens in highly textured images [11]). Thus, one needs an adequate performance criteria that allows assessing a correctness of a similar block search. It is also important how accurately is similarity threshold estimated. To solve these problems, it could be nice to have a tool for studying a wide set of images, noise models, similarity metrics implemented as a software benchmark. The purpose of this paper is to create and implement a benchmark for finding efficient similarity metrics and with detailed analysis corresponding to different practical cases. The final version of the benchmark is supposed to be extendable for adding more noise models and metrics. It is also assumed that the obtained data can assist similarity threshold setting.

To speed-up computations of these metrics, their CUDA implementation has been made. The proposed benchmark consists of the following operations: noise modelling, similar blocks introduction, similar blocks search, and performance assessment.

Similarity as a distance

The tasks of similar patch search can be often reduced to a similarity assessment for data samples represented as blocks or vectors. The latter way is the most used one. To consider similar blocks search efficiency, we have chosen eight different similarity metrics and two domains of data representation: spatial and discrete cosine transform (DCT) domains. All considered metrics are able to work with the vectorized data. Note that metrics can be divided into two large "families": metrics-distances and correlation metrics [12]. Distances between two blocks as well as similarity coefficients can also be considered as a similarity measure-like distance.

In this paper we will consider the following eight similarity metrics. The first three are classical metrics commonly used in image processing and which are special cases of general Minkowski distance: Manhattan (l_1 norm) (1), Euclidean (l_2 norm) (2) and Chebyshev (l_∞ norm) (3) distances. Some alternative metrics have appeared in other fields of multidimensional data processing. They are robust and have low computational complexity, and, are the modifications of of Minkowski distance. The Manhattan metric has efficient modifications: Canberra (4) and Bray-Curtis (5) distances which can deal with vectorized data samples. Other two modifications of Euclidean distance, Hellinger (6) and Mahalanobis (7) distances, are frequently used for data clustering and image processing. Finally, Pearson correlation can be easily transformed into a distance (8):

$$d_{l1} = \sum_{i=0}^{n} |x_i - y_i| \tag{1}$$

$$d_{l2} = \sqrt{\sum_{i=0}^{n} (x_i - y_i)^2} \tag{2}$$

$$d_{l\infty} = \max_{i=0..n}|x_i - y_i| \quad (3)$$

$$d_C = \sum_{i=0}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|} \quad (4)$$

$$d_{BC} = \frac{\sum_{i=0}^{n}(x_i - y_i)}{\sum_{i=0}^{n} x_i + \sum_{i=0}^{n} y_i} \quad (5)$$

$$d_H = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=0}^{n}(\sqrt{x_i} - \sqrt{y_i})^2} \quad (6)$$

$$d_M = \sqrt{(x - y)^T S^{-1}(x - y)} \quad (7)$$

$$d_P = \frac{\sum_{i=0}^{n} x_i * y_i - \frac{\sum_{i=0}^{n} x_i * \sum_{i=0}^{n} y_i}{n}}{\sqrt{\left(\sum_{i=0}^{n} x_i^2 - \frac{(\sum_{i=0}^{n} x_i)^2}{n}\right)\left(\sum_{i=0}^{n} y_i^2 - \frac{(\sum_{i=0}^{n} y_i)^2}{n}\right)}} \quad (8)$$

where d is the corresponding distance calculated by a given metric, x and y are vectors of image blocks, i is the element index in the vector, n is the number of elements in the vector, S defines mutual standard deviation of compared vectors.

Time and memory complexities of these 8 similarity metrics are presented in Table 1, where N means the number of simple operations (addition, multiplication, exponentiation, modulo operation); M relates to the size of the covariation matrix for Mahalanobis distance. For further analysis and runtime tests, we have used only Canberra, Bray-Curtis, Euclidean, Hellinger, Chebyshev and Manhattan distances due to their low complexity (Pearson and Mahalanobis metrics are excluded from the further consideration due to high computational burden). To prove how fast the selected metrics can be calculated, we have run some tests. Table 2 shows runtime in milliseconds for the considered distances' calculation for the reference block and 1000 blocks of interest. Distances are implemented using C++ and C++ with CUDA. Note that all metrics except Chebyshev have smaller runtime for CUDA. The Chebyshev case can be explained by effective realization of max operation in C++. The distance calculation for the reference block and 100000 blocks of interest has a significant difference in the runtime. All these metrics have distinctly smaller runtime using CUDA. In addition, CUDA implementation demonstrates similar runtime even when the search has performed for much large number of blocks.

As it has been mentioned in Introduction, similar block search can be performed with an priori known threshold. Figure 1 presents the algorithm of threshold estimation for the considered metrics for different noise intensities. After an initial image from the database is loaded, we have to perform test image generation with introduced blocks and to choose a reference block for a search. Similar block search is carried out in the following way: collect a map of calculated distances between reference blocks and other blocks of interest in image, aggregate similar block sets (distance to a reference block is less than a threshold), evaluate search efficiency and threshold value change until all introduced blocks have been found. Finally, obtain the threshold value and other search parameters.

To perform all above listed procedures, we have used images from Tampere17 image database [13] as test images. Tampere17 has 300 both color and grayscale high-quality and noise-free images. For experiments, we have chosen 10 images with different content like homogenous and heterogeneous regions, regular and non-regular structures, textures. Additive white Gaussian noise (AWGN) with zero mean is used as a noise model.

Table 1. Similarity metrics time and memory complexity

Metric	Time complexity	Memory complexity
Canberra	O(5N)	O(2N)
Bray-Curtis	O(3N)	O(2N+N^2)
Euclidean	O(3N + 1)	O(N^2)
Hellinger	O(4N + 1)	O(2N)
Mahalanobis	O(3N+2(N*M))	O(4N + M)
Pearson	O(15N + 7)	O(15N)
Chebyshev	O(N)	O(2N)
Manhattan	O(2N)	O(2N)

Table 2. Runtime test for 1000 and 100000 iterations of metrics' calculation

Metric	C++, ms		CUDA, ms	
Iterations	1000	100000	1000	100000
Canberra	0.064	64.13	0.775	0.882
Bray-Curtis	0.638	63.405	0.547	0.783
Euclidean	0.646	63.306	0.551	0.791
Hellinger	1.169	114.9	0.907	0.987
Chebyshev	0.01	0.942	0.425	0.546
Manhattan	0.62	62.68	0.541	0.781

To determine the threshold for the considered metrics, 50 blocks were choosen in 10 test images. The selected group of blocks consists of the same block that is further used as the reference. After images are corrupted by the noise, all introduced blocks become different and any metric provides different distances. The reference block has been chosen in the following way. The entire image is divided into 8×8 pixel blocks with estimation of their local activity (characterized by local variance). After all estimates of local activity are collected together with the associated block coordinates, the histogram is obtained. Then, all blocks are divided into three categories: low, middle and high local activity blocks. An example of introducing a group of similar blocks with high local activity into one test image is given in Figure 2.

The threshold is established taking into account the efficiency of introduced similar blocks search. The example of calculated distances under noisy conditions (orange) and noise-free distances is shown in Figure 3. Estimated thresholds are given below in absolute values for 8-bit grayscale images: Canberra – STD*0.18, Bray-Curtis – 0.25, Euclidean STD*10, Hellinger – 44, Chebyshev – 220, Manhattan – 9200. Note that Canberra and Euclidean distances have noise level dependent thresholds unlike other metrics. When the noise STD is not known apriori, the use of these metrics can be problematic and a preliminary estimation of noise STD is desired. Otherwise, other metrics are more convenient to use.

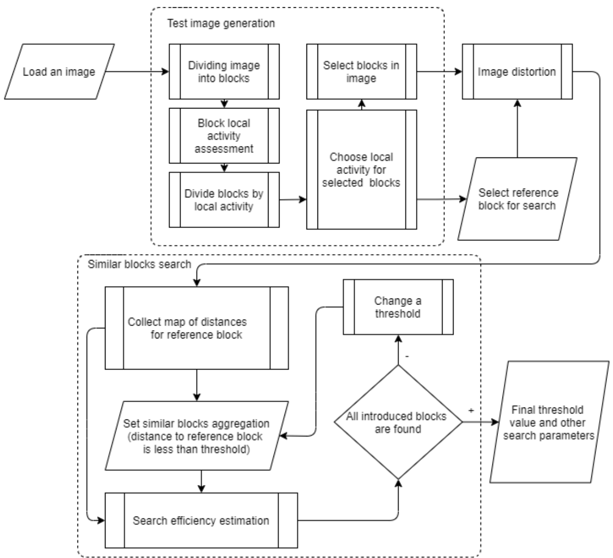

Figure 1. Algorithm scheme of optimal threshold estimation

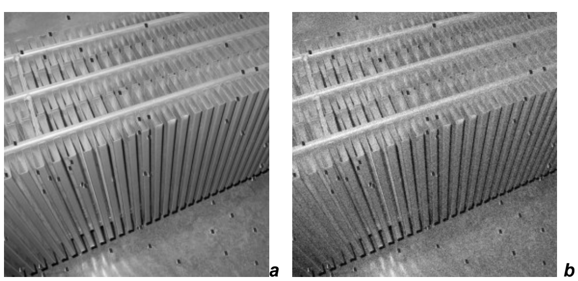

Figure 2. Example of group of introduced similar blocks in test image (a) and noisy image (b)

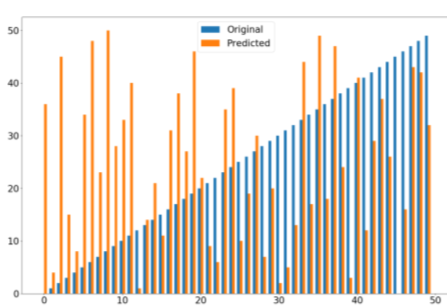

Figure 3. Calculated and predicted thresholds for Hellinger distance and 50 introduced blocks, the test image is corrupted by AWGN with STD = 15

Proposed benchmark for similarity metrics' analysis

Tests with synthetic images

The first experiment for similarity metrics' analysis has been carried out using generated synthetic images. The block diagram of a search for similar blocks in synthetic images using earlier obtained thresholds is presented in Figure 4. To analyze the efficiency of similarity metrics for blocks of regular structures, the following experiment has been performed. We have generated four test synthetic images: "Cells", "Steps", "Gradient" and "Points" presented in Figure 5. All the obtained images have been distorted by AWGN with the noise STDs equal to 3, 5, 10, 15, 20, 25 and 30.

Due to that fact that the generated images have predictable and regular structure, any reference block has a certain number of similar (exactly the same) blocks. Hence, we already know where the similar blocks are and can easily distinguish with other blocks. All metrics have been applied for aforementioned noisy conditions. Experiment for each generated test image and noise STD have been repeated 50 times. They included arbitrary choice of the reference block, distances map collection and the search efficiency estimation. An example of generated test images fragments and the calculated distance map is given in Figure 6. The reference block contains the intersection of two lines.

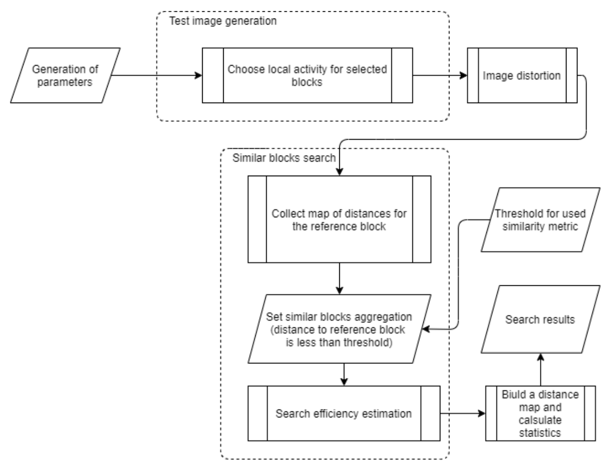

Figure 4. Algorithm of similar blocks search in synthetic images

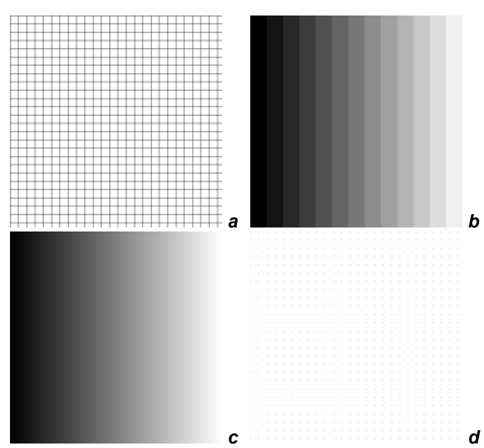

Figure 5. Generated noise-free test images: "Cells" (a), "Steps" (b), "Gradient" (c), "Points" (d)

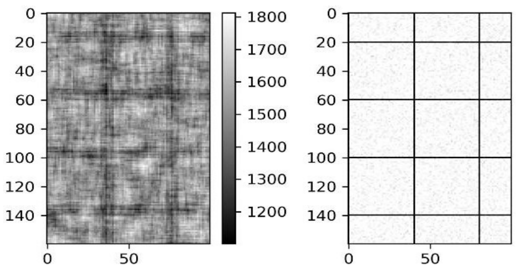

Figure 6. *Fragments of distances map and corresponding image fragment for Euclidean distance in test image "Cells" corrupted by AWGN with STD = 10*

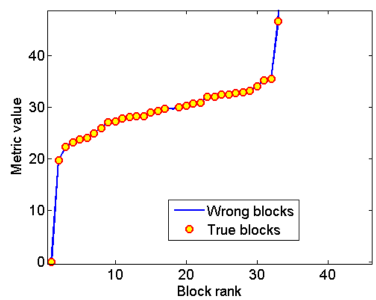

Figure 7. *Sorted distances values and ranks for Canberra metric with marked ones which belong to introduced blocks*

To assess a search efficiency, we propose to use two criteria: E is search efficiency – the ratio between the numbers of found introduced blocks and their whole number (9) and R is a rank estimate – the ratio between ranks of found introduced blocks in the sorted set and their whole number (10).

$$E = \sum_{j=0}^{n} m \Big/ \sum_{j=0}^{n} j \tag{9}$$

$$R = \sum_{j=0}^{n} r_j \Big/ \sum_{j=0}^{n} j \tag{10}$$

where j is the index of block in the sorted set, n is the number of blocks, r_j is the rank of introduced block in the set.

Experiments have been carried out for four test images and distance calculation in spatial domain, the search for every case has been performed for an entire image. The obtained results have been averaged for E and R criteria. The obtained results are presented in Figures 8 and 9. Similar experiment for generated images has been performed in DCT domain. The reference and considered blocks during the search have been transformed using DCT to check metrics' efficiency (see the results in Figures 10 and 11).

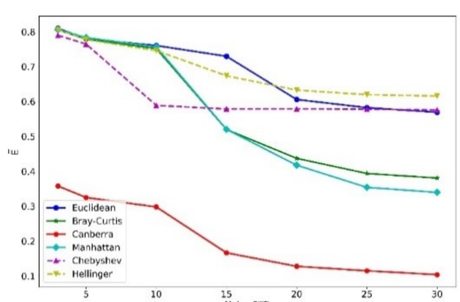

Figure 7. *Averaged E estimates for similarity metrics and four synthetic images (metric calculation in spatial domain)*

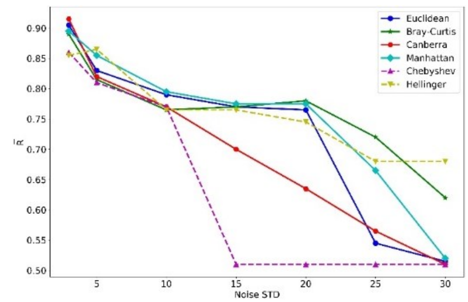

Figure 8. *Averaged R estimates for similarity metrics and four synthetic test images (metric calculation in spatial domain)*

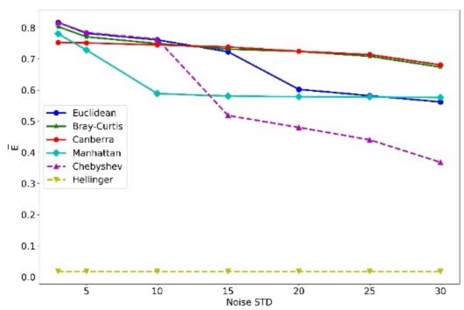

Figure 10. *Averaged E estimates for similarity metrics and four synthetic images (metric calculation in DCT domain)*

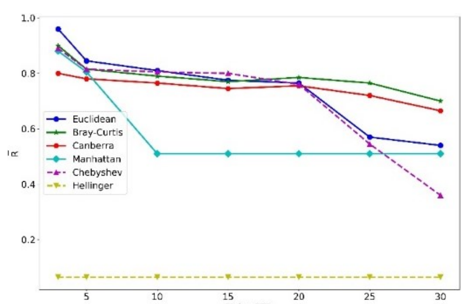

Figure 11. *Averaged R estimates for similarity metrics and four synthetic test images (metric calculation in DCT domain)*

According to the presented results, the Canberra metric has the worst efficiency in search of regular structures in spatial domain, the Hellinger distance shows the best efficiency according to both E and R criteria. In opposite to spatial domain, the Canberra and Bray-Curtis distances have the best efficiency of search in regular structures in DCT domain. The Hellinger and Manhattan distances show the worst results. The Euclidean and Chebyshev distances demonstrate low efficiency when noise STD exceeds 20.

Tests with real images

The second experiment for similarity metrics analysis has been carried out using real-life images from Tampere17 database. The algorithm of similar blocks search in real images using the earlier obtained thresholds under noisy conditions with arbitrary introduction of identical block group is illustrated in Figure 12. The presented scheme is a quite similar to the algorithm for a threshold estimation in Figure 1. To analyze the efficiency of the similarity metrics for blocks of features in real-world images, the following experiment has been carried out. We have used ten test images from Tampere17 image database. As previously, all obtained images have been distorted by AWGN with the following noise STDs: 3, 5, 10, 15, 20, 25, and 30. Figure 13 presents an example of similar blocks introduction into real-life image. The dark points in distance maps mean small distances that correspond to similarity to the reference block. On the contrary, light color pixels correspond to other (dissimilar) blocks with large distances.

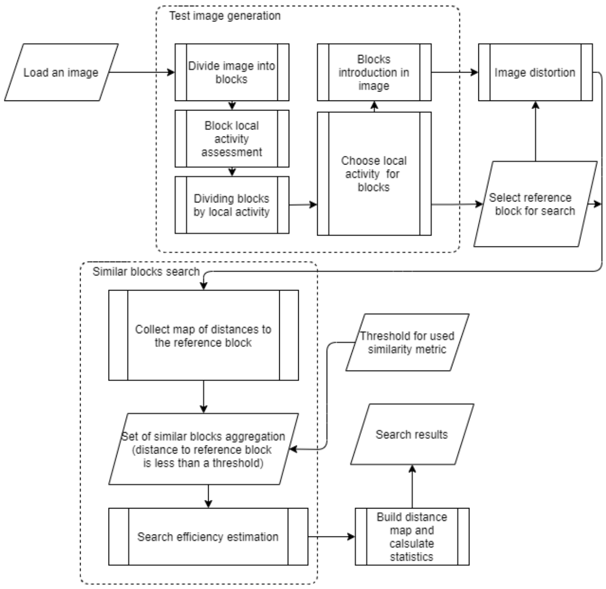

Figure 12. *Algorithm of similar blocks search in real images*

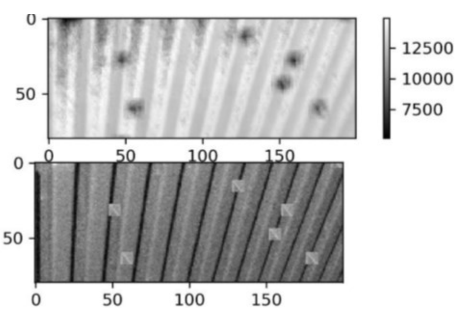

Figure 13. *Fragments of distance map and the corresponding image fragment for Manhattan distance in real test image corrupted by AWGN with STD = 10*

Figures 14 and 15 present averaged results for ten test images and metric calculation in the spatial domain. The results for DCT domain are shown in Figures 16 and 17. It should be noted that all metrics do not provide 100% result even for low noise intensity in real life images. The best results are demonstrated by Manhattan and Bray-Curtis distances for spatial domain. The Euclidean metric shows low efficiency according to *E* criteria. The Canberra, Hellinger and Chebyshev metrics have low search efficiency when noise STD exceeds 15 according to both *E* and *R* criteria. The Euclidean distance finds the group of similar blocks with higher ranks in the sorted set but the total number of blocks is smaller than for Manhattan and Bray-Curtis metrics.

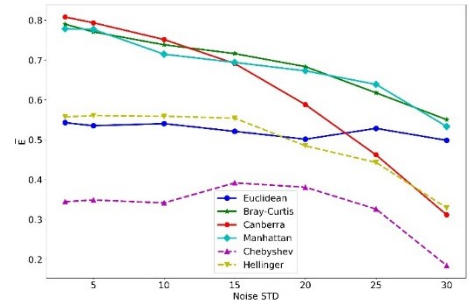

Figure 14. *Averaged E estimates for similarity metrics and ten real life test images (metric calculation in spatial domain)*

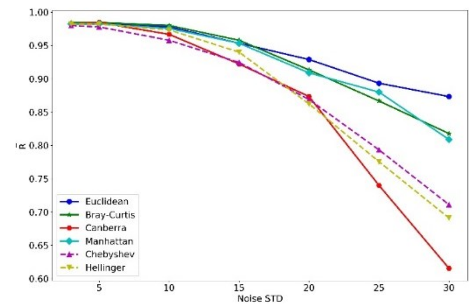

Figure 15. *Averaged R estimates for similarity metrics and ten real life test images (metric calculation in spatial domain)*

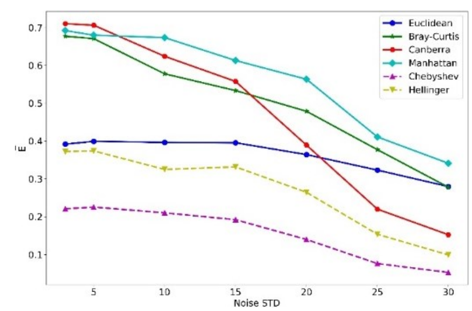

Figure 16. *Averaged E estimates for similarity metrics and ten real life test images (metric calculation in DCT domain)*

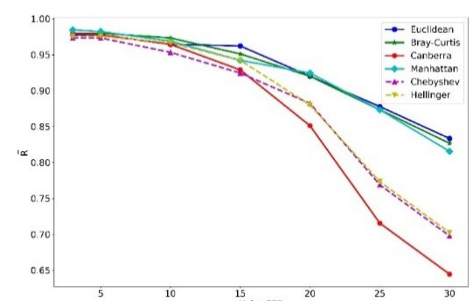

Figure 17. *Averaged R estimates for similarity metrics and ten real life test images (metric calculation in DCT domain)*

In DCT domain, we have similar results. The Euclidean, Hellinger and Chebyshev distances have low efficiency expressed in terms of E criterion. That means that the total number of found introduced blocks is unsatisfactory. The best results are shown by the Manhattan and Bray-Curtis metrics. R and E criteria complement each other and show, for instance, that Euclidean metric finds only a part of introduced blocks with high ranks.

Finally, let us summarize the obtained results. Due to the higher computational burden, we have excluded Mahalanobis and Pearson similarity metrics. This characteristic is crucial for real-time applications that often exploits similar blocks search. Other metrics have appropriate results in runtime tests and can be easily used in practice with different implementations like C++ realization or CUDA-based calculation. Thresholds estimations for metrics have also demonstrated interesting results. Euclidean and Canberra distances need a priori known or pre-estimated blindly STD of the noise. The first test with generated synthetic images shows that Hellinger distance is the best choice for spatial domain according to both E and R criteria while Bray-Curtis and Canberra distances work better in the DCT domain. However, synthetic images are well structured and we also had to check metrics' efficiency in real-life images. The second experiment has demonstrated that Bray-Curtis and Manhattan distances found more introduced similar blocks according to both E and R criteria (for the case of metric calculation in spatial domain). In DCT domain, the Bray-Curtis and Manhattan metrics show higher search performance than other metrics. It is well seen that the Euclidean distance which is the most used metric in image processing does not provide the best efficiency.

Conclusions

Two experiments with the generated synthetic and real images have been performed for similar blocks search. Spatial and DCT domains have been exploited to represent image blocks and calculate distances using the considered similarity metrics. Two criteria have been used to estimate similar blocks search efficiency under noisy conditions for AWGN model.

All metrics have been analyzed for their time and memory complexity. Two fast implementations using C++ and C++ with CUDA have been realized with the runtime estimation results. The obtained results can be used, e.g., in non-local denoising methods like BM3D, various methods of image and video compression, etc.

The proposed benchmark can be easily extended to other noise models, similarity metrics, test images and testing strategies, search efficiency criteria. It should be mentioned that the benchmark is extendable and can be used by the research community. The novelty consists in the following: we conduct analysis of similar blocks search for various noise models and scenarios; we have analysed similarity metrics in different cases; the fast parallel implementation of the proposed benchmark has been developed.

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Authors Biography

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Karen Egiazarian received his Ph.D. from Moscow M. V. Lomonosov State University, Russia, in 1986, and his Doctor of Technology in signal processing from Tampere University of Technology, Finland, in 1994. He is leading a "Computational imaging" group and a professor at the Department of Computing Sciences. He is an IEEE Fellow, editor-in-Chief of the Journal of Electronic Imaging and a member of the DSP Technical Committee of the IEEE Circuits and Systems Society. His main research interests are in the field of computational imaging, efficient signal processing algorithms, image/video restoration and compression.

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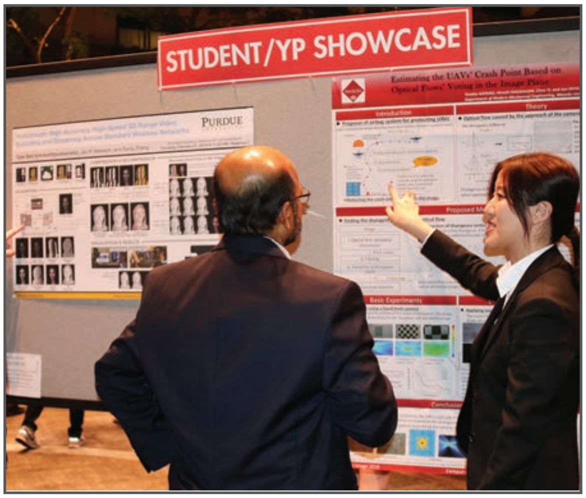

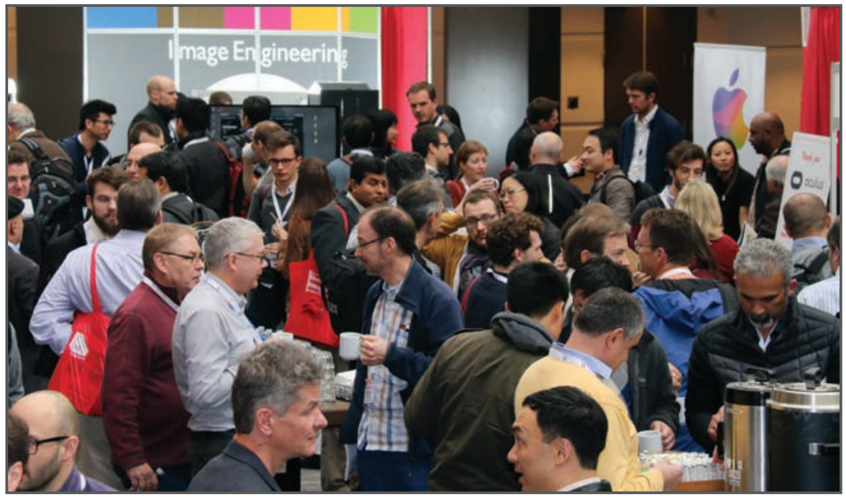

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