Volume 5, Issue 7, July 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Performance Evaluation of Fuzzy Sift and Canny Feature Extraction

Simranjeet Kaur (Research Scholar)*
CSE&GIMET Amritsar
Punjab, India

Gagandeep Singh Saini
CSE&GIMET Amritsar
Punjab, India

Sandeep Kaur
CSE& BCET Gurdaspur
Punjab, India

Abstract— Feature extraction concerns with finding shapes in computer images. This requires extraction like the eyes, the ears and the nose, which are the most important face features The main goal of feature extraction is to recover and improve the efficiency of analysis and classification. SIFT is an algorithm in Computer visualization to detect and describe local features in images. Matching features across dissimilar images in a familiar problem in computer visualization. This research work has focused on the SIFT & Canny based feature extraction method. The overall objective of this paper is to improve the Fusion based SIFT & Canny using fuzzy logic to enhance the results further. The use of fuzzy membership function has the ability to enhance the results further by using the various fuzzy if then rules. The comparison between traditional SIFT and integrated approach is also drawn among the proposed and the existing technique. The comparison has clearly shown that the proposed technique outperforms over the available techniques.

Keywords— Digital Image Processing, Feature Extraction, Fuzzy Logic, SIFT, Canny Edge detector.

I. INTRODUCTION

Digital image processing is that the use of computer algorithms to perform image processing on digital pictures. As a subcategory or field of digital signal processing, digital image processing has several benefits over analog image processing. It permits a far wider vary of algorithms to be applied to the computer file and may avoid issues like the build-up of noise and signal distortion throughout processing. Digital image processing is enhancing a picture or extracting data or options from a picture Computerized routines for data extraction (example pattern recognition, classification) from remotely supposed pictures to get classes of knowledge regarding specific options.

SIFT (Scale Invariant Feature Transform)

SIFT is an algorithm in Computer visualization to detect and describe local features in images. The algorithm was published by David Lowe in 1999. Matching features across dissimilar images in a familiar problem in computer visualization.

Canny Edge Detector

Canny also produced a computational theory of edge detection illuminating why the technique works. The main purpose of edge detection in common is to significantly decrease the quantity of data in an image, while preserving the structural properties to be used for further image processing. Edges in artificial scenes are often sharper and fewer complex than those in natural scenes, and improves the performance of any edge detector.

Feature Extraction

Feature extraction concerns with finding shapes in computer images. To be able to recognise faces routinely, for example, one approach is to extract the piece features. This requires extraction like the eyes, the ears and the nose, which are the most important face features. To find them, we can use their shape: the white part of the eyes is ellipsoidal; the mouth can appear as two lines, as do the eyebrows.

II. LITERATURE SURVEY

Chen, Yong et al. (2014) [1] proposed a new image mosaic method of combining the improved SIFT algorithm with Canny feature edge detection based on the traditional scale invariant feature transform (SIFT) algorithm. Firstly they extracted feature points of the image with the SIFT algorithm. Then, they constructed an improved 18-dimensional feature descriptor consisting of 12 gradient values in a circular window, three cumulative gray-scale values and three gray-scale differences in a concentric circular window. Second, this method preserved the features in 16-neighborhood of the Canny edge image. Then, the extracted feature points search for the coarse matching points through the BBF, and the coarse matching points are purified with the random consistency algorithm, which calculates the transformational matrix H among the images with these purified feature points. Lu, J. et al. (2009) [2] proposed the novel algorithm detects local extrema in Zoser Pyramid and assigns their orientations. Secondly, it extracts edges by Canny Detector and for each keypoint tests its attributes vectors with 49 dimensions by statistic histograms technique according to comparative distances and orientations between the key point and other neighboring points on edges. Finally, it got related pixels of two images by similar between two Descriptors. SAR images are often blurred and lack of stable details, the algorithm could achieve more reliable detection and process three times faster than SIFT. Dellinger et al. (2015) [3] introduced a SIFT-like algorithm specifically dedicated to SAR imaging, which is named SAR-SIFT. The algorithm includes both the detection of key points and the computation of local descriptors. A new gradient definition, yielding an orientation and a magnitude that are robust to speckle noise, is first introduced. It is then used to adapt several steps of the SIFT algorithm to SAR images. They studied the improvement brought by this new algorithm, as compared with existing approaches. They presented an application of SAR-SIFT to the registration of SAR images in different configurations, particularly with different incidence angles. Sarangi, Sunita, and N. P. Rath (2007) [4] proposed a fuzzy-based approach for edge detection. The fuzzy conclusion rules are defined in such a way that the fuzzy inference system (FIS) output is high only for those pixels belonging to edges in the input image. The strength to compare and illuminate variations were also taken into account while instituting these rules. In this paper, they had proposed an approach that combines the canny method with fuzzy inference system for determining edges of an image. Li, Yang et al. (2012) [5] proposed a fast SIFT algorithm based on Sobel edge detector. Sobel edge detector is useful to produce an edge group scale space and SIFT detector detects the extreme point under the constraint of the edge group scale space. The experimental results show that the proposed algorithm decreased the redundancy of key points and speeds up the implementation while the similar rate between dissimilar images maintains at a high level. As the threshold of Sobel detector increases, numeral of key points decreases and matching speed got higher. Jiang, Qin, and Qiang Wang (2010) [6] discussed to avoid the large-scale damage that caused by fire happening or occurring in huge space building, there are numerous studies about image-processing techniques for automatic real-time flame detection. Adaptive Canny edge algorithm and flame geometric features or attributes are joint to check fired area of video data that is generated by a normal camera monitoring. The proposed selection principle was efficient in improving the performances of established canny operator. Experimental results showed that the proposed approach was stronger to noise, and it helps to divide successive frames fired area. Luke, Robert H et al. (2005) [7] proposed the use of the scale invariant feature transform to match areas between stereo images. The three dimensional position of matched points are then computed. Each matched area is additionally matched to a record of known objects. After projecting the three dimensional locations onto a horizontal plane, the spatial relationship between pairs of objects were then described linguistically using a system of fuzzy rules. Then explored the method to help or facilitate human-like communication with a robot. Wang, Yang Chen et al. (2012) [8] "A fuzzy-based threshold method proposed in image processing of SIFT which was used in visual navigation of small UAVs. By adjusting the thresholds of SIFT online fuzzily, that provided a stable number of features detected from aerial image sequence. The visual navigation estimated the motion of the small UAV by tracking and matching that features extracted from the consecutive image frames. Real experiments verified the stability and advantage of that method in comparison with the fixed and PID-based threshold methods. This proposed method was able to stabilize the number of features regardless of the changes of the aerial images. Mikolajczyk et.al (2003) [9] Described an approach to recognizing poorly textured objects that might contain holes and tubular parts, in cluttered scenes under arbitrary viewing conditions. To this end they developed a number of novel components. First, they introduced a new edge-based local feature detector that was invariant to similarity transformations. The features were localized on edges and a neighborhood is estimated in a scale invariant manner. Second, the neighborhood descriptor computed for foreground features is not affected by background clutter, even if the feature was on an object boundary. Third, the descriptor generalizes Lowe's SIFT method to edges. An object model was learned from a single training image. The object is then recognized in new images in a series of steps which apply progressively tighter geometric restrictions. Sarangi et al. (2007) [10] "Edge detection was an important aspect of image processing. There are different methods for improving edge detection. Paper proposed a fuzzy-based approach for edge detection. The fuzzy inference rules were defined in such a way that the fuzzy inference system (FIS) output was high only for those pixels belonging to edges in the input image. A robustness to contrast and lighting variations were also taken into account while instituting these rules. They had proposed an approach that combines the canny method with fuzzy inference system for determining edges of an image. Sinaie et al. (2009) [11]"A hybrid edge detection method based on fuzzy sets and cellular learning automata is proposed. At first, existing methods of edge detection and their problems were discussed and then a high performance method for edge detection, that could extract edges more precisely by using only fuzzy sets than by other edge detection methods, are suggested. After that the edges improve incredibly by using cellular learning automata. In the end, that compared it with popular edge detection methods such as Sobel and Canny. The proposed method did not need parameter settings as canny edge detector does, and it could detect edges more smoothly in a shorter amount of time while other edge detectors cannot. Caldelli et al. (2012) [12] "One of the simplest and most used methods to alter the content of a digital image is to copy-move a portion of it onto another area with the intent, usually, to hide something awkward. In image forensics scientific community, this kind of modification was generally detected by resorting at techniques based on SIFT features that provide a local description which was robust to global geometric transformations the image may undergo. On such a basis, they investigated the effectiveness of some methodologies which introduced a local warping onto the copy-pasted patches in order to reduced the detection capability of SIFT-based approaches. That analysis was particularly interesting in a real scenario of forensic security. Four diverse local warping techniques had been taken into account and experimental results with respect to final perceptual quality of the forged image were presented. Plascencia, Li Chao et al. (2010) [13] "Edge detection was a core technology in image processing and recognition. Because classical edge detection operators such as Roberts, Sobel and Canny operator were sensitive to noise, and traditional edge detection algorithm based on mathematical morphology was insufficient for complex features. Proposed a multi-structure and multi-scale morphological adaptive algorithm based on image fusion that could reasonably consider noise reduction and preserved the detailed edge information. Finally, the experiment results indicated that the novel algorithm ensured the continuity, integrity, and accurate location of image edge when applied to iris recognition and AGVs vision navigation. Biswas et al. (2012) [14].Canny's edge detection algorithm is a classical and robust method for edge detection in gray-scale images. The two significant features of this method are introduction of Non-Maximum Suppression and double thresholding of the gradient image. Due to poor illumination, the region boundaries in an image may become vague, creating uncertainties in the gradient image. In this paper, an algorithm based on the concept of type-2 fuzzy sets to handle uncertainties that automatically selects the threshold values needed to segment the gradient image using classical Canny's edge detection algorithm has been proposed. The results show that our algorithm works significantly well on different benchmark images as well as medical images.

III. PROPOSED METHODOLOGY

In this methodology following steps has been followed:

Step 1: Initially insert input image.
Step 2: Apply Scale-invariant feature transform (SIFT) to input image.
Step 3: Apply canny Edge detector to input image.
Step 4: Apply Fuzzy membership based fusion to image.
Step 5: Evaluate Parameters of Fusion image.
Step 6: End

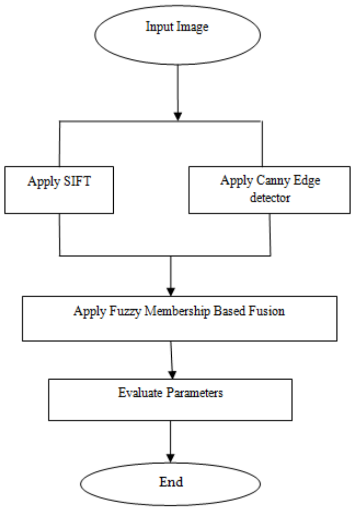

Figure 2: Flowchart for Fuzzy based SIFT and Canny Edge Detector

IV. RESULTS AND DISCUSSIONS

In this section the input image has been taken and different functions have been performed on it like canny edge detector and Image with key points mapped.

Figure 3: Input image

Figure 4: Shows Canny Edge Detector Image

Canny edge detector function has been performed on the input image i.e. in figure 3 and the output is shown in figure 4.

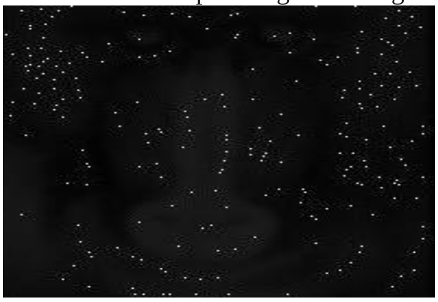

Figure 5: Image with key points mapped

Figure 5 shows the image with key points by taking from figure 3 as input image.
Experiment 1: In first experiment Intensity Increase. When The Image with key points mapped onto it in Figure 5 Then we get image after changing the intensity and Second Image with Key points Mapped onto it.

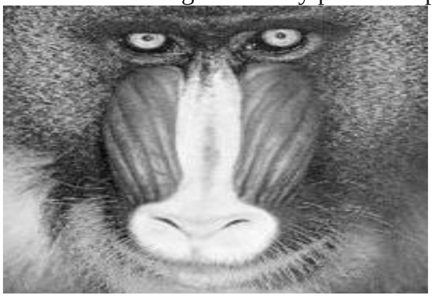

Figure 6: Image after changing the Intensity

Figure 6 shows the Image after changing the Intensity by taking the figure 5 as an input image and second image is also mapped on it that has been shown in figure 7.

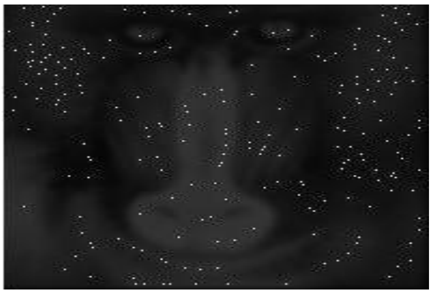

Figure 7: Shows 2nd image Mapped onto it

Experiment 2: In second experiment intensity decrease. When The Image with key points mapped onto it in Fig 5 then we get image after changing the intensity and Second Image with Key points Mapped onto it.

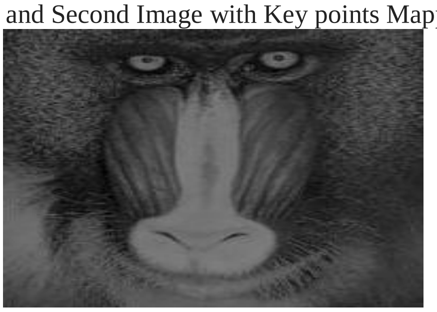

Fig8: Shown the Image after changing the Intensity

Fig 9: shown the 2nd image Mapped onto it

Figure 6 shows the Image after changing the Intensity by taking the figure 5 as an input image and second image is also mapped on it that has been shown in figure 9.

Table 1: Comparison of Existing and Proposed RMSE

Image Name	**Increased Intensity**			**Decreased Intensity**		
	Increased level	**Existing**	**Proposed**	**Decreased Intensity**	**Existing**	**Proposed**
BABOON	1	97.8155	67.7651	0.1	91.8149	66.9318
LENA	1.4	89.7571	13.3485	0.3	84.4414	15.5694
LENA1	1.8	96.6471	18.1668	0.5	92.0189	19.4059
PEPPERS	2	90.1947	22.7158	0.7	91.8259	20.9904
TESTFI	2.3	96.1548	22.0816	0.8	100.0192	21.8770
BABOON	2.6	103.4060	60.8192	0.9	97.3405	60.0541
LENA	3	104.7435	62.0950	1	105.1365	61.3284
PEPPERS	3.7	95.3602	54.8942	1.1	96.4451	56.4399
PEPPER1	4	102.7304	22.2268	1.3	98.9174	60.3612
FLOWER	5	109.2889	39.2992	1.5	99.8071	39.7363

Table 2: Comparison of Existing and Proposed PSNR

Image Name	**Increased Intensity**			**Decreased Intensity**		
	Increased level	**Existing**	**Proposed**	**Decreased Intensity**	**Existing**	**Proposed**
BABOON	1	8.3226	11.5107	0.1	8.8725	11.6181
LENA	1.4	9.0694	25.9422	0.3	9.5997	24.2853
LENA1	1.8	8.4270	22.9452	0.5	8.8533	22.3721
PEPPERS	2	9.0272	21.0042	0.7	8.8715	21.6902
TESTFI	2.3	8.4214	21.2502	0.8	8.1291	21.3311
BABOON	2.6	7.8399	12.4500	0.9	8.3649	12.5599
LENA	3	7.7283	12.2697	1	7.6957	12.3776
PEPPERS	3.7	8.5435	13.3403	1.1	8.4452	13.0991
PEPPER1	4	7.8968	21.1933	1.3	8.2253	12.5156
FLOWER	5	7.3593	16.2431	1.5	8.1476	16.1470

Table 3: Comparison of Existing and Proposed Normalized cross correlation

Image Name	**Increased Intensity**			**Decreased Intensity**		
	Increased level	**Existing**	**Proposed**	**Decreased Intensity**	**Existing**	**Proposed**
BABOON	1	0.0105	0.0218	0.1	0.0119	0.0223
LENA	1.4	0.0124	0.5612	0.3	0.0140	0.4125
LENA1	1.8	0.0107	0.3030	0.5	0.0118	0.2655
PEPPERS	2	0.0123	0.1938	0.7	0.0119	0.2270
TESTFI	2.3	0.0108	0.2051	0.8	0.0100	0.2089
BABOON	2.6	0.0094	0.0270	0.9	0.0106	0.0277
LENA	3	0.0091	0.0259	1	0.0090	0.0266
PEPPERS	3.7	0.0110	0.0332	1.1	0.0108	0.0314
PEPPER1	4	0.0095	0.2024	1.3	0.0102	0.0274
FLOWER	5	0.0084	0.0647	1.5	0.0100	0.0633

Table 4: Comparison of Existing and Proposed Average Difference

Image Name	**Increased Intensity**			**Decreased Intensity**		
	Increased level	**Existing**	**Proposed**	**Decreased Intensity**	**Existing**	**Proposed**
BABOON	1	47.8394	22.9606	0.1	42.1499	22.3993
LENA	1.4	40.2817	0.8909	0.3	35.6517	1.2120
LENA1	1.8	46.7033	1.6502	0.5	42.3374	1.8829
PEPPERS	2	40.6754	2.5800	0.7	42.1600	2.2030
TESTFI	2.3	46.2287	2.4380	0.8	50.0192	2.3930
BABOON	2.6	53.4640	18.4949	0.9	47.378	18.0325
LENA	3	54.8560	19.2789	1	55.2685	18.8058
PEPPERS	3.7	45.4678	15.0669	1.1	46.5083	15.9273
PEPPER1	4	52.7677	2.4702	1.3	48.9233	18.2174
FLOWER	5	59.7203	7.7221	1.5	49.8073	7.8949

Table 5: Comparison of Existing and Proposed MSE

Image Name	**Increased Intensity**			**Decreased Intensity**		
	Increased level	**Existing**	**Proposed**	**Decreased Intensity**	**Existing**	**Proposed**
BABOON	1	9567.8760	4592.1141	0.1	8429.9775	4479.8696
LENA	1.4	8056.3417	178.1823	0.3	7130.3490	242.4077
LENA1	1.8	9340.6669	330.0323	0.5	8467.4997	376.5884
PEPPERS	2	8135.0846	516.0086	0.7	8432.0012	440.5986
TESTFI	2.3	9245.7435	487.5988	0.8	10003.8497	478.6012
BABOON	2.6	10692.7915	3648.9724	0.9	9475.16500	3606.4967
LENA	3	10971.1969	3855.7856	1	11053.6904	3761.1671
PEPPERS	3.7	9093.5682	3013.3772	1.1	9301.6552	3185.4620
PEPPER1	4	1055.5405	494.0313	1.3	9784.6567	3643.4789
FLOWER	5	11944.0658	1544.4268	1.5	9961.4555	1578.9768

GRAPHS

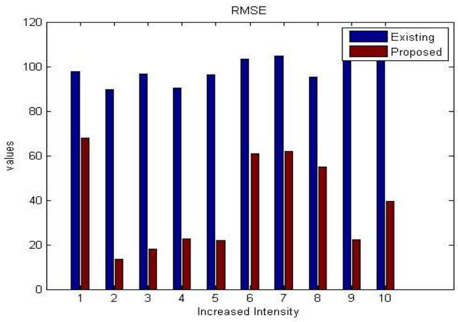

Figure 13: Shows the Comparison of RMSE

Figure 13 shows the comparison of proposed and existing RMSE by taking the values from table 1.

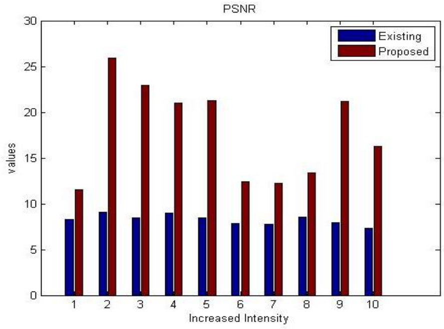

Figure 14: Shows the Comparison of PSNR

Figure 14 shows the comparison of proposed and existing PSNR by taking the values from table 2.

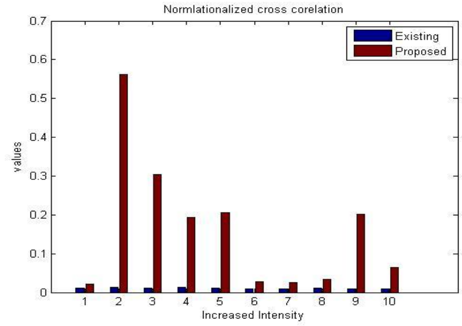

Figure 15: Comparison of normalized cross correlation

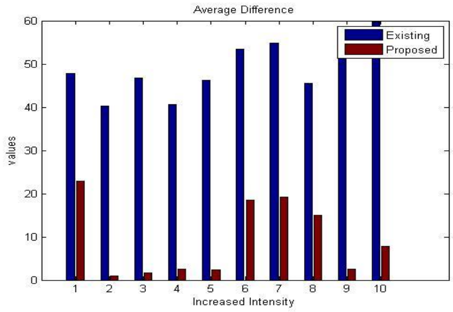

Figure 16: Shows the Comparison of Average Difference

Figure 16 shows the Comparison of proposed and existing Average Difference by taking the values from table 3.

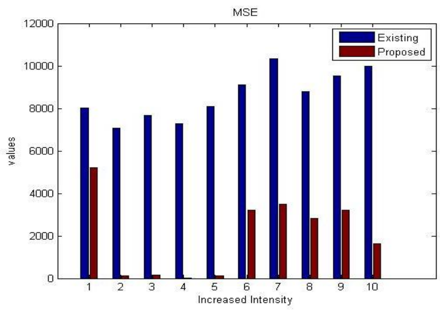

Figure 17: Shows the Comparison of MSE

Figure 17 shows the Comparison of proposed and existing Average Difference by taking the values from table 4.

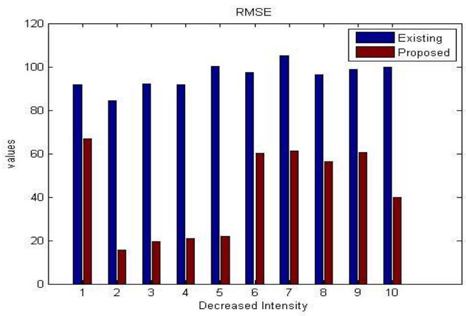

Figure 18: Shows the Comparison of RMSE

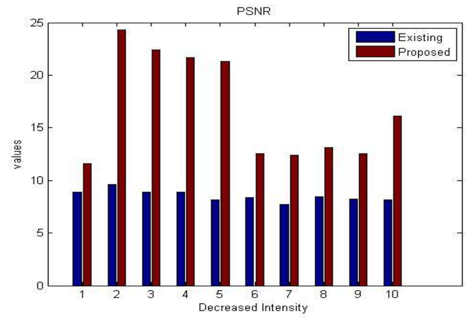

Figure 19: Shows the Comparison of PSNR

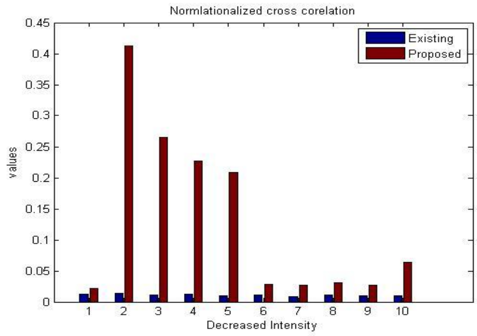

Figure20.comparison of normalized cross corelation

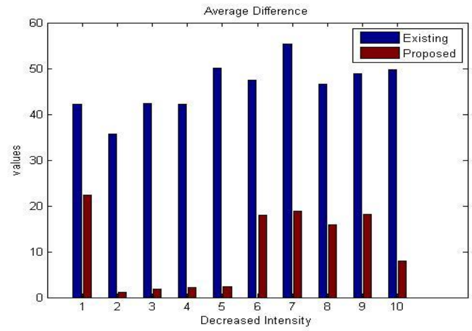

Figure21: Shows the Comparison of PSNR

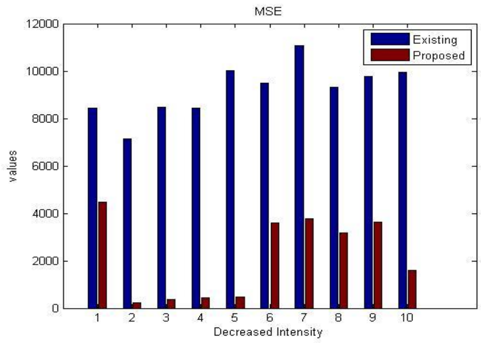

Figure22: Shows the Comparison of PSNR

V. CONCLUSIONS AND FUTURE WORK

Digital image processing is enhancing a picture or extracting data or options from a picture Computerized routines for data extraction from remotely supposed pictures to get classes of knowledge regarding specific options. In this paper work has focused on the SIFT & Canny based feature extraction method. The use of fuzzy membership function has the ability to enhance the results further by using the various fuzzy if then rules. The Fuzzy base proposed technique is designed and implements mosaic feature extraction approach in MATLAB tool with the help of image processing toolbox.

This work has not considered the use of any evolutionary approach to detect the features in more promising manner. Therefore in near future we will modify SIFT based feature extraction approach using evolutionary optimization based algorithms. Also this work has considered limited attack on images, therefore in near future some more attacks will also be considered.

REFERENCES

[1] Chen, Yong, Min Xu, Huan-lin Liu, Wei-na Huang, and Jiang Xing.(2014) "*An improved image mosaic based on Canny edge and an 18-dimensional descriptor*." Optik-International Journal for Light and Electron Optics 125, no. 17: 4745-4750.

[2] Lu, J., B. Wang, H. M. Gao, and Z. Q. Zhou.(2009) "SAR images matching based on local shape descriptors." In *Radar Conference, 2009 IET International*, pp. 1-4. IET.

[3] Dellinger, Flora, Julie Delon, Yann Gousseau, Julien Michel, and Florence Tupin (2015) *"SAR- SIFT: A SIFT-Like Algorithm for SAR Images."* 1-14.

[4] Sarangi, Sunita, and N. P. Rath. (2007) *"Performance analysis of fuzzy-based canny edge detector.*" In *Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on*, vol. 3, pp. 272-276. IEEE.

[5] Li, Yang, Lingshan Liu, Lianghao Wang, Dongxiao Li, and Ming Zhang.(2012)*"Fast SIFT algorithm based on Sobel edge detector."* In *Consumer Electronics, Communications and Networks, 2012 2nd International Conference on*, pp. 1820-1823. IEEE.

[6] Jiang, Qin, and Qiang Wang**.**(2010) *"Large space fire image processing of improving canny edge detector based on adaptive smoothing."* In Innovative Computing & Communication, 2010 Intl Conf on and Information Technology & Ocean Engineering, 2010 Asia-Pacific Conf on (CICC-ITOE), pp. 264-267. IEEE.

[7] Luke, Robert H., N. Blisard, James M. Keller, and Marjorie Skubic. (2005)*"Linguistic Spatial relations of three dimensional scenes using SIFT key points."* In *Robot and Human Interactive Communication, 2005. ROMAN 2005. IEEE International Workshop on*, pp. 704-709. IEEE.

[8] Wang, Chaolei, Tianmiao Wang, Jianhong Liang, Yang Chen, and Cong Wang (2012). "A fuzzy-based threshold method applied in SIFT for visual navigation of small UAVs." In *Industrial Electronics and Applications (ICIEA), 2012 7th IEEE Conference on*, pp. 807-812. IEEE.

[9] Mikolajczyk, Krystian, Andrew Zisserman, and Cordelia Schmid.(2003) "Shape recognition with edge-based features." In *British Machine Vision Conference (BMVC'03)*, vol. 2, pp. 779-788. The British Machine Vision Association.

[10] Sarangi, Sunita, and N. P. Rath (2007). "Performance analysis of fuzzy-based canny edge detector." In *Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on*, vol. 3, pp. 272-276. IEEE.

[11] Sinaie, Saman, et. al .(2009). "A Hybrid Edge Detection Method Based on Fuzzy Set Theory and Cellular Learning Automata." In *Computational Science and Its Applications, 2009. ICCSA'09. International Conference on*, pp. 208-214. IEEE.

[12] Caldelli, R., I. Amerini, L. Ballan, G. Serra, et.al (2012). "On the effectiveness of local warping against SIFT-based copy-move detection." In *Communications Control and Signal Processing (ISCCSP), 2012 5th International Symposium on*, pp. 1-5. IEEE, 2012.

[13] Li, Chao, Lindu Zhao, and Shengnan Sun (2010). "An adaptive morphological edge detection algorithm based on image fusion." In *Image and Signal Processing (CISP), 2010 3rd International Congress on*, vol. 3, pp. 1072-1076. IEEE.

[14] Biswas, Ranita, and Jaya Sil (2012). "An improved canny edge detection algorithm based on type-2 fuzzy sets." *Procedia Technology* 4, pp 820-824.

