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NEW APPROACH TO EDGE DETECTION ON DIFFERENT LEVEL OF WAVELET DECOMPOSITION

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Abstract. This paper proposes a new approach to edge detection on the images over which the wavelet decomposition was done to the third level and consisting of different levels of detail (small, medium and high level of detail). Images from the BSD (Berkeley Segmentation Dataset) database with the corresponding ground truth were used. Daubechies wavelet was used from second to tenth order. Gradient and Laplacian operators were used for edge detection. The proposed approach is applied in systems where information is processed in real time, where fast image processing is required and in systems where high compression ratio is used. That is, it can find practical application in many systems, especially in television systems where the level of details in the image changes. The new approach consists in the fact that when wavelet transform is applied, an edge detection is performed over the level 1 image to create a filter. The filter will record only those pixels that can be potential edges. The image is passed through a median filter that filters only the recorded pixels and 8 neighbors of pixel. After that, the edge detection with one of the operators is applied onto the filtered image. F measure, FoM (Figure of Merit) and PR (Performance Ratio) were used as an objective measure. Based on the obtained results, the application of the proposed approach achieves significant improvements and these improvements are very good depending on the number of details in the image and the compression ratio. These results and improvements can be used to improve the quality of edge detection in many systems where compressed images are processed, that is, where work with images with a high compression ratio is required.

Keywords: Edge detection, wavelet decomposition, compression, F measure, figure of merit, performance ratio

1 INTRODUCTION

In recent years, multimedia systems have recorded tremendous growth and progress, which means that image resolutions got higher increasing the complexity of the system and the complexity of the image. It is necessary to achieve as much compression as possible so these images can be streamed, stored and processed more easily. Today's trends require more technology to be involved, so in television systems we have a virtual reality (VR), augmented reality (AR) and a combination of them. Since it is necessary to have lower bitrate and achieve a high compression ratio and to process an image in VR or AR environment, it is necessary to perform certain operations over images such as segmentation, edge detection, etc. [1].

Edge detection is one of the fundamental processes in image processing. This also means the segmentation of the image where the segmentation of the desired object is performed by detecting the edge. Edge detection is based on the fact that there are sudden changes in the gray intensity between the objects. Edge detection significantly reduces the image analysis process by using less data and at the same time storing all the necessary information. Many edge detection techniques have been tried, but gradient and Laplacian methods have proved to be the best [2, 3]. Gradient methods for edge detection find the maximum and minimum gradient of the image intensity, all in the first derivative of the image. Laplacian methods are based on finding zero crossing in the second derivative of the image [4]. The gradient of the image can be calculated as [4, 5]:

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

where $f\left(x,y\right)$ represents the image at the location $\left(x,y\right)$ where x and y are the coordinates of the row and column. The gradient $\nabla f\left(x,y\right)$ contains the information about gray change. The gradient of $\nabla f\left(x,y\right)$ can be calculated [4, 5]:

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

where $e\left(x,y\right)$ can be used as an edge detector and can also be defined as the sum of the absolute values of the partial derivative f_x and f_y [4, 5]:

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

Based on these theoretical principles, the gradient and Laplacian methods are proposed. The gradient methods include Sobel, Prewitt, Robert, while the Laplacian include LoG (Laplacian of Gaussian). The classic use of the Canny operator is a gradient method, but in some parts, it also contains elements of the Laplace approach [6, 7, 8].

The analysis of the frequency domain using Fourier transform is very useful for signal analysis because the frequency domain is very important for the consideration of the nature of the signal and the influence of the noise over it. The disadvantage of this technique is the loss of time domain information. When viewing the Fourier transform in a frequency domain, it is difficult to say when a certain event occurred, or when some frequencies occurred. To overcome this problem, only a small part ("window") of the signal is analyzed at a time, and this window slides over the signal applying the Fourier transform on it. In this way, part of the frequency information is lost in order to get an information about the time when a certain frequency has occurred. Wavelet transformation is used to solve this problem. It allows the use of different window sizes for different frequencies. The basic difference between the wavelet transformation and the short-time Fourier transform is that the window length changes at the wavelet transform and in this way the frequency and time resolution can be changed. The basic idea of each wavelet transform is to present an arbitrary function $x(t)$ as a superposition of a wavelet set or basic functions. The basic functions are derived from a prototype called mother wavelet, by scaling or translating this function. The wavelet transformation of the $x(t)$ signal is given in Equation (4) [9, 10]:

$$\psi\left(\tau, s\right) = \frac{1}{s} \int_{-\infty}^{\infty} x\left(t\right) * \psi^{*}\left(\frac{t-\tau}{s}\right) \mathrm{d}t \tag{4}$$

where τ is a translation, and s is a scaling, while ψ is a "mother" wavelet, and ψ^* is conjugally complex of ψ. When processing images in a spatial domain, the operation is discretized. Discrete wavelet transformation (DWT) is defined as [9, 10]:

$$DWT_{x}^{\psi}\left(\tau, s\right) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x\left(t\right) * \psi^{*}\left(\frac{t-\tau}{s}\right) \mathrm{d}t. \tag{5}$$

The discrete wavelet transformation (DWT) can be presented as a matrix $\psi\left(c\right)$ and DWT coefficients can be obtained by taking an internal product between the signal and the wavelet matrix [9, 10]:

$$DWT_{x}^{\psi}\left[n, s\right] = \frac{1}{\sqrt{|s|}} \sum_{n} x\left[n\right] \psi_{n,s}^{*}\left[n\right]. \tag{6}$$

Special family of wavelet functions has been developed for DWT. They are generally divided into orthogonal or biorthogonal and are characterized by a high-pass and low-pass filters [11]. Daubechies wavelet belongs to a family of orthogonal functions and the main feature is the possibility of the maximum number of vanishing moments for a predefined supported length. Types of Daubechies (db) wavelets that are most commonly used in practical applications are dbN, where N represents the order as well as the number of vanishing moments in the supported interval from 0 to 20. By increasing the order of the Daubechies wavelet, better characteristics are obtained, but the complexity of the implementation, the price of the system and errors in the calculations rise. In practical applications, orders 2 to 10 are most commonly used [10, 12, 13].

A very important advantage of the wavelet transform is that it uses a multiresolution analysis that allows analysis of different signal frequencies at different frequency resolutions. For high-frequency parts, shorter windows are used, which ensures good time domain resolution, while longer parts of the lower frequencies have longer windows, thus giving good information about the frequencies. If the signal is passed through a set of two filters, low-pass and high-pass, its frequency content will be split into two equal-width ranges. The output from these filters contains half the frequency of the original signal and the same number of samples as the original signal. 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 increases. The high-pass filter transmits high-frequency content, i.e. signal details. The low-pass signal transmits low-frequency content, or signal approximation. This approximation signal can be further fed through two filters and the process can be repeated until the desired decomposition level is reached. The complete information on the original signal is contained in the last approximation signal and all the detail signals [14, 15].

Higher compression ratio disrupts the quality of the image, resulting in a large loss of information, and hence makes it difficult to process them, for example, to do an edge detection or facial recognition [16, 17]. The decomposition significantly degrades the image quality, but besides this degradation there are various types of noise that further impair the image quality. To solve this problem or to control it, the various types of filters have been developed [18, 19].

In this paper we used the characteristics of wavelet transform in order to image compression, or as a method on which some algorithms for image compression is based, such as JPEG2000 and SPIHT. Images from the BSD database are compressed to the third decomposition level which resulted in a high degree of compression.

2 SYSTEM MODEL AND PROPOSED APPROACH

In this paper, the BSD (Berkeley Segmentation Dataset) image database was used for analysis, with its corresponding ground truth images [20]. Table 1 lists the selected images from the BSD database meeting the complexity criteria [16], that is, each image consists of a different level of detail: small, medium, and high level of detail. The number of details was calculated by making 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 value of the amplitude of the components belonging to the quadrants is calculated [16]: DCT in quadrant 1 (dctd); DCT in quadrants 2 and 3 (dctm); DWT in quadrant 1 (dwtd); DWT in quadrants 2 and 3 (dwtm).

	Images	**dctd**	**dctm**	**dwtd**	**dwtm**
Criterion L	#135 069	1.544	2.517	0.181	0.354
Criterion M	#35 010	3.838	6.197	1.199	2.048
Criterion H	#8 143	7.868	15.241	3.181	6.336

Table 1. Criteria

Figure 1 gives a flow diagram of the proposed approach. In the proposed approach, firstly, the BSD and the ground truth images are read on which the DWT is applied to the third decomposition level using the Daubechies wavelet (optionally from 2 to 20). Since grayscale images are needed, a conversion is made, and variables are created for filters and new images. In order to assign input values to a filter, it is necessary to perform edge detection on level 1 images. Values stored in the filter are information about location of pixels pointing at the potential edge. The compressed image on which the detection is performed is a binary image and passing through the loop, each pixel is examined. If it is equal to the 1, that is, there is an edge, the median filter is used on the pixel and 8 neighbors of pixel. In other words, only those pixels that are relevant for the edge detection are passed through the filter. After that, the detection is applied and the results are compared, as shown in Figure 1. The algorithm is applied to all edge detection operators (Canny, LoG, Sobel, Prewitt, Robert).

The algorithm consists of the following steps:

Step 1 (Read image): Read the original image. If it is a color image, converts it to a grayscale image.

Step 2 (DWT): DWT is applied to the third decomposition level onto a read image, whereby as a result, three images are obtained: image from level 1, image from level 2 and image from level 3. The next steps in the algorithm are applied separately for an image from each level.

Step 3 (Edge detection): On level 1 image, an edge detection is used by selecting one of detectors (Canny, LoG, Sobel, Prewitt, Roberts). The image with detected edges serves to create a filter that will contain only those pixel coordinates where the edges are located.

Step 4 (Filtering image): Every pixel in the image is analyzed and if it is equal to 1, the filter records its coordinates.

Step 5 (Filtering 8-neighbors of pixel): If the condition in step 4 is fulfilled, filtering is done by filtering 8 neighbors of pixel relative to the current pixel using the median filter (Figure 2). So, only those image pixels that can be edges are filtered. The neighbors of pixel are extracted using the following formula:

If current pixel $P(i,j)$ is edge then use following neighbor pixels:

$$f(P_{i,j}) = f(P_{i-1,j-1}), f(P_{i-1,j}), f(P_{i-1,j+1}), f(P_{i,j-1}), f(P_{i,j}), f(P_{i,j+1}), \\ f(P_{i+1,j-1}), f(P_{i+1,j}), f(P_{i+1,j+1}) \quad (7)$$

and use median filter only on those pixels.

Step 6 (Edge detection on filtered image): Edge detection is applied on a filtered image.

For filtering level 2 and level 3 images, coordinates from level 1 image are used.

The proposed algorithm has a quadratic complexity and can be represented as:

$$O(row, col) = 8(row-2)(col-2)+1. \quad (8)$$

In Figure 3, the complexity of the algorithm is given, depending on the number of pixels in the row (row) and the number of pixel in columns (cols).

In order to accurately and precisely present how well the edge detection is done, it is necessary to calculate Precision, Specificity, Sensitivity and Accuracy or F measure [21]. F measure (F1 score) is a harmonic mean of precision and recall and it combines precision and recall according to the formula [21]:

$$F = \frac{2 * Precision * Recall}{Precision + Recall} \times 100. \quad (9)$$

F is within the limits of $0 \leq F \leq 1$, ideally, F is equal to 1. In the results, F is multiplied by 100 and represents a percentage value.

Figure of Merit (FoM) was proposed by Pratt [22] and is a measure for estimating the accuracy of detected edges. In other words, it represents the deviation of the actual (calculated) point of the edge from the ideal point of the edge, and is defined as:

$$FoM = \frac{1}{\max[I_d, I_i]} \sum_{k=1}^{I_d} \frac{1}{1+\delta e^2(k)} \quad (10)$$

where I_d is the number of points on the detected edge, and I_i is the number of points on the ideal edge, $e(k)$ represents the distance between the detected edge and the ideal edge, and δ is scaling constant and is usually 1/9. FoM is within $0 \leq FoM \leq 1$. In this case, FoM is multiplied by 100 and represents a percentage value. The higher the FoM is, the better the detected edge is [22].

As an objective measure of the edge detection credibility, Performance Ratio (PR) was used too. The PR is ideally equal to infinity. The PR is calculated as the ratio of the true edges to false ones [23, 24]:

$$PR = \frac{\text{True Edge(Edge pixels identified as Edges)}}{\text{False Edges(Non Edge pixels identified as Edges)+(Edge pixels identified as Non Edge pixels)}} \times 100. \tag{11}$$

3 RESULTS

3.1 F Measure

Tables 2, 3 and 4 show the F values before and after the application of the proposed approach on image with a small, medium and high number of details, respectively, over which db (from 2^{nd} to 10^{th} order) wavelet transform to the third decomposition level was applied. These tables show the values obtained for the five operators.

From Table 2 it can be seen that based on the obtained results, in the first decomposition level, using the proposed approach, improvements were achieved with the Canny operator in almost all cases, except for db4. A similar situation occurs when a LoG operator is used, with the exception that improvements have not been achieved in the case of db6. Using the proposed approach and image with low details, significant improvements have been achieved at the second level, where all operators record improvements in F values, except in the case of db8 with Prewitt and Sobel operators. In the third level, only Canny and LoG record improvements in F values using the proposed approach.

In the image with a medium number of details, very small improvements have been achieved in some operators at the first level, or the values are generally similar, without major deviations, as can be seen in Table 3. The situation is different with the second and third decomposition levels, where improvements are achieved by all operators, with the difference that improvements are higher in the third level.

In the case where the image consists of a high number of details, using the proposed approach, a similar or slightly better F value is obtained. At the second level, improvements are generally achieved with gradient operators, while at the third level, using the proposed approach, better values are obtained for all operators.

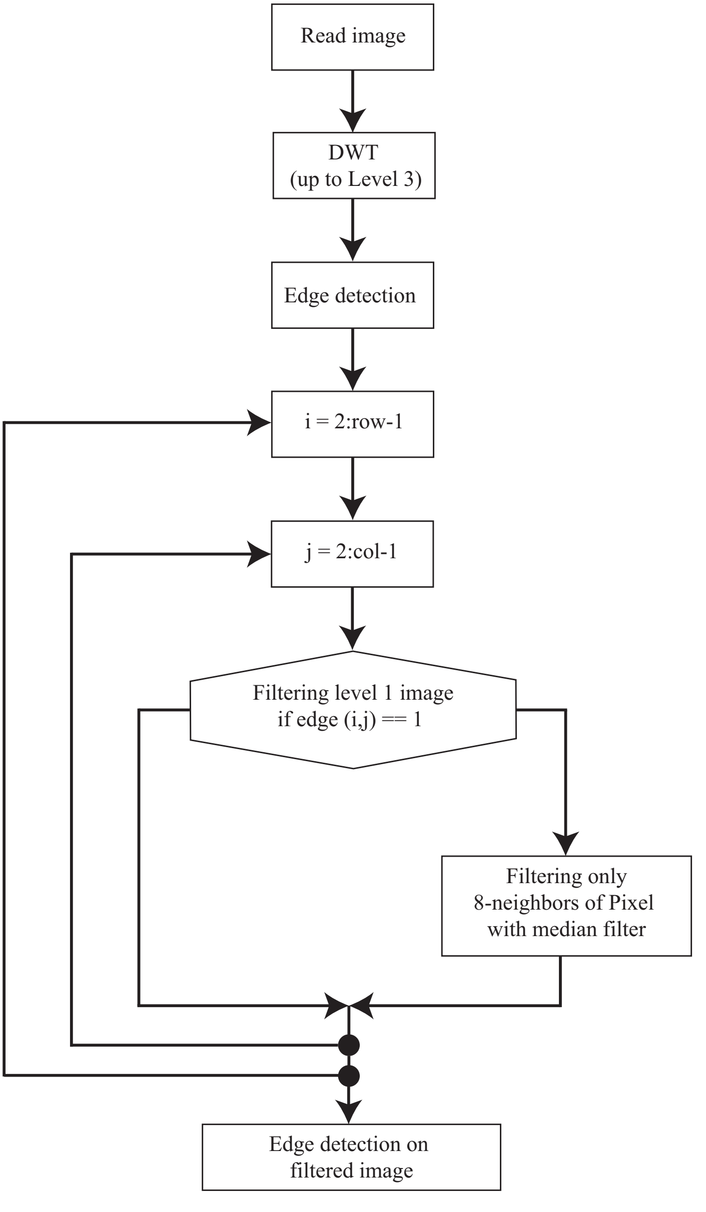

Figure 1. Proposed approach

$P_{i-1,j-1}$	$P_{i-1,j}$	$P_{i-1,j+1}$
$P_{i,j-1}$	$P_{i,j}$	$P_{i,j+1}$
$P_{i+1,j-1}$	$P_{i+1,j}$	$P_{i+1,j+1}$

Figure 2. Extraction neighbors of pixel

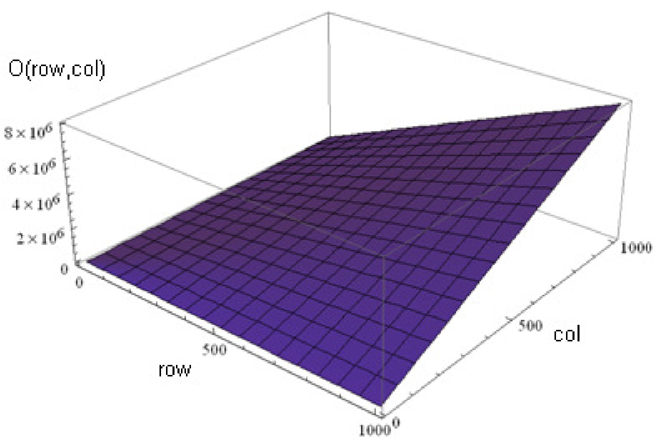

Figure 3. Complexity of proposed algorithm

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	0.365	**0.378**	0.379	0.364	0.368	**0.380**	0.363	**0.365**	0.371	**0.375**
	LoG	0.311	**0.314**	0.313	**0.317**	0.311	0.299	0.300	**0.303**	0.311	**0.315**
	Prewitt	0.362	0.342	0.355	0.346	0.366	**0.364**	0.322	**0.345**	0.380	0.362
	Sobel	0.365	0.336	0.356	0.349	0.371	0.363	0.325	**0.346**	0.377	0.362
	Roberts	0.536	**0.563**	0.503	**0.579**	0.519	**0.576**	0.551	**0.566**	0.514	**0.582**
Level2	**Canny**	0.278	**0.305**	0.246	**0.269**	0.203	**0.225**	0.189	**0.194**	0.194	**0.211**
	LoG	0.256	**0.274**	0.235	**0.256**	0.191	**0.211**	0.205	**0.207**	0.186	**0.202**
	Prewitt	0.269	**0.302**	0.285	**0.339**	0.285	**0.321**	0.338	0.301	0.279	**0.351**
	Sobel	0.264	**0.306**	0.284	**0.320**	0.281	**0.314**	0.333	0.303	0.278	**0.333**
	Roberts	0.299	**0.416**	0.350	**0.453**	0.397	**0.456**	0.448	**0.486**	0.433	**0.495**
Level3	**Canny**	0.108	**0.160**	0.113	**0.169**	0.096	**0.170**	0.100	**0.158**	0.106	**0.172**
	LoG	0.128	**0.173**	0.148	**0.190**	0.132	**0.187**	0.148	**0.174**	0.144	**0.176**
	Prewitt	0.147	0.203	0.189	0.241	0.184	0.247	0.180	0.251	0.194	0.256
	Sobel	0.146	0.201	0.187	0.229	0.182	0.235	0.179	0.240	0.195	0.244
	Roberts	0.183	0.276	0.208	0.255	0.218	0.297	0.256	0.335	0.268	0.348

Table 2. F values for an image with a low number of details (LD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	0.318	0.316	0.322	0.318	0.321	0.317	0.321	0.319	0.321	0.320
	LoG	0.234	0.234	0.235	**0.236**	0.235	**0.236**	0.236	0.236	0.237	0.236
	Prewitt	0.299	0.222	0.219	**0.220**	0.225	0.225	0.218	**0.219**	0.226	0.226
	Sobel	0.229	0.223	0.220	0.219	0.226	0.226	0.217	**0.219**	0.227	0.225
	Roberts	0.250	0.249	0.267	**0.268**	0.268	0.258	0.274	0.267	0.282	0.270
Level2	**Canny**	0.295	**0.302**	0.299	**0.312**	0.297	**0.312**	0.298	**0.312**	0.300	**0.309**
	LoG	0.213	0.211	0.207	**0.213**	0.211	**0.213**	0.209	**0.214**	0.207	**0.212**
	Prewitt	0.205	**0.209**	0.170	**0.182**	0.160	**0.184**	0.158	**0.182**	0.164	**0.185**
	Sobel	0.205	**0.209**	0.169	**0.180**	0.161	**0.182**	0.158	**0.178**	0.163	**0.183**
	Roberts	0.153	**0.154**	0.157	**1.196**	0.158	**0.183**	0.155	**0.177**	0.162	**0.179**
Level3	**Canny**	0.186	**0.238**	0.199	**0.246**	0.215	**0.252**	0.203	**0.250**	0.204	**0.250**
	LoG	0.134	**0.153**	0.111	**0.135**	0.088	**0.111**	0.081	**0.104**	0.076	**0.100**
	Prewitt	0.118	**0.138**	0.092	**0.118**	0.078	**0.115**	0.072	**0.110**	0.075	**0.110**
	Sobel	0.118	**0.135**	0.092	**0.114**	0.078	**0.109**	0.072	**0.104**	0.075	**0.105**
	Roberts	0.078	**0.081**	0.065	**0.088**	0.042	**0.054**	0.034	**0.046**	0.035	**0.047**

Table 3. F values for an image with a medium number of details (MD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	0.222	0.219	0.219	**0.220**	0.220	0.219	0.219	**0.220**	0.220	**0.221**
	LoG	0.192	0.192	0.190	0.189	0.192	0.192	0.192	**0.193**	0.192	0.191
	Prewitt	0.171	0.167	0.164	**0.166**	0.178	0.175	0.165	**0.166**	0.172	0.169
	Sobel	0.170	0.165	0.164	**0.165**	0.177	0.174	0.163	**0.165**	0.170	0.168
	Roberts	0.161	0.152	0.166	0.163	0.163	0.157	0.170	0.162	0.164	0.157
Level2	**Canny**	0207	**0.207**	0.216	**0.224**	0.205	**0.215**	0.215	**0.220**	0.214	**0.220**
	LoG	0.177	0.176	0.182	0.183	0.172	**0.176**	0.174	**0.175**	0.179	**0.182**
	Prewitt	0.159	**0.166**	0.139	**0.145**	0.127	**0.143**	0.135	**0.141**	0.133	**0.150**
	Sobel	0.157	**0.166**	0.139	**0.144**	0.127	**0.142**	0.133	**0.140**	0.133	**0.147**
	Roberts	0.123	0.123	0.129	**0.167**	0.125	**0.143**	0.135	**0.149**	0.142	0.159
Level3	**Canny**	0.145	**0.184**	0.154	**0.175**	0.154	**0.197**	0.161	**0.190**	0.162	**0.190**
	LoG	0.121	**0.148**	0.104	**0.133**	0.094	**0.114**	0.084	**0.108**	0.077	**0.102**
	Prewitt	0.110	**0.136**	0.077	**0.102**	0.078	**0.114**	0.073	**0.103**	0.077	**0.111**
	Sobel	0.109	**0.133**	0.077	**0.098**	0.078	**0.112**	0.073	**0.100**	0.078	**0.110**
	Roberts	0.087	**0.089**	0.064	**0.088**	0.067	**0.084**	0.064	**0.079**	0.070	**0.087**

Table 4. F values for an image with a high number of details (HD)

3.2 Figure of Merit

Tables 5, 6 and 7 show the FoM values before and after the application of the proposed approach on image with a small, medium and high number of details, respectively, over which db (from 2^{nd} to 10^{th} order) wavelet transform to the third decomposition level was applied. These tables show the values obtained for the five operators.

From Table 5 it can be seen that in the first decomposition level, the best values are obtained for the Canny operator, where in almost all cases it gives better values, except in the case of db4. By comparing Table 5 with Table 2, it can be seen that using FoM objective measurements, improvements have been made in the same or similar cases. By increasing the compression, that is, in Levels 2 and Levels 3, using the proposed approach, better FoM values were obtained, and greater improvements were achieved, especially in the third level.

In the case of an image with a medium number of details, in the first level, Canny gave the best results, in other words, better values were achieved. In the second level, in the case of db2, improvements were achieved only with the Canny operator, while other operators gave similar, but lower values. In other cases, the proposed algorithm records substantially better FoM values. For images with a medium number of details, the best edge detection enhancements have been achieved in the third level using the proposed algorithm.

Since the compression ratio is higher in the image with a high number of details, based on this fact, it can be concluded that the detection will be much worse. Also, in the case of images with a high number of details, the best improvements are achieved with the Canny operator at all levels. Based on the results obtained, it can be seen that the best improvements are achieved in the third level.

3.3 Performance Ratio

Tables 8, 9 and 10 show PR values before and after applying the proposed approach using five edge detection operators and three wavelet decomposition levels. Table 8 shows the values for an image with a low number of details. Based on the results obtained, it appears that improvements have been made with certain operators. However, based on the values obtained in Table 8, it can be seen that the old PR values and new PR values obtained using the proposed approach have greatest difference when using the Robert operator.

Table 9 contains the PR values obtained for an image with medium number of details. From Table 9 can be seen that the new values obtained are best in the second and third decomposition levels. In other words, the best improvements are achieved in the second and third levels, depending on the operator used and the order of the db wavelet.

Table 10 contains PR values obtained for an image with a high number of details. Based on these results, it can be seen that improvements have been achieved using the proposed approach, especially in the third decomposition level.

Wavelet		db2		db4		db6		db8		db10	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	88.955	**91.928**	89.461	89.272	85.982	**91.960**	86.025	**86.914**	88.767	**89.626**
	LoG	89.163	89.024	90.209	**90.514**	86.915	85.582	83.605	**85.108**	89.779	88.556
	Prewitt	91.784	**91.937**	92.341	92.327	92.358	**92.572**	92.664	92.632	92.868	92.540
	Sobel	91.891	91.712	92.678	**92.695**	92.423	**92.466**	93.031	92.934	92.891	92.742
	Roberts	95.150	**95.387**	89.419	**95.816**	86.680	**95.561**	93.837	95.613	83.259	**95.653**
Level2	**Canny**	61.727	**66.006**	51.308	**52.452**	40.207	**41.320**	31.974	**34.924**	36.049	**37.174**
	LoG	75.006	**79.220**	60.472	**66.126**	47.187	**51.753**	45.955	**50.186**	44.379	**49.053**
	Prewitt	82.182	76.052	88.824	**92.094**	88.654	**91.490**	89.074	**91.115**	88.676	**91.615**
	Sobel	82.785	77.091	88.818	**91.599**	88.581	**91.498**	88.979	**90.786**	88.716	**91.575**
	Roberts	82.494	**85.980**	89.832	88.389	91.016	88.300	91.281	**91.386**	91.877	**92.731**
Level3	**Canny**	6.045	**9.491**	34.316	**38.640**	27.035	**34.575**	25.158	**33.672**	26.926	**33.476**
	LoG	42.385	**48.432**	49.201	**53.907**	47.312	**50.844**	48.132	**51.458**	48.646	**52.246**
	Prewitt	52.036	**55.246**	78.675	**71.700**	78.136	**85.231**	76.196	**85.186**	75.841	**84.392**
	Sobel	52.113	**55.991**	78.606	**73.264**	78.088	**86.561**	76.190	**84.761**	75.837	**84.193**
	Roberts	57.384	**74.222**	78.821	**81.909**	77.951	**81.587**	78.839	**82.599**	78.901	**82.152**

Table 5. *FoM* values for an image with a low number of details (LD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	83.334	**82.917**	83.593	**83.835**	83.633	**83.926**	83.596	**83.773**	83.715	**84.068**
	LoG	76.358	76.351	76.984	76.892	77.003	76.875	77.216	76.957	77.230	77.050
	Prewitt	65.096	64.526	63.403	63.351	63.694	63.564	63.058	62.834	63.696	63.335
	Sobel	65.061	64.397	65.553	63.420	63.948	63.449	63.076	62.941	63.705	63.444
	Roberts	58.484	**58.800**	60.477	58.903	56.160	55.423	58.046	56.431	57.563	56.511
Level2	**Canny**	80.273	**80.650**	80.260	**80.889**	80.963	**81.348**	80.921	**81.384**	81.200	**81.295**
	LoG	73.433	73.272	73.300	**73.418**	73.474	**73.511**	73.261	73.002	73.519	73.504
	Prewitt	60.830	60.702	55.991	**56.815**	55.317	**56.128**	54.346	**55.447**	55.118	56.228
	Sobel	60.843	60.732	56.057	**56.975**	55.354	**56.375**	54.463	**55.598**	55.177	**56.389**
	Roberts	54.327	50.858	50.265	**51.582**	46.033	**46.891**	43.300	**43.996**	43.972	**44.406**
Level3	**Canny**	70.628	**75.211**	68.835	**73.034**	68.847	**73.556**	66.794	**71.193**	66.968	**71.698**
	LoG	61.503	**61.749**	51.323	**53.911**	44.316	**47.050**	41.310	**43.968**	39.284	**41.870**
	Prewitt	49.680	**50.908**	40.509	**44.000**	36.667	**40.527**	34.840	28.934	35.081	**38.936**
	Sobel	49.618	**51.109**	40.543	**43.917**	36.654	**40.182**	34.910	38.611	35.098	**38.686**
	Roberts	42.298	38.790	31.990	**34.236**	19.143	**20.251**	15.979	**16.983**	16.216	**17.198**

Table 6. FoM values for an image with a medium number of details (MD)

Wavelet		db2		db4		db6		db8		db10	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	70.111	**71.230**	69.127	**71.555**	67.787	**70.466**	68.057	**69.417**	68.420	**70.459**
	LoG	80.612	80.029	80.713	80.131	81.016	80.593	80.894	80.399	81.020	80.543
	Prewitt	64.338	63.895	58.063	**58.180**	62.165	61.852	59.804	**59.969**	60.513	60.454
	Sobel	64.259	63.817	58.435	**58.711**	62.340	62.180	59.992	**60.167**	60.924	60.659
	Roberts	52.692	52.351	56.121	53.588	49.446	47.979	53.204	51.154	49.377	47.762
Level2	**Canny**	79.241	**79.417**	80.766	**80.868**	79.811	**79.977**	80.195	**80.628**	79.964	**81.130**
	LoG	74.034	73.853	74.988	74.765	74.498	74.087	73.826	73.502	75.316	74.986
	Prewitt	57.164	56.225	51.862	51.670	50.198	**51.235**	47.020	**47.824**	50.519	**51.654**
	Sobel	57.186	56.503	51.594	51.833	50.409	**51.258**	47.040	**47.927**	50.545	**51.554**
	Roberts	48.516	45.265	45.511	**46.339**	42.075	41.858	37.190	**37.934**	39.990	**40.475**
Level3	**Canny**	69.148	**73.049**	66.302	**70.065**	67.704	**71.391**	66.096	**69.790**	66.069	**70.312**
	LoG	61.954	**63.395**	51.619	**54.322**	45.840	**48.129**	41.824	**44.563**	39.693	**41.655**
	Prewitt	48.604	**50.094**	36.487	**39.421**	32.028	**35.209**	29.176	**32.407**	29.650	**33.184**
	Sobel	48.670	**50.230**	36.407	**39.104**	32.080	**35.073**	29.309	**32.294**	29.656	**32.994**
	Roberts	41.724	37.448	29.368	**31.066**	21.038	**21.889**	19.951	**20.950**	20.829	**21.832**

Table 7. FoM values for an image with a high number of details (HD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	28.695	**30.234**	30.519	28.649	29.164	**30.704**	28.526	**28.800**	29.527	**29.945**
	LoG	22.532	**22.923**	22.798	**23.225**	22.589	21.305	21.473	**21.741**	22.573	**23.038**
	Prewitt	28.367	26.024	27.553	26.478	28.856	28.676	23.739	**26.379**	30.706	28.426
	Sobel	28.795	25.315	27.667	26.757	29.537	28.484	24.113	**26.399**	30.201	28.388
	Roberts	57.813	**64.519**	50.543	**68.677**	53.857	**67.983**	61.243	**65.303**	52.937	**69.606**
Level2	**Canny**	19.222	**21.983**	16.320	**18.378**	12.742	**14.538**	11.667	**12.021**	12.019	**13.333**
	LoG	17.165	**18.843**	15.345	**17.218**	11.803	**13.387**	12.855	**13.068**	11.443	**12.642**
	Prewitt	18.380	**21.641**	19.978	**25.675**	19.899	**23.619**	25.535	21.490	19.300	**26.996**
	Sobel	17.914	**22.085**	19.811	**23.516**	19.587	**22.875**	24.922	21.730	19.224	**24.930**
	Roberts	21.227	**35.587**	26.948	**41.347**	32.925	**41.833**	40.560	**47.205**	38.156	**48.936**
Level3	**Canny**	6.045	**9.491**	6.356	**10.141**	5.286	**10.217**	5.549	**9.375**	5.909	**10.356**
	LoG	7.358	**10.470**	8.717	**11.731**	7.600	**11.502**	8.702	**10.541**	48.646	**52.246**
	Prewitt	8.616	**12.775**	11.630	**15.895**	11.256	**16.399**	11.010	**16.723**	12.019	**17.248**
	Sobel	8.517	**12.598**	11.485	**14.844**	11.135	**15.399**	10.871	**15.795**	12.077	**16.171**
	Roberts	11.221	**19.060**	13.107	**17.118**	13.978	**21.112**	17.214	**25.186**	18.270	**26.741**

Table 8. PR values for an image with a low number of details (LD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	23.355	23.137	23.791	23.282	23.609	**23.231**	23.603	23.428	23.612	23.480
	LoG	15.246	**15.296**	15.399	**15.421**	15.350	**15.459**	15.426	15.413	15.538	15.431
	Prewitt	14.814	14.285	14.024	**14.098**	14.485	14.477	13.920	**14.028**	14.634	14.595
	Sobel	14.872	14.320	14.108	14.003	14.558	**14.568**	13.888	**14.006**	14.651	14.536
	Roberts	16.694	16.557	18.245	**18.317**	18.306	17.373	18.887	18.219	19.595	18.454
Level2	**Canny**	20.906	**21.648**	21.376	**22.659**	21.166	**22.678**	21.246	**22.690**	21.387	**22.407**
	LoG	13.539	13.402	13.020	**13.546**	13.366	**13.549**	13.234	**13.610**	13.059	**13.478**
	Prewitt	12.883	**13.215**	10.217	**11.158**	9.525	**11.262**	9.404	**11.097**	9.781	**11.356**
	Sobel	12.865	**13.208**	10.178	**11.005**	9.568	**11.110**	9.390	**10.842**	9.730	**11.182**
	Roberts	9.013	**9.132**	9.337	**12.206**	9.369	**11.179**	9.167	**10.777**	9.362	**10.936**
Level3	**Canny**	11.428	**15.604**	68.835	**73.034**	13.660	**16.821**	12.749	**16.686**	12.776	**16.643**
	LoG	7.454	**9.010**	6.240	**7.788**	4.806	**6.272**	4.410	**5.796**	4.104	**5.568**
	Prewitt	6.705	**8.030**	5.085	**6.670**	4.245	**6.477**	3.867	**6.152**	4.040	**6.210**
	Sobel	6.700	**7.825**	5.088	**6.452**	4.237	**6.091**	3.870	**5.821**	4.040	**5.867**
	Roberts	4.250	**4.427**	3.472	**4.805**	2.185	**2.855**	1.765	**2.435**	1.816	**2.471**

Table 9. PR values for an image with a medium number of details (MD)

Wavelet		**db2**		**db4**		**db6**		**db8**		**db10**	
	Operator	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**	**Old**	**New**
Level1	**Canny**	70.111	**71.230**	69.127	**71.555**	67.787	**70.466**	68.057	**69.417**	68.420	**70.459**
	LoG	80.612	80.029	80.713	80.131	81.016	80.593	80.894	80.399	81.020	80.543
	Prewitt	64.338	63.895	58.063	**58.180**	62.165	61.852	59.804	**59.969**	60.513	60.454
	Sobel	64.259	63.817	58.435	**58.711**	62.340	62.180	59.992	**60.167**	60.924	60.659
	Roberts	52.692	52.351	56.121	53.588	49.446	47.979	53.204	51.154	49.377	47.762
Level2	**Canny**	79.241	**79.417**	80.766	**80.868**	79.811	**79.977**	80.195	**80.628**	79.964	**81.130**
	LoG	74.034	73.853	74.988	74.765	74.498	74.087	73.826	73.502	75.316	74.986
	Prewitt	57.164	56.225	51.862	51.670	50.198	**51.235**	47.020	**47.824**	50.519	**51.654**
	Sobel	57.186	56.503	51.954	51.833	50.409	**51.258**	47.040	**47.927**	50.545	**51.554**
	Roberts	48.516	45.265	45.511	**46.339**	42.075	41.858	37.190	**37.934**	39.990	**40.475**
Level3	**Canny**	69.148	**73.049**	66.302	**70.065**	67.704	**71.391**	66.096	**69.790**	66.069	**70.312**
	LoG	61.954	**63.395**	51.619	**54.322**	45.840	**48.129**	41.824	**44.563**	39.693	**41.655**
	Prewitt	48.604	**50.094**	36.487	**39.421**	32.028	**35.209**	29.176	**32.407**	29.650	**33.184**
	Sobel	48.670	**50.230**	36.407	**39.104**	32.080	**35.073**	29.309	**32.294**	29.656	**32.994**
	Roberts	41.724	**37.448**	29.368	**31.066**	21.038	**21.889**	19.951	**20.950**	20.829	**21.832**

Table 10. PR values for an image with a high number of details (HD)

4 CONCLUSIONS

This paper proposed a new approach to edge detection in the images on which the wavelet decomposition was applied to the third level. As mother wavelet, Daubechies was used from the second to the tenth order. The analyzed images are categorized into three complexity criteria, so they consist of a small, medium and high number of details. F measure, FoM, and PR were used for an objective measure. The proposed approach provides significant improvements in edge detection for almost all operators (Canny, LoG, Prewitt, Sobel).

Depending on the number of details in the image, the decomposition level as well as db wavelet, the improvements are different. With a small number of details, the greatest improvements were achieved with the Canny operator. Other operators also achieved improvement but depending on the db wavelet order. Based on the obtained results, in the image with a small number of details, it can be seen that best improvements are achieved in the third level using Laplacian operators. In the image with the medium number of details, in the first level similar results are generally obtained, while in the second and the third levels improvement is made using the proposed approach. For images with a high number of details, better or similar values are obtained using the proposed approach. What can be concluded is that in the second level, the best values are obtained by gradient operators.

Considering that the compression ratio is higher of the image with a higher number of details, based on this fact, it can be concluded that the detection will also be poorer, and consequently there will be a lower F values, FoM values and PR values. Since the proposed approach is intended for systems where compression is used, i.e. compressed image processing, it can be concluded that increasing the degree of compression also provides a better difference, or better value using the proposed approach.

Today's systems require image quality to be as good as possible, with as much compression as possible in order to process these images in real time, such as edge detection, segmentation, streaming, streaming in systems using augmented reality, etc. The proposed approach can find many practical applications in all systems where real-time information needs to be processed, especially in television systems, but it also provides a good basis for the direction of future research related to compression and edge detection.

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