IMPACT OF BRIGHTNESS AND COMPLEXITIES TO EDGE DETECTION WITH ROBERTS AND CANNY OPERATOR ON COMPRESSED IMAGES

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Abstract

The paper presents an analysis of edge detection and compression in images over which wavelet decomposition was performed up to the third level and which consists of different levels of detail (low, medium, and high level of detail). Images from the BSD (Berkeley Segmentation Dataset) database with the appropriate groundtruth were used. Daubechies wavelet was used from second to tenth order. The images were analyzed for three levels of brightness (low, medium, and high). PSNR (Peak Signal to Noise Ratio) objective measure was used for compression results and F (F1 score), was used as objective measurement for edge detection. Based on the obtained results, the change in brightness affects the performed edge detection, as well as the compression depending on the degree. When the number of details in the image was low, Roberts proved to be the best operator for edge detection, while in cases with medium and high number of details in the image, Canny proved to be the best operator. The analysis is important for practical application in many systems, especially in television systems where the number of details in the image changes, as well as brightness.

Keywords: edge detection, compression, television, complexity, image brightness.

INTRODUCTION

Edge detection is one of the fundamental processes in image processing. It also entails image segmentation where edge detection extracts the desired object. Edge detection is based on the fact that there are sudden changes in the gray intensity between the pixels. Edge detection significantly reduces the image analysis process by using a smaller amount of data while storing all the necessary information. Many edge detection techniques have been proposed, but Gradient and Laplacian methods have proven to be the best. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. Laplacian methods are based on finding zero crossings in the second derivative of the image [1,2]. The gradient of the image can be calculated as [2,3]:

$$f(x,y) = \frac{\partial f}{\partial x} i + \frac{\partial f}{\partial y} j \tag{1}$$

Where *f(x, y)* represents the image at the location *(x, y)* where x and y are rows and columns of coordinates. Gradient $\nabla f(x,y)$ contains information about changes in gray color. The gradient of $\nabla f(x,y)$ can be calculated [2,3]:

$$(x,y) = \sqrt{f_x^2 + f_y^2} \tag{2}$$

Where *e(x, y)* can be used as edge detector and can also be defined as the sum of the absolute values of the partial derivative f_x and f_y, where f_x and f_y are partial derivatives of the function *f* by *x* and *f* by *y* [2,3]:

$$e(x,y) = |f_x(x,y)| + |f_y(x,y)| \tag{3}$$

Based on these theoretical principles, the mentioned Gradient and Laplacian methods were proposed. Gradient methods include Sobel, Prewitt, Robert, while Laplacian methods include LoG (Laplacian of Gaussian).

The classical use of the Canny operator is one of the gradient methods, but in some parts, it also contains elements of the Laplacian approach. Edge detection is brought down to convolution with appropriate directional masks [4].

Compression is one of the most important processes in image processing. Depending on the needs, various compression techniques and compression algorithms are applied, such as compression based on discrete cosine transform (DCT) or based on discrete wavelet transformation (DWT) [1]. The paper focuses on compression based on wavelet transformation.

Special families of the wavelet functions have been developed for DWT. They are generally divided into orthogonal or biorthogonal and characterized by high pass and low pass filters [5]. Daubechies wavelet belongs to a family of orthogonal functions and its main feature is the possibility of the maximum number of vanishing moments for some predefined supported length. Types of Daubechies (db) wavelets most commonly used in practical applications are dbN, where N represents the order as the number of vanishing moments in a supported interval from 0 to 20. By increasing the order of the Daubechies wavelet, better characteristics are obtained, but the complexity of the implementation as well as the price of the system and errors in the calculations rises also. In practical applications, orders from 2 to 10 are most used. [6-8].

A particularly important advantage of wavelet transformation is that it uses multiresolution analysis that allows the analysis of different signal frequencies at different frequency resolutions. For high frequency parts, shorter windows are used, which ensures a good time resolution, while for lower frequency parts, longer windows are used, which ensures a good information about the frequencies. If the signal is pass through two filters, low-pass and high-pass, its frequency content will be split into two ranges with equal width. The output of these filters contains half the frequency content of the original signal and the same number of samples. By decimating or by passing the input signal through the low-pass filter, the number of samples is halved so that the time resolution is also halved, while the frequency resolution is increased. The high-pass filter passes the high-frequency content or signal details. The low-pass filter passes low frequency content or signal absorption. This approximation signal can be passed again through two filters and the process can be repeated until the required decomposition level is reached. The complete original signal information is contained in the last approximation signal and all detail signals [9,10].

Decomposition significantly degrades the image quality, but in addition to that degradation, there are various types of noise that further impair the image quality. Different types of filters have been developed to solve or control this problem [11].

SYSTEM MODEL

In this paper, the BSD (Berkeley Segmentation Dataset) image database was used for analysis, with its corresponding groundgruth images [12]. Table 1 gives the values for selected images from the BSD database and they are selected to meet the criteria of complexity [13], that is, each image consists of a different level of detail: low (LD), medium (MD) and high (HD). The number of details was calculated by applying DCT and DWT on the high frequency components (details), which are divided into four quadrants, along both directions (x and y). After that, the mean absolute amplitude value of the components belonging to the quadrants [13] is calculated: DCT and quadrant 1 (DCTD); DCT and quadrants 2 and 3 (DCTM); DWT and quadrant 1 (DWT); DWT and quadrants 2 and 3 (DWTM).

TABLE I. CRITERIA

Criterion	*Images*	*DCTD*	*DCTM*	*WTD*	*WVTM*
Low	#135069	1.544	2.517	0.181	0.354
Medium	#35010	3.838	6.197	1.199	2.048
High	#8143	7.868	15.241	3.181	6.336

As an objective quality measure for the influence of wavelet decomposition, PSNR (Peak Signal to Noise Ratio) [14] was used.

The PSNR is defined as [14]:

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \quad (4)$$

where MAX_I is the maximum pixel value of the image. When the pixels are represented by B bits per sample, MAX_I is 2^B-1. MSE is the mean square error, so for images $x\ (n_1, n_2)$ and $y\ (n_1, n_2)$ with dimensions N_1xN_2, MSE is defined as [14]:

$$MSE = \frac{1}{N_1N_2}\sum_{n_1}^{N_1}\sum_{n_2}^{N_2}[x(n_1n_2) - y(n_1n_2)]^2 \quad (5)$$

Typical PSNR values, for images where lossy compression is used, are between 30 and 50 dB. If the PSNR is above 40 dB, the compressed image has almost no difference from the original. For acceptable image quality PSNR should be above 30 dB [14].

To demonstrate it more accurately and precisely how well edge detection is done, Precision, Specificity, Sensitivity and Accuracy should be calculated. Based on these measures, the F measure (F1 Score) was used [15]. F measure (F1 score) is a harmonic mean of precision and recall and it combines precision and recall according to the formula [14-16]:

$$F = \frac{2*Precision*Recall}{Precision+Recall}x100 \quad (6)$$

F ranges from 0 ≤ F ≤ 1, ideally, F is equal to 1. In the results, F is multiplied by 100 and represents a percentage value.

Considering that in systems implemented in practice, especially in television systems, the brightness change in the image is quite common phenomenon. the above-mentioned images are also analyzed in different brightness levels: low (-100), medium (0) and high brightness (+100). The brightness changes are done in Matlab.

RESULTS

Figure 1 shows the PSNR values for the three decomposition levels for an image with a low number of details. The results for three different levels of brightness are shown. From Figure 1, it can be seen that when decomposition levels increase, the PSNR greatly decreases. When the image with a low number of details is brightened, it significantly degrades the image, so in all cases from db2 to db10, the best PSNR values are obtained for a brightness of -100. Comparing the results when the db order increases, that is the vanishing moment increases, in the case of db4 and brightness=0, only second decomposition level gives better PSNR values, in all other combinations, the increase of the brightness, decreases PSNR values. Since the values of the third decomposition level are about 30 dB, the images at that level are of acceptable quality for further processing.

Figure 2 shows the PSNR values for the three decomposition levels for an image with a medium number of details. The results for three levels of brightness when increasing the order of db wavelet are shown.

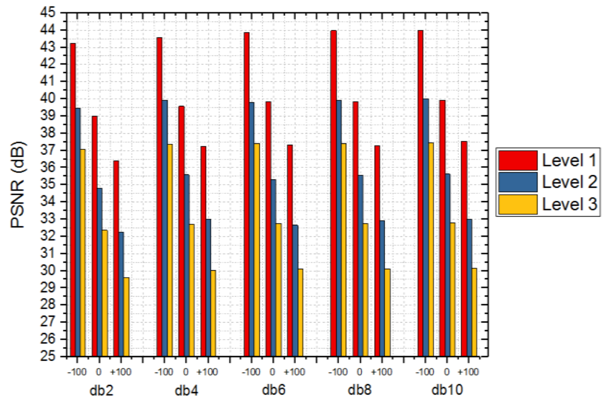

Fig. 1. *PSNR [dB] values for three decomposition levels for LD image.*

In this case, the increase in the decomposition level significantly decreases PSNR values. By increasing order of db from order 2 to order 10, the PSNR values increase. In this case, when the brightness was at -100, the best PSNR values, that are acceptable for further processing, were obtained. However, further increase of brightness to +100 gave almost identical values as in the case when brightness was 0, but the values are still a bit better. Comparing the results shown in Figure 1 where the number of details is low, the best results were achieved when the brightness was at -100 and in the case of the medium number of details in the images. The values obtained at the first decomposition level at all brightness levels are acceptable, while at the second and third decomposition level are at the margin of acceptable.

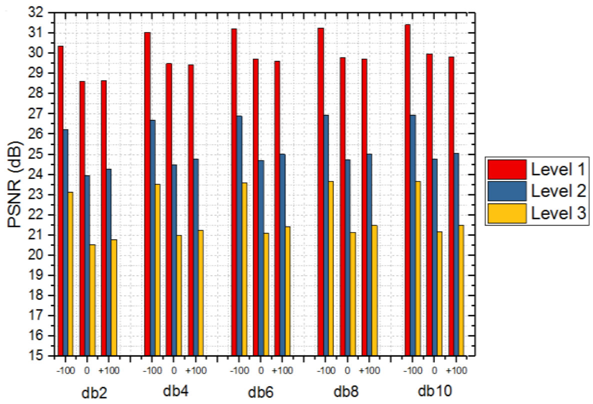

***Fig. 2.** PSNR [dB] values for three decomposition levels for MD image.*

Figure 3 shows the PSNR values for the three decomposition levels for an image with a high number of details. The best values were obtained at brightness -100, while with the further increase in brightness, PSNR values significantly decreased at all three decomposition levels. By increasing the wavelet vanishing moment, higher PSNR values were obtained, but the decrease is still present with the increase of brightness. When the brightness is 0, the values obtained at the second and third decomposition levels are not acceptable for processing, while at the first level in all cases of brightness values are at the margin of acceptable. Compared to the case of an images with a small and medium number of details, lower values were obtained by increasing the brightness and the best values were obtained at a brightness of -100. However, on images with a high and medium number of details, when the brightness is at +100, better values are obtained than when it is at 0, which differs from the case when the number of details in the image is low.

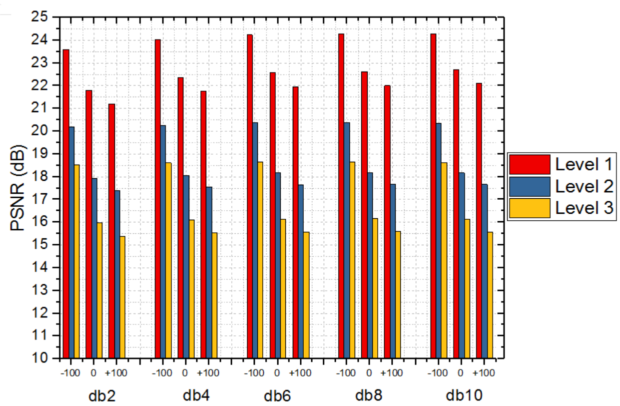

***Fig. 3.** PSNR [dB] values for three decomposition levels for HD image.*

Considering the results obtained in [17], it can be seen that Roberts and Canny record the best results in different degrees of compression and different wavelet transformations. When there is a low number of details in the image then it is Roberts best operator, when it is medium and high then it is Canny best operator. Based on this fact, Figure 4, Figure 5 and Figure 6 show the F values obtained for these two operators for the three decomposition levels and for the three levels of brightness, respectively.

The images were compressed by wavelet transformation to the third decomposition level using db from the second to the tenth order.

Figure 4 shows the case when the number of details in the image was low. Based on the obtained results, it can be seen that the values dropped significantly in the third decomposition level, however, in some cases the quality is acceptable for the detection of edges. With a higher degree of compression, Roberts scores better values, while Canny gets very poor results in the third decomposition level. Also, the brightness changes affected the Canny operator the most, except in the third level.

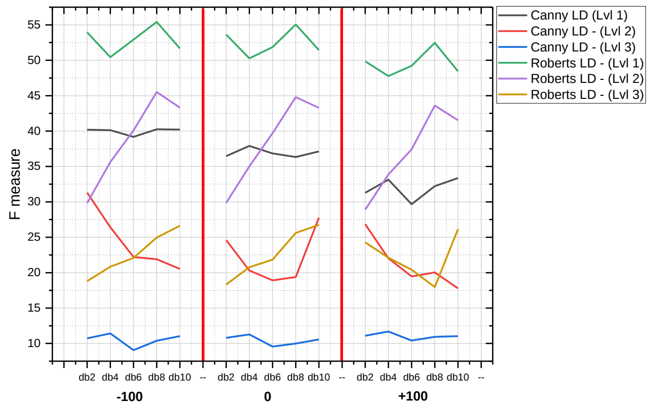

***Fig. 4.** F values for three decomposition levels and brightness for LD images.*

In Figure 5 can be seen that with the medium number of details in the image the situation is different compared to the results shown in Figure 4. When the number of details in the image is medium, Canny records the best results except when brightness was medium (0). Compression significantly affects the Roberts operator, where good edge detection is not possible in the third decomposition level at -100 and +100 brightness.

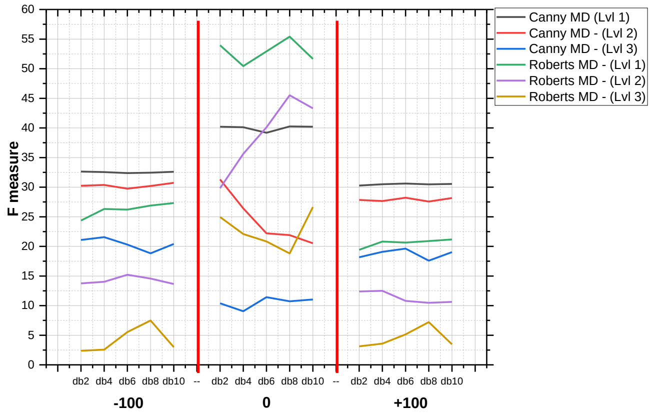

Fig. 5. *F values for three decomposition levels and brightness for LD images.*

Figure 6 shows the case when the number of details in the image was high. Based on the results shown in this figure, it can be seen that the Canny operator gave significantly better results than the Roberts operator. Compression affected Roberts operator significantly more than Canny operator. The values obtained for the Roberts operator show that it is not possible to perform useful edge detection under these conditions. Also, from the obtained results it can be seen that the change in brightness did not affect the detection much as in the case of low and medium details.

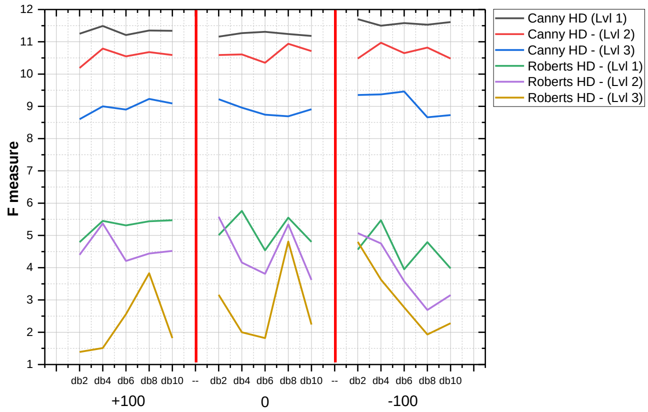

Fig. 6. *F values for three decomposition levels and brightness for LD images.*

CONCLUSIONS

This paper provides an overview and analysis of edge detectors over images consisting of different detail levels (complexity), which are then compressed by wavelet transformation to the third level, using Daubechies from the second to the tenth order. The analyzed images are categorized into three complexity criteria, so that they consist of low, medium, and high number of details. As objective measures, PSNR was used to assess quality degradation during wavelet decomposition (compression), and F measures was used to assess the quality of edge detection. Considering that in television systems a very frequent change of brightness is common, especially in live shows that are, the paper also analyzes the influence of brightness for the values: -100 (low), 0 (original or normal), +100 (high). Depending on the number of details in the image, level of decomposition as well as order of db, the compression is different, for example, when the number of details in the image is small, the best compression is achieved. Increasing the db order from 2 to 10 increases the PSNR values (quality). The brightness effect significantly changes the PSNR values during decomposition and with increase of db order from 2 to 10, so, the compression in different levels is differently affected. Also, the change in brightness affects the edge detection, the changes are visible in images with more details. When the number of details in the image is low, the best detection is achieved using the Roberts. With a low number of details in the image, detection is also possible in the third decomposition level where the best values are obtained for the Roberts operator. When the number of details in the image is medium and high, the best results in all three decomposition levels are obtained by the Canny operator. So, when there was low detail in the image, Roberts achieved better values even at higher compression ratios. When the number of details in the image is medium and high, the Canny operator is a better solution. Compression significantly affected Canny operator detection when the number of details in the image was low. When the number of details in the image was medium and high, the compression significantly affected the Robrets operator. Changes in brightness were most affected when the number of details in the image was medium.

In edge detection systems and algorithms, there is a preprocessing technique that regulates the level of brightness based on histogram optimization, however, the fact is that light will affect edge compression and detection. Today's systems require that the image quality be as good as possible, with the highest possible degree of compression in order to process these images in real time, such as edge detection, segmentation, streaming, streaming in augmented reality systems, etc.

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