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A ROUGH SETS BASED EDGE DETECTOR AND ITS PERFORMANCE VERIFICATION

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ABSTRACT

Edge detection is performed to identify the edges contained in images for use in applications such as human action recognition, etc. Gradient based edge detectors such as Sobel, Canny, Roberts and Prewitt detectors are commonly used, while the soft computing based edge detection techniques are gaining popularity recently. This paper presents a rough sets based edge detector. The proposed edge detector first computes the roughness value of each pixel and then compares it with a threshold value to identify it as an edge pixel or not. Three standard images (cameraman, peppers and walk-cycle) have been used to verify its performance. Output images from the proposed, Canny, Sobel, Roberts and Prewitt, Fuzzy and the ANFIS edge detectors were compared in terms of visual appearance, performance ratio, Entropy and Structural Similarity Index. The proposed edge detector has been found to yield better results for all the standard images considered, based on the stated measures.

KEYWORDS: *Adaptive Neuro-Fuzzy Inference System, Edge Detectors, Entropy, Fuzzy Logic, Performance Ratio, Rough Sets, Structural Similarity Index.*

I. Introduction

A set of curved line segments of digital images, having oriented localized changes in pixel intensities are called the edges. Edge detection is the process of extracting edges from digital images. It has applications in image segmentation, image reconstruction, machine vision, human action recognition, etc. [1]. Several edge detectors are found in literature and in practical use.

The edge detector classifies an edge to be true or false by comparing a simple measure (e.g. gradient) of a pixel with certain threshold. It may be possible that some true edges being recognized incorrectly as false edges and vice versa. Canny [2] used edge continuity as a norm for classifying the edges to avoid using simple measures that usually lead to false classifications. He and Yung [3] proposed Edge Likelihood Index (ELI) as a composite measure to improve the performance of Canny detector. The ELI uses the curvature along with the gradient and length or continuity to distinguish the true and false edges using an empirical threshold. Zhang et al. [4] proposed an improved Sobel detector and an automatic thresholding algorithm based on this detector and the genetic algorithm (GA). Zhang and Zhao [5] solved the positioning problems of Sobel detector by using a high-pass Butterworth filter. Deng et al. [6] proposed an improved algorithm that handles the anti-noise ability and edge continuity problems of Sobel detector. They further proposed a fusion approach using this improved algorithm, wavelet transform, and Canny and Prewitt detectors keeping their respective advantages to get a near ideal edge detection. More information on traditional edge detectors can be found in [7-9].

Edge detectors generally use a single resolution, which may lead to unsatisfactory results as the edges of an image usually occur at multiple resolutions and represent transitions of multiple gradient levels. Siddique and Barner [10] proposed a multi-resolution, multi-rate wavelet decomposition based edge detection method to address this issue. Chen and Acton [11] proposed a multi-resolution edge detector based on morphological pyramid (MP) structure, created by successive morphological filtering and sub-sampling of the original image. The boundaries detected at coarse scale representations of MP are used to identify the discontinuities at higher resolutions. Niya and Aghagolzadeh [12] proposed a wavelet decomposition based edge detector. This detector classifies the image pixels as candidate edge points by double thresholding using extended Otsu's thresholding method, followed by applying a directional wavelet-based edge detector to classify candidate edge points as edge or non-edge points. Heric and Zazula [13] proposed an adaptive version of the directional wavelet-based edge detector. Deng and Iyengar [14] proposed a probabilistic relaxation labelling scheme, consisting of a nonlinear update function derived from Markov random field theory and Bayes formula and a dictionary construction method. In another attempt, Uemura et al. [15] proposed a boundary code based method, defined using edge formation of pixels derived from the homogeneity of 4 neighbourhoods (right, up, left and down) by an interest pixel.

Soft computing tools such as Fuzzy Logic, Artificial Neural Network (ANN), Ant Colony Algorithm, etc. have gained popularity among the researchers. The fuzzy logic appears to have contributed a large number of edge detection algorithms among them. Cheung and Chan [16] proposed the fuzzy one-mean derivative filter (FOM-DF), obtained by modifying the fuzzy one-mean (FOM) algorithm, as one of the earliest works using fuzzy logic. The output of FOM-DFs is a convex combination of input samples. This prevents the occurrence of overflow and ensures the robustness of edge detection in noisy images containing a mixture of white Gaussian noise and outliers. A fuzzy Sobel method based on Sugeno-type fuzzy reasoning strategy [17], modified fuzzy Sobel detector [18], fuzzy reasoning based edge detector for noisy images [19], multiple thresholding based on fuzzy 3-partition approach [20], competitive fuzzy edge detector [21], heuristic edge detector using fuzzy rule-based classifier [22], pixel's gradient and standard deviation values based fuzzy edge detector [23], improved fuzzy edge detectors [24-25], etc. are some of the other detectors based on fuzzy logic. The ANN based detectors [26-27], combined ANN and fuzzy logic based edge detection and enhancement [28-30], an adaptive neuro-fuzzy inference system (ANFIS) based edge detector [31] and ant colony algorithms based approach [32] have also been reported. For more information on the soft computing techniques based edge detectors, the interested reader is directed elsewhere [33-34].

The foregoing discussions reveal the nature of ongoing research on edge detectors and enhancements applied to them through different approaches wherein the soft computing tools are found to play a major role. Detection of false edges as true edges and vice versa is still a prevalent problem, while thresholding poses another important problem. A rough sets based edge detector is proposed in this paper with the presumption that it may yield better results than the fuzzy sets as rough sets express imprecision by a boundary region calculated using upper and lower approximation of the sets rather than partial membership functions used in fuzzy sets. The performance of proposed edge detector is compared with existing edge detectors, viz. Roberts, Prewitt, Sobel, Fuzzy and ANFIS edge detectors, in terms of visual appearance and other performance metrics using standard images.

Rest of the paper is organized as follows. Section 2 describes about various existing edge detectors, while Section 3 briefs about the concepts of rough sets and describes about the proposed rough sets based edge detector. The quantitative measures used for performance evaluation of edge detectors are discussed in Section 4. The results obtained based on standard images using the proposed and existing edge detectors are presented and discussed in Section 5. Finally, Section 6 presents the conclusion and future scope.

II. Existing Edge Detectors

2.1. Gradient-based Edge Detectors

For a two-variable image intensity function f(x, y), the gradient at each pixel of the image is a 2D vector. Its gradient, given by Eq. (1), points to the direction of largest possible intensity change and its magnitude, given by Eq. (2), is the rate of change along that direction [1].

$$\nabla f = grad(f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (1)$$

$$M(x,y) = mag(\nabla f) = \sqrt{g_x^2 + g_y^2} \quad (2)$$

The Sobel, Canny, Roberts and Prewitt edge detectors [3, 34] that fall under this category have been implemented for comparison purposes. Their convolution kernels are shown in Figure 1.

(a) Sobel kernel

G_x:

-1	0	+1
-2	0	+2
-1	0	+1

G_y:

+1	+2	+1
0	0	0
-1	-2	-1

(b) Gaussian filter used in Canny detector

$\frac{1}{115}$ ×

2	4	5	4	2
4	9	12	9	4
5	12	15	12	5
4	9	12	9	4
2	4	5	4	2

(c) Roberts kernel

G_x:

+1	0
0	-1

G_y:

0	+1
-1	0

(d) Prewitt kernel

G_x:

-1	0	+1
-1	0	+1
-1	0	+1

G_y:

+1	+1	+1
0	0	0
-1	-1	-1

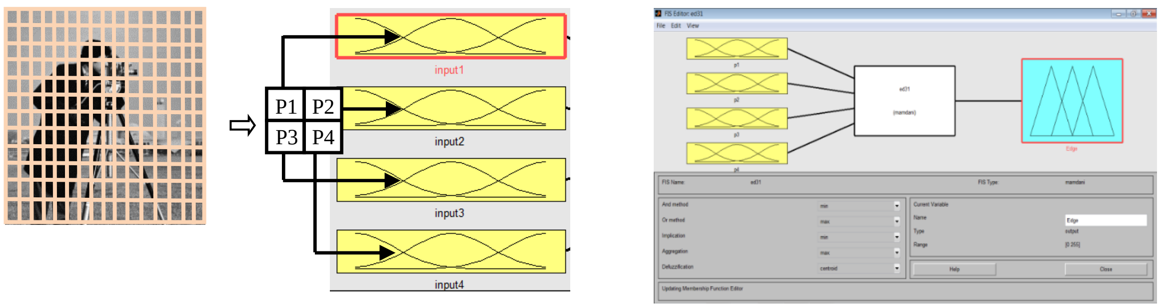
Figure 1. Convolution Kernels

2.2. Soft Computing-based Edge Detectors

Two soft computing techniques based edge detectors, viz. Fuzzy and ANFIS detectors, have also been implemented. The following sub-sections briefly describe about these edge detectors.

2.2.1. Fuzzy Edge Detector

Fuzzy edge detector first transforms the input image data from grey level plane to membership plane. The present implementation takes its input from a 2×2 window as shown in Figure 2. The membership values are then modified using a fuzzy rule-base containing 16 rules that have been designed to mark a pixel as Black, White or Edge [23-25]. Defuzzification is carried out finally to transform the data back to grey level plane to detect edges.

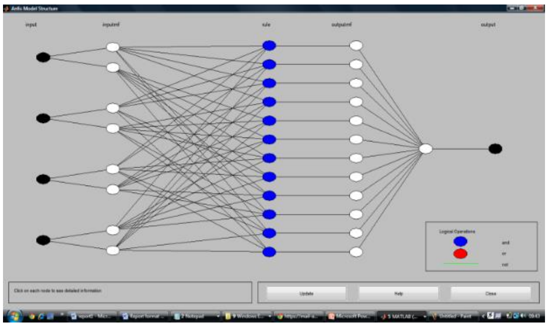


(a) Mapping of input image using 2×2 window (b) FIS with 4 inputs and one output

Figure 2. Fuzzy inference system for fuzzy edge detection

2.2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS) Edge Detector

The ANFIS edge detector uses a combination of fuzzy logic and artificial neural network (ANN). The fuzzy logic element grasps the learning capabilities of the ANN element to enhance the performance using a priori knowledge. The ANFIS constructs a Sugeno-type FIS based on the given input-output dataset. The membership function parameters are adjusted using a backpropagation and least square method based hybrid algorithm [26, 31]. The ANN used in this implementation (Figure 3(a)) has an input layer with 4 neurons, an output layer with 1 neuron and a hidden layer with 12 neurons. The training dataset is formed such that the pixel values of four inputs (2×2 window) are arranged in first four columns and the output is arranged in the last column (Figure 3(b)). The training is done with datasets containing all edge patterns and some non-edge patterns. The constant value at the output neuron is used by ANFIS to classify a pixel as an edge (1) or non-edge (0) pixel.



(a) ANN structure

Input				Output
1	2	3	4	
83	81	87	89	0
81	76	89	81	0
174	199	179	201	1
199	170	201	179	0
170	180	179	178	0
105	113	100	114	0
113	121	114	115	0
:	:	:	:	:
:	:	:	:	:

(b) Sample training dataset

Figure 3. The ANN model and the sample training set used with ANFIS detector

III. Proposed Rough Sets based Edge Detector

Rough sets provide an approximation to the crisp sets [40]. Rough sets can lead to useful forms of granular computing for the analysis and processing of inaccurate, incomplete or uncertain information in images. Rough sets have found applications in image processing, such as medical image processing [37, 44-47], segmentation of images [41], measurement of ambiguity in images [42-43], etc. A brief description of the proposed rough sets based edge detection algorithm follows.

Let a universe U be consisting of pixels of an image that may be partitioned into granules based on their properties. The granules can be used to approximate the object regions in an image using rough sets. The degree of granulation (Ω) plays a vital role in ascertaining the roughness attributes of an attribute. This value is obtained by dividing the whole set of pixels into White (W_t) and Black (B_t) granules based on a threshold t (Eq. (3)).

$$W_t = \{P_i \mid P_i \in U, P_i > t\};\ B_t = \{P_i \mid P_i \in U, P_i <= t\} \tag{3}$$

Next, the lower and upper approximation of each granule are determined. The lower approximations of the white set (W_t) and black set (B_t) are given by:

$$\underline{W_t} = \{P_i \mid P_i \in U, [P_i]_\Omega \subseteq W_t\};\ \underline{B_t} = \{P_i \mid P_i \in U, [P_i]_\Omega \subseteq B_t\} \tag{4}$$

Similarly, the upper approximations are expressed as:

$$\overline{W_t} = \{P_i \mid P_i \in U, [P_i]_\Omega \cap W_t \neq \phi\};\ \overline{B_t} = \{P_i \mid P_i \in U, [P_i]_\Omega \cap B_t \neq \phi\} \tag{5}$$

Therefore, an image can be represented as a rough set comprising the upper and lower approximation sets and the roughness of white and black granules may be computed using Eq. (6) [35, 37]:

$$R_{W_t} = 1 - \frac{|\underline{W_t}|}{|\overline{W_t}|} = \frac{|\overline{W_t}| - |\underline{W_t}|}{|\overline{W_t}|};\ R_{B_t} = 1 - \frac{|\underline{B_t}|}{|\overline{B_t}|} = \frac{|\overline{B_t}| - |\underline{B_t}|}{|\overline{B_t}|} \tag{6}$$

where, the values in | | represents the cardinality of the set. Next the boundary values are calculated using Eq. (7).

$$BN(W_t) = \overline{W_t} - \underline{W_t};\ BN(B_t) = \overline{B_t} - \underline{B_t} \tag{7}$$

As stated before, a set is said to be rough only if it has a non-empty boundary. Pixels in the boundary region are classified as edge or non-edge pixels, depending on their roughness by comparison with a threshold value. The proposed edge detector is described as follows.

Algorithm 1 Proposed rough sets based edge detection algorithm

Input Given Image
Output Edge Detected Image
Steps

1. Normalize the input image, i.e. the image to a scale of [0, 1].
2. Choose a threshold value t

3. Form two granules based on t using Eq. (3)
4. Find the lower and upper approximations using Eq. (4) and Eq. (5)
5. Calculate the roughness measure using Eq. (6)
6. Calculate the boundary values using Eq. (7)
7. If the roughness value of pixels in the boundary region is more than threshold, then mark the pixels as edges

IV. Metrics for Performance Evaluation of Edge Detectors

The performance of edge detectors can be expressed using qualitative or quantitative measures. In this paper, visual quality of output the images is used as a qualitative measure and performance ratio (PR), entropy (H) and structure similarity index (SSIM) are used as quantitative measures. The quantitative measures are briefly described below.

4.1. Performance Ratio (PR)

The performance ratio (PR) can be calculated using Eq. (8). True edges are the edge pixels identified as edges, false edges are non-edge pixels identified as edges and non-edge pixels are wrongly detected edge pixels. A higher PR value means better quality of detected edges. The output of Canny detector is taken as ground truth [36] for calculating the performance ratio.

$$PR = \frac{True\ Edges}{False\ Edges + Non-edge\ Pixels} \times 100 \tag{8}$$

4.2. Entropy (H)

Shannon introduced the concept of entropy in quantifying the information content and is viewed in a similar manner in the context of images [43]. The Shannon's entropy in evaluating the information content of an image is:

$$H = -\sum_{i=1}^{G} d(i) \ln_2 \{d(i)\} \tag{9}$$

where, G is the number of grey levels of the image's histogram ranging between 0 and 255 and d(i) is the normalized frequency of occurrence of each grey level. For example, a simple binary image of two equally distributed grey levels of 0 and 255 will have an entropy (H) of 1 bit/pixel as computed using Eq. (9). This implies an information content of 1 bit in each pixel of this image. For the images with unequal grey level frequencies, entropy would also change. If an image has a higher entropy, it holds more number of bits/pixel and there is more chance for that extra information to be noise [44].

4.3. Structural Similarity Index (SSIM)

Structural similarity index (SSIM) exploits the spatial inter-dependency of pixels in order to quantify the visual quality between original and noise-removed images. Eq. (10) and Eq. (11) can be used to compute the SSIM value, which lies in the range [-1, 1]. Two images will have their SSIM indices to be 1 when they are identical [48].

$$SSIM = [l(x,y)]^{\alpha} + [c(x,y)]^{\beta} + [s(x,y)]^{\gamma} \tag{10}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1};\ c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2};\ s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{11}$$

where, l(x, y) is the luminance comparison c(x, y) is the contrast comparison and s(x, y) is the structure comparison. The terms μ_x and μ_y denote the mean of an image at x and y, σ_x and σ_y denote the standard deviation at x and y (Eq. (12)) and σ_{xy} denotes the correlation (Eq. (13)). C_1, C_2 and C_3 are small positive constants, which combat the stability issues when the sum of squares of μ_x and μ_y or that of σ_x and σ_y becomes close to zero (Eq. (14)). The coefficients α, β and γ in Eq. (11) are positive exponents that adjusts the components contribution to the overall SSIM. All their values have been taken as 1.

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i ; \mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i ; \sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)^2} ; \sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i-\mu_y)^2} \quad (12)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)(y_i-\mu_y) \quad (13)$$

$$C_1 = (K_1 L)^2;\ C_2 = (K_2 L)^2;\ C_3 = C_2 / 2 \quad (14)$$

where, K_1 and K_2 are small constants less than 1 and L is the dynamic range of pixel values. The values of K_1 and K_2 and L have been arbitrarily taken as 0.01, 0.03 and 255 respectively. The output of Canny detector is taken as ground truth [36] for calculating the SSIM values.

V. Results and Discussion

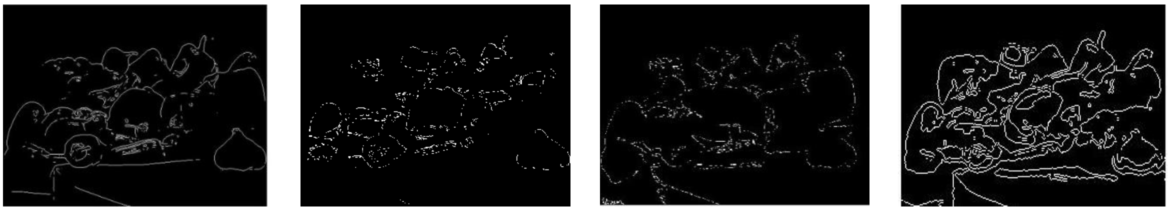
The existing (Canny, Sobel, Prewitt, Roberts, Fuzzy and ANFIS) and the proposed edge detectors have been implemented using MATLAB. The comparison between existing and proposed detectors are made in terms of visual appearance, performance ratio (PR), entropy (H) and structural similarity index (SSIM) using different standard images. The Cameraman, Peppers and Walk-cycle images are used in this paper. Figure 4 shows the edges detected by different edge detectors using these standard images. Edges detected from cameraman image (Figure 4(A)) using the Canny detector reveals more information in terms of number edges, but there are many false edges too. The proposed rough sets edge detector appears to be equally informative, but at the same time detects fewer false edges than Canny detector. Similar results are observed with peppers (Figure 4(B)) and walk-cycle (Figure 4(C)) images. The other detectors detect either too few or too many edges. Some amount of distortions or blurs are observed with all detectors perhaps due to input image quality.

(a) (b) (c) (d)

(e) (f) (g) (h)

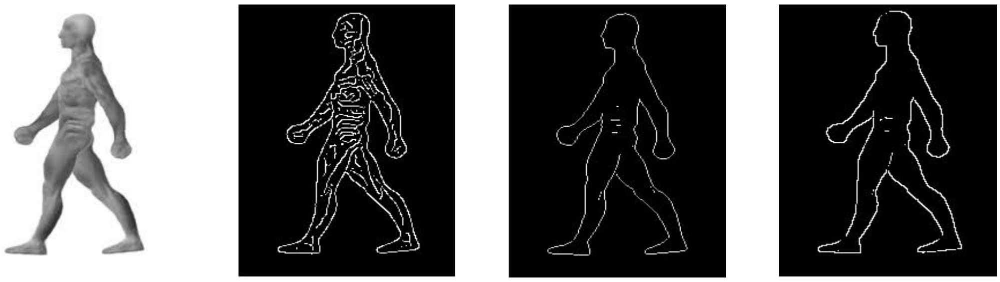
(A) The Cameraman image

(a) (b) (c) (d)



(e) (f) (g) (h)

(B) The Peppers image



(a) (b) (c) (d)

(e) (f) (g) (h)

(C) The Walk-cycle image

Figure 4**.** Comparison of the existing and proposed edge detectors (a) Original image; (b) Canny; (c) Sobel; (d) Roberts; (e) Prewitt; (f) Fuzzy; (g) ANFIS; (h) Proposed

Considering the potential use of walk-cycle images in human action recognition, further analysis has been carried out by varying the thresholds (Figure 5). The Canny detector and proposed detector are the only detectors that respond to all thresholds used. The Sobel, Roberts and Prewitt detectors did not find any edges beyond a threshold of 0.2. Even Canny detector fails to capture internal edges beyond the threshold of 0.2 while the proposed detector captures some of them resulting in more details.

Threshold	Canny	Sobel	Roberts	Prewitt	Rough Sets
0.1					
0.2					
0.4		No edges detected	No edged detected	No edges detected	

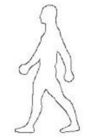
0.6		No edges detected	No edges detected	No edges detected	
0.8		No edges detected	No edges detected	No edges detected	

Figure 5. Comparison of different edge detectors using different thresholds

Table 1 shows the comparison between the existing and proposed detectors in terms of performance ratio (PR). While traditional detectors underperform in terms of lower PR values, the soft computing based detectors (i.e. Fuzzy and ANFIS) and the proposed rough sets based detector yield higher PR values consistently. The PR values of the proposed detector is the highest among all the detectors and in all examples and hence superior. Table 2 shows the comparison of different edge detectors based on entropy (H). Among the traditional edge detectors, Canny detector is considered better and it has a lower entropy as compared to other traditional edge detectors for all images considered. The entropy of Fuzzy detector is found to be slightly lower among the soft computing based detectors. Entropy of the proposed edge detector is found to be much lower than that of the Canny detector for all images, thereby proving its superior performance.

Table 1 Performance Ratio (PR) of different edge detectors

Image	Sobel	Roberts	Prewit	Fuzzy	ANFIS	Rough Sets
Cameraman	87.33	78.62	79.26	159.02	163.76	175.24
Peppers	99.21	98.49	98.32	99.981	102.35	111.21
Walk-cycle	78.09	76.74	77.05	80.54	81.67	94.52

Table 2 Entropy (H) of different edge detectors

Image	Sobel	Canny	Roberts	Prewit	Fuzzy	ANFIS	Rough Sets
Cameraman	0.3938	0.3732	0.3922	0.3951	0.3728	0.3843	0.3249
Peppers	0.4946	0.4505	0.4954	0.4945	0.4342	0.4512	0.3844
Walk-cycle	0.3715	0.3542	0.3695	0.3718	0.3317	0.3914	0.3013

Table 3 shows the Structural Similarity Index (SSIM) of different detectors, computed with Canny detector as ground truth. The proposed detector yields higher values of SSIM for all input images and hence superior to other edge detectors. Table 4 shows the computational time taken by different edge detectors. It may be seen that the Fuzzy and ANFIS detectors take much longer times, which must be due to the time needed for their training. Among the other detectors, Canny and proposed detectors take slightly longer times but produce better results than other detectors.

Table 3 Structural Similarity Index (SSIM) of different edge detectors

Image	Sobel	Robert	Prewit	Fuzzy	ANFIS	Rough Sets
Cameraman	0.8353	0.8314	0.8356	0.8021	0.8042	0.8362
Peppers	0.7518	0.7504	0.7514	0.7275	0.7234	0.7497
Walk-cycle	0.9347	0.9494	0.9437	0.9337	0.9213	0.9501

Table 4 Computational Times (in seconds) of different edge detectors

Image	Sobel	Canny	Roberts	Prewitt	Fuzzy	ANFIS	Rough Sets
Cameraman	1.05	1.31	1.09	1.05	12.71	21.23	1.21
Peppers	1.01	1.84	1.03	1.22	17.03	31.24	1.80
Walk-cycle	0.94	1.06	0.94	0.84	11.09	20.94	1.03

VI. Conclusions

A rough sets based edge detector has been proposed in this paper. It uses a normalized image to form two types of granules, viz. White and Black, and calculates the roughness values based on lower and upper approximations. The pixels in boundary region are then found by comparison with a threshold to mark the distinct edges. Output images of the proposed detector are compared with that of Canny, Sobel, Prewitt, Roberts, Fuzzy and ANFIS edge detectors based on the visual appearance and entropy. It has been found that the proposed edge detector performs better than all these edge detectors based on the above measures. The comparison based on structural similarity index and performance ratio, computed with Canny edge detector as the ground truth, reveals that the proposed edge detector works much better than Sobel, Prewitt, Roberts, Fuzzy and ANFIS edge detectors. In terms of computational time required, it has been found that the proposed detector takes slightly longer than traditional edge detectors, but much lower than soft computing based edge detectors.

As future scope, the proposed edge detector can be enhanced by the addition of adaptive thresholding. It may also be possible to verify its performance based on certain additional measures. Further, its use in applications such as human action recognition system can also be explored.

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