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DCT Domain Best Shot System

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Abstract: Digital video sequences may lead to visible degradation due to different kind of artefacts. Among them, blurring degradation is easily visible and annoying also for image and video processing non-experts. Blurring distortion is commonly caused by the object motion, camera shake or out of focus. To avoid this kind of degradation, also due to video compression, quality metrics for measuring sharpness are important to suppress worst images, to take the best shot in a burst of subsequent pictures. In this way, we obtain better looking video for the final user. In this paper, we present a low cost DCT-based single step algorithm, which requires no additional memory, so it is suitable for real time processing. It is a simple but robust method and it obtains similar visual results compared to more sophisticated algorithm (also not DCT-based). Moreover, the measure proposed takes into consideration not only blurring, but also other visual quality attributes, like brightness and orientation.

Keywords: Discrete Cosine Transform, Image quality, Blurring, Brightness, Sharpness.

1. Introduction

Image based algorithms performances usually depend on the quality of the processed shot. When sequences of images are acquired by a generic device (e.g. digital still camera, mobile phone, smart glasses, etc.), it is important to take the best one to obtain a more pleasant shot and to help further steps (video quality post-processing, classification, etc.). So, it is crucial to have a system obtaining a quality measure to discard worst frames and maintain the best ones for each chosen burst of pictures in the taken sequences.

Moreover, in low memory devices, if the video must also be stored, it is important to acquire directly compressed images to reduce memory occupancy (e.g.: JPEG for still images and MPEG, MPEG-2, MPEG-4, H263 for videos). These standards usually make use of block based Discrete Cosine Transform (DCT), usually composed by 8x8 block.

One of the most unpleasant artefacts for final user is the blurring, which affects salient features like contours and results in a drastic quality degradation. In this field, different quality measures have been proposed in literature: exponential probability density function [1], scale tree with sub-band decomposition [2], non-linear operation [3], average and standard deviation [4], pixel correlation [5]. However, most of them are heavy and not suitable for real-time processing.

The proposed algorithm is partially inspired by a simple real-time DCT algorithm [6], which uses DCT coefficients to estimate a quality measure, based on the blurring of the images. Basically the aforementioned algorithm is composed by two steps: in the first step, Luma DCT coefficients (greater than a fixed threshold, to avoid noise) are used to build the histogram; in the second step, the quality measure is calculated as the sum of the weights of a fixed matrix (also in this case greater than another estimated threshold) in correspondence of the values of the calculated histogram. Even if the method is really simple and suitable for real-time processing, it considers jointly DC and AC coefficients, which may lead to incorrect quality, it takes into consideration only blurring and it is a two-steps algorithm, which needs to store the histogram in memory.

An interesting and very reliable metric is the Frequency Selective Weighted Median (FSWM) [7]. It is fundamentally a cross-like 5×5 filer, in which horizontal and vertical median are calculated and the final metric value is the squared sum of the two calculated medians. Even if the FSWM filter is a very reliable measure, it is a YUV domain non-linear measure and it is not suitable for the DCT domain, thus it is not functional for low memory devices. However, since it is important to have a reference metric to validate our system, we also used this metric to validate our experiments.

In this article, we propose a quality metrics working in the DCT domain. It allows selecting the best shot in a burst of frames and it is an extension of our previous work [8]. Our contribution consists in reducing memory requirements (histogram is no more needed) and reducing computation time, also joining to satisfying results. Moreover, it is based on three features of increasing importance: blurring, which tends to discard more blurred images; brightness, which tends to discard bad exposed images; orientation, which tends to discard more oblique images.

In the next Section 2 the proposed algorithm is deeply described, then in Section 3 the comparison with other state of the art techniques are depicted. Finally, conclusions and future works are described in Section 4.

2. Proposed Algorithm

The proposed DCT based algorithm can be inserted before or after the Quantizer step of the standard JPEG, as indicated in Fig. 1.

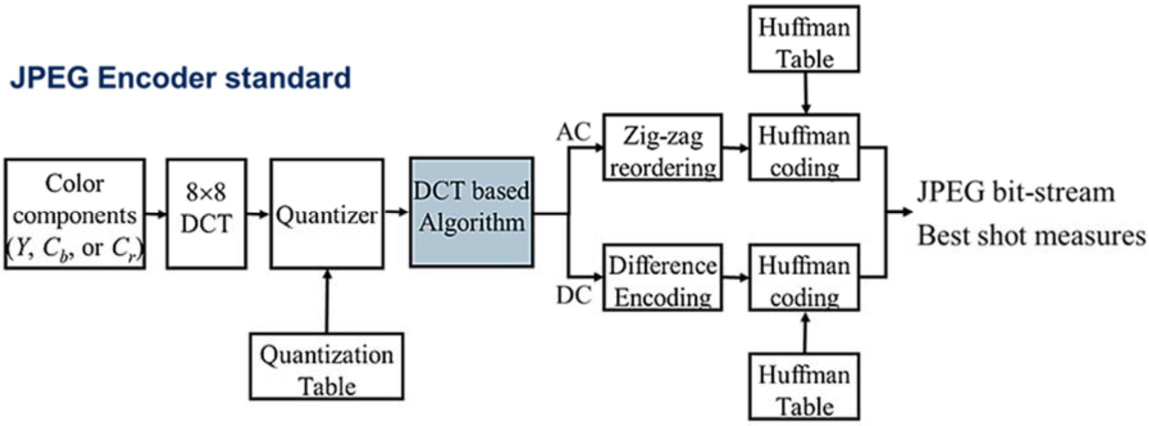

Fig. 1. Proposed system inserted in JPEG encoder standard.

At the end of the encoding process (apart the JPEG bit-stream) the *Best shot measures,* to make proper decisions, will be available. Of course, it is better to put the algorithm before the quantizer step, in this way it will work also in the case of different quantization applied in different blocks, otherwise (if the algorithm is positioned after the quantizer) it will be needed to scale proportionally the weights in case of different quantization applied block by block.

Our solution is applied just on Luma *DC* and *AC* coefficients of all 8×8 DCT blocks of the whole image. Position of *DC* coefficient and indexes of *AC* coefficients in each block are indicated in Table 1.

The algorithm calculates efficiently (i.e., in a single step) several quality measures for each 8×8 block of the whole image, as follows:

$$OQ = OQ + \sum_{i=1}^{63} w_i : (\mathrm{AC(i)} \neq 0), \tag{1}$$

$$DC_{mean} = DC_{mean} + DC, \tag{2}$$

$$HQ = HQ + \sum_{i=1}^{7} w_i : (\mathrm{AC(i)} \neq 0), \tag{3}$$

$$VQ = VQ + \sum_{i=8}^{56\,(step=8)} w_i : (\mathrm{AC(i)} \neq 0), \tag{4}$$

where *OQ* is the overall quality, that is the sum of the weights of the not-null *AC* coefficients (higher values means better quality); *DC_mean* (possibly at the end divided by the number of blocks) is the mean of DC coefficients of the whole image (values near to central value e. g. 128 means better quality); *HQ* is the horizontal quality, that is the sum of the weights of the first row of not-null *AC* coefficients (higher values means better quality), and *VQ* is the vertical quality, that is the sum of the weights of the first column of not-null *AC* coefficients (higher values means better quality); w_i are weights as indicated in Table 2.

Table 1. Indexes of AC coefficients.

DC	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
16	17	18	19	20	21	22	23
24	25	26	27	28	29	30	31
32	33	34	35	36	37	38	39
40	41	42	43	44	45	46	47
48	49	50	51	52	53	54	55
56	57	58	59	60	61	62	63

Table 2. Weights used for AC coefficients.

	w1	w2	w3	w4	w5	w6	w7
w1	w1	w2	w3	w4	w5	w6	w7
w2	w2	w2	w3	w4	w5	w6	w7
w3	w3	w3	w3	w4	w5	w6	w7
w4	w4	w4	w4	w4	w5	w6	w7
w5	w5	w5	w5	w5	w5	w6	w7
w6	w6	w6	w6	w6	w6	w6	w7
w7	w7	w7	w7	w7	w7	w7	w7

It is easy to note that the system is fast, and no extra memory is required: just seven weights (w_i) are required. To correctly choose these weights, the following vinculum should be considered:

$$w_7 \geq w_6 \geq w_5 \geq w_4 \geq w_3 \geq w_2 \geq w_1 \quad (5)$$

A good choice for them, experimentally validated, is the following:

$$w_i = 2^{i-1}, i = 1..7 \quad (6)$$

Moreover, it is possible, if necessary, to use different weights depending on, for instance, the DC coefficient. This to emphasize that in the case the quantization step is different from one block to another, the weights should be scaled proportionally.

The quality measures are tested incrementally: by first the *OQ* measure is considered. If the two *OQ* measures are similar (e.g., they differ for a small amount in percentage), then the second measure *DC_mean* is taken into consideration. Thereafter if the two *DC_mean* measures are similar, the best *HQ* and *VQ* measures are considered. In this way, after having taken the most suitable measure, the best quality image is chosen among images.

3. Experimental Results

Several tests have been executed in different conditions: a dataset of simulated sequences with increasing blurring (simulated with neighborhood average and Gaussian smoothing filters) has been generated; also images with increasing brightness and rotation, examining also DC coefficient value and horizontal quality have been taken in consideration; finally real sequences, acquired with smart glasses [9] have been added to the test set. In all tested conditions the proposed algorithm reaches better performances than *Prior Art* algorithm described in [6] and comparable performances to the more complex *FSWM* algorithm presented in [7].

To have a complete overview, one example for each testing will be shown. In all the graphics depicted: the horizontal axis indicates the frame number, the vertical axis indicates the value of the quality measure, *FSWM* indicates the reference algorithm [7], *Prior Art* indicates the work from [6], *Proposed* indicates our suggested solution.

The most important aspect in terms of quality impact is for sure the blurring. For this reason, we tested this artefact using artificial images with two kind of blurring: neighborhood average filtering and Gaussian filtering. In the first case, as shown in Fig. 2, the behavior of *Proposed* algorithm is similar to reference *FSWM* algorithm and it detects better the peak (Frame 1), while the *Prior Art* algorithm does not distinguish well images starting from a certain blurring, that is it consider practically equal frames 4 and 5, while quality of these images is visually very different as indicated in Fig. 3.

Similar considerations can be done also for the second case (Gaussian filtering), as shown in Fig. 4. In fact, again, the behavior of *Proposed* algorithm is similar to reference *FSWM* algorithm and it detects better the peak (Frame 1), while the *Prior Art* algorithm does not distinguish well images starting from a certain blurring, i.e., it considers practically equal frames 3, 4 and 5, while visual quality of these images is visually very different as indicated in Fig. 5.

The second aspect in order of quality impact (after blurring) is the brightness. As shown in Fig. 6, considering pictures taken with increasing brightness, the *OQ* value of *Proposed* algorithm is similar for frames from 4 to 9, while *Prior Art* algorithm (apart last frame) gives practically the same quality measure. *FSWM* algorithm, instead, is capable to distinguish well also this artefact and it correctly indicates the central Frame 6, as the best one. The visual impact of these images is shown in Fig. 7.

While in the previous examples the frame to choose was simply identified for the presence of a peak in the slot of the images taken, now it is not possible just with the proposed *OQ* value. In this case, since *OQ* values difference in percentage is less than a threshold (e. g. 1 %), we should take as best shot the picture with the DC coefficient value near to central value e. g. 128.

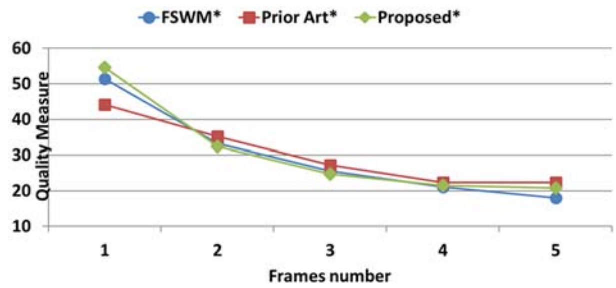

Fig. 2. Normalized output of reference (FSWM), Prior Art and Proposed quality for increasing blurring (using a neighborhood average filtering).

Fig. 3. Detail of frames taken with increasing blurring (using a neighborhood average filtering).

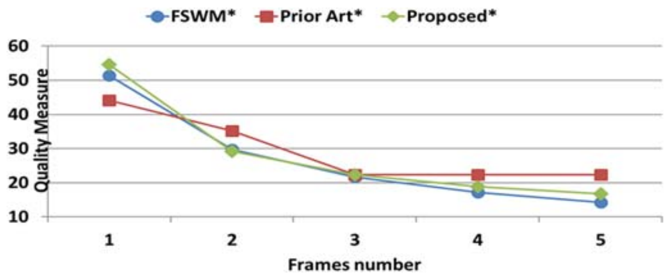

Fig. 4. Normalized output of reference (FSWM), Prior Art and Proposed quality for increasing blurring (using a Gaussian filtering)

Fig. 5. Detail of frames taken with increasing blurring (using a Gaussian filtering).

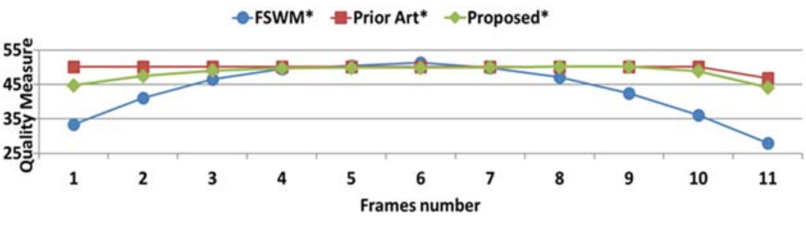

Fig. 6. Normalized output of reference (FSWM), Prior Art and Proposed quality for increasing brightness.

Fig. 7. Detail of frames taken with increasing brightness.

To take the better exposed image, we should consider the media of the DC coefficients (*DC_mean*) of the whole image. In this case, as shown in Fig. 8, the proposed algorithm will choose Frame 6, because its *DC_mean* (120) is the nearest to target 128.

The third aspect in order of quality impact (after blurring and brightness) is the orientation. As shown in Fig. 9, considering pictures taken with increasing rotation, the *OQ* value of *Proposed* algorithm is really similar for all frames apart for Frame 4 and the *Prior Art* algorithm (apart third and last frame) gives practically the same quality measure. Moreover, also *FSWM* algorithm is (of course) not capable to distinguish well this kind of artefact, giving (apart last frame) the same quality measure. The visual impact of these images is shown in Fig. 10.

It is easy to understand, since all images have similar brightness, that apart *OQ* values, also *DC_mean* values are similar. In this case, the *Proposed* algorithm will consider the horizontal AC coefficients (*HQ*) and vertical AC coefficients (*VQ*) to take the best orientated image that is the picture with the higher *HQ* and *VQ* values. As shown in Fig. 11 and Fig. 12, higher *HQ* and *VQ* values are in correspondence of Frame 1, which will be correctly identified as best shot in this sequence.

At last, let us consider a real short sequence of images taken by glasses. As shown in Fig. 13, the behavior of *Proposed* algorithm is similar to reference *FSWM* algorithm: the best two images of the real sequence are well detected, through the two peaks (Frames 4 and Frame 14). Visual impact of these two frames and surrounding pictures are shown respectively in Fig. 14 and Fig. 15. It is to note that the *Prior Art* algorithm does not distinguish well the two peaks (Frame 14 is not chosen), while the visual quality of peaks and surrounding images is different.

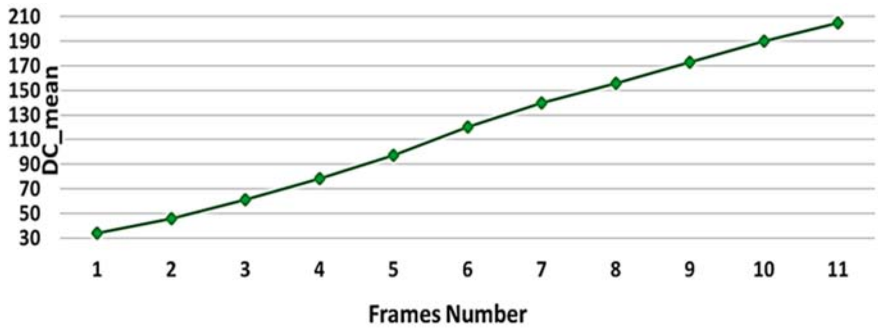

Fig. 8. DC-mean value in the case of increasing brightness.

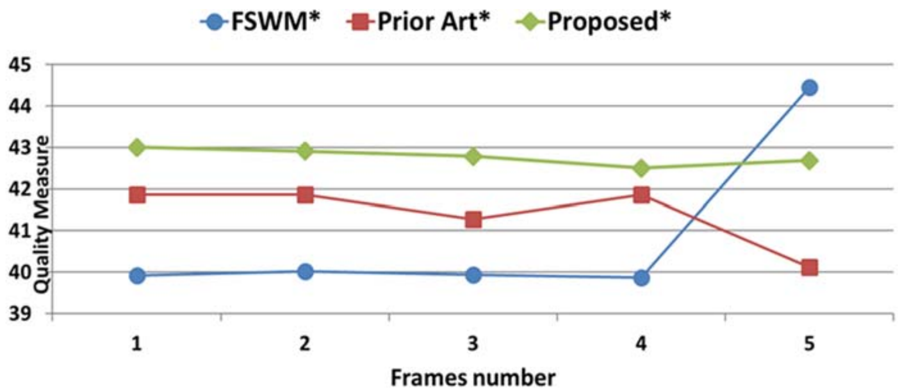

Fig. 9. Normalized output of reference (FSWM), Prior Art and Proposed quality for increasing rotation.

Fig. 10. Frames taken with increasing rotation.

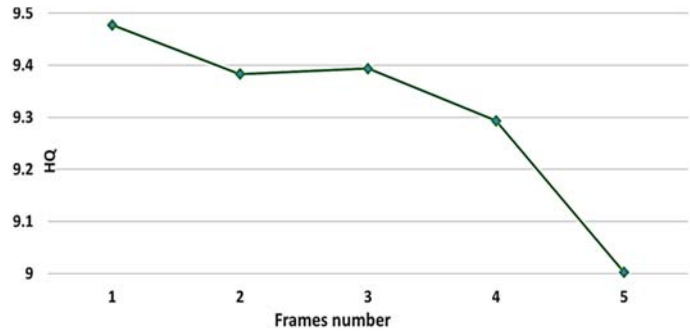

Fig. 11. AC horizontal coefficient value (HQ) in the case of increasing rotation.

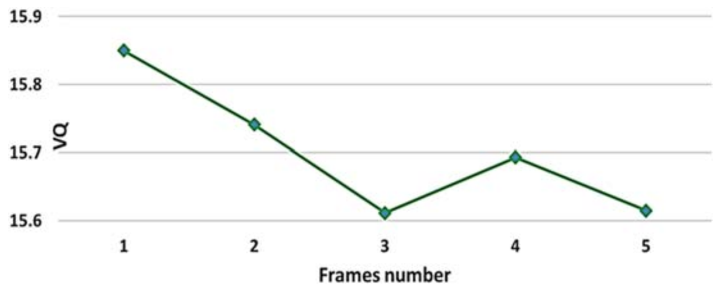

Fig. 12. AC vertical coefficient value (VQ) in the case of increasing rotation.

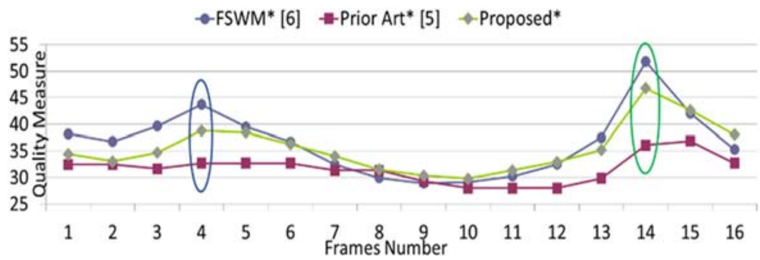

Fig. 13. Normalized output of reference (FSWM), Prior Art and Proposed quality for images taken by smart glasses.

Fig. 14. Detail of frames taken around the first peak (frame 4) of sequences taken by smart glasses.

Fig. 15. Detail of frames taken around the second peak (frame 14) of sequences taken by smart glasses.

4. Conclusions

A really fast single-step DCT-based quality metric has been developed to select the best shot in a burst of frames, so easily used for real-time processing in low cost devices, with the characteristic to avoid any further memory for the whole processing. In addition, apart to take into consideration the more relevant effect of blurring, the proposed solution considers also other important visual attributes, that is brightness and orientation of the pictures. It has been experimentally tested on a representative dataset of scenes obtaining significant improvements in a subjective manner compared to other simple DCT-based metrics and it reaches similar results compared to a good reference (not DCT domain) metric.

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