Fuzzy Logic Applied to Improvement of Image Resolution using Gaussian Membership Functions

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Abstract. The resolution in images is a perceptible detail measure. If the resolution increases, perception of fine details, edges, clearness of the objects and image quality increases too. Video surveillance cameras usually have a standard resolution for video surveillance applications, commonly in VGA resolution (640 x 480 pixels). This video image in most of the cases does not provide enough information to identify a person or an object, the cameras with low resolution deliver poor data information and poor information in detailed images to maximize its size. If an area needs more resolution, it is necessary an algorithm that achieve this without the loss of inherent characteristics. We selected the fuzzy logic theory to solve these problems. This technique is used to improve image resolution. It helps in processes where ambiguity and vagueness in the data interpolation are present, this is due to the non-linearity of image information (edges, fine details, textures, etc.). The proposed Gaussian membership functions have non-linear characteristics, so they obtain good results in interpolation process.

Keywords: Super resolution, Gaussian functions, color images, fuzzy interpolation

1 Introduction

Video surveillance is one of the most important applications in the security systems, it helps to detect intruders, identify and prevent crimes, it is useful to deliver evidence of crimes. This technique is known as “Super resolution”. It is also used in:

– Traffic Monitoring.
– Land traffic characteristics such as speed, and acceleration.
– Industrial processes improving.
– Business management.
– Medical activities.

The super resolution is needed in applications like recognition, image analysis, medical imaging for a better diagnosis, and applications where a zoom is required, this for a specific area of interest and it is where the super resolution becomes essential, for example, video surveillance, satellite imagery and more [1-6].

However, the high resolution images are not always available, this is because it is often costly to obtain a high resolution image and sometimes may not be feasible due to the limitations of the sensor, among others. These drawbacks can be solved using mathematical image processing algorithms, which are relatively inexpensive, leading to the concept of super-resolution. This gives us an advantage because it can cost less and systems of existing low-resolution images are still used [7].

Agree to the surveillance monitoring respect to a large open area using a camera, means losing important details to enable the people feature analysis or identification. The images are important in the analysis of crime as well as evidence of abuse. A possible solution to these problems is to enhance low resolution video surveillance systems with advanced algorithms that realize complex activities, such as increasing resolution in the images.

Phenomena found every day are imprecise, i.e., have the ambiguity and vagueness implied in the scene captured. This imprecision can be associated in its shape, position, time, color, texture, or even semantic in the scene. This is the behavior of the images [8].

Fuzzy logic is conceptualized as a generalization of classical logic. It is a branch of artificial intelligence that allows specification vagueness to handle information. The first logic of vagueness was developed in 1920 by the philosopher Jan Lukasiewicz, visualized with possible joint membership degree values of 0 and 1, then the un-extended to an infinite number of values between 0 and 1 [9].

In 1960, Lofti Zadeh creates a powerful tool, known as fuzzy logic to model imprecise data in which the inference rules are formulated in a very general way making use of fuzzy categories, Lukasiewicz combines the concepts of logic and sets defining by membership degrees.

2 Method

The edge-based line average (ELA) algorithm is a well-known interpolation method in the spatial domain. Linear interpolation is the most commonly used method for de-interlacing. The edge-based line average (ELA) algorithm uses directional correlation among pixels to perform linear interpolation. There are three detection directions as shown in Fig.1, which are vertical, and diagonal. In each direction, the difference is calculated [10].

ELA looks for the possible edge direction and then applies the line average along the selected direction. This algorithm works well when the edge directions are estimated correctly but, otherwise, it introduces errors and degrades the image quality. In this paper is presented a new membership function is presented which improves the robustness of the original ELA algorithm, see Fig 4 Gaussian membership functions.

The inputs of the algorithms are computed as the absolute difference values of the luminance differences in the three directions (a, b, c) shown in Fig. 1.

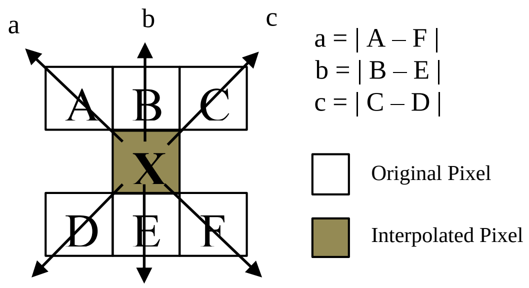


Fig. 1. Pixels involved in ELA 3+3 algorithm.

The fuzzy rules to connect the fuzzy values are found in Table 1.

Table 1. Fuzzy Rule for ELA 3 + 3 [5]

IF	ANTECEDENTS	THEN	CONSEQUENT
1 ____	**a** is *medium*, **b** is *big* and **c** is *big*		(A + F) / 2
2 ____	**a** is *big*, **b** is *big* and **c** is *medium*		(C + D) / 2
3 ____	**a** is *small* and **b** is *big* and **c** is *small*		(A + C + D + F) / 4
4 ____	otherwise		(B + E) / 2

The fuzzy rules 1 and 2, delivers values near to 1 (≈ 1) when the correlation is big in one direction while deliver small values (≈ 0) in the opposite directions. In both cases, the result is obtained by interpolating the average value of the luminance (A+F)/2 or (C+D)/2.

The fuzzy rule 3, estimates the fuzzy value of an edge because of the correlation, in this case, if big (≈ 1) for both directions illustrated in Fig. 1. In this case, we get a result interpolating the four pixels (A+C+D+F)/4. Finally, in the fuzzy rule 4, the otherwise antecedent parameter is obtained interpolating in vertical direction agree to (B+E)/2.

This method works using an amplification factor equal to 2 as shown in Fig. 2.

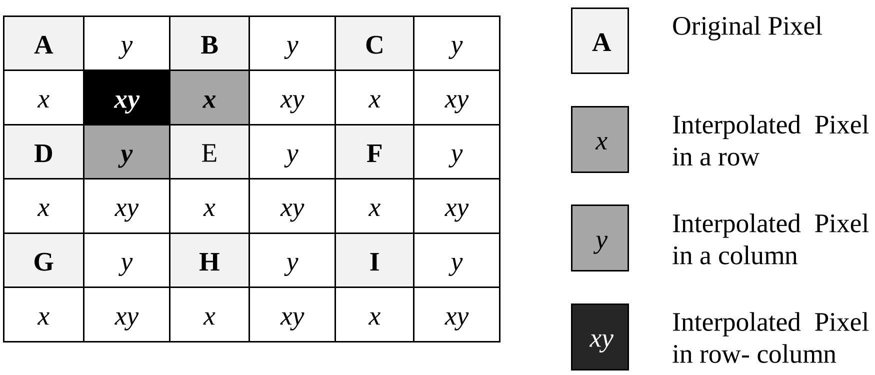


Fig. 2. Pixels involved to resolution increase with an amplification factor of two.

According to Fig. 2 are used eight pixels from the original image, these pixels are labeled as: **A, B, C, D, E, F, G, H, F**; first is interpolate the **pixel “*x*”** in the row, this is achieved using **A, B, C, D, E and F** pixels, second interpolate the **pixel “*y*”** in the column **A, B, D, E, G and H**, and finally interpolate the **pixel “*xy*”** row-column using the eight pixels that are located around the pixel “xy”. Four of the pixels are from the original image and the other ones were previously interpolated.

The ELA module increases the processing window up to 5+5 pixels. The **ELA 5 + 5** algorithm consider the closest pixels to the external ends **(A’, C’, D’, F’)** as shown in Fig. 3 which includes two new directions (**a'** and **c')**.

Consequently, the fuzzy inference system has six fuzzy rules instead of 4 as in the ELA 3 + 3 algorithm, these fuzzy rules are shown in the Table 2 [11].

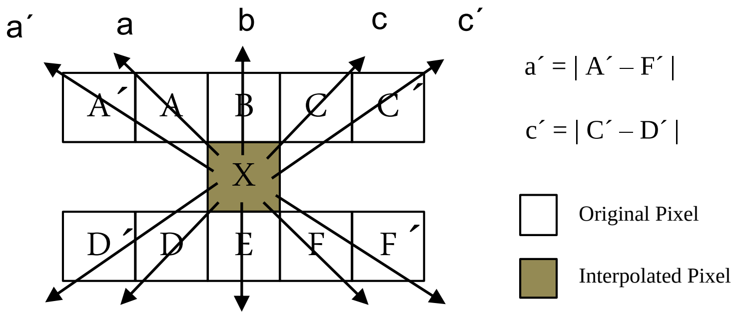


Fig. 3. Pixels used in the ELA 5+5 algorithm.

Table 2. Fuzzy Rule for ELA 5 + 5

IF	ANTECEDENT	THEN	CONSEQUENT
1)	**a´** is *medium* and **a** is *big* and **b** is *big* and **c** is *big* and **c´** is *big*		(A´ + F´) / 2
2)	**a´** is *big* and **a** is *big* and **b** is *big* and **c** is *big* and **c´** is *medium*		(C´ + D´) / 2
3)	**a´** is *medium* and **a** is *medium* and **b** is *big* and **c** is *big* and **c´** is *big*		(A + F) / 2
4)	**a´** is *big* and **a** is *big* and **b** is *big* and **c** is *medium* and **c´** is *big*		(C + D) / 2
5)	**a** is *small* y b is *big* y c is *small*		(A + C + D + F) / 4
6)	otherwise		(B + E) / 2

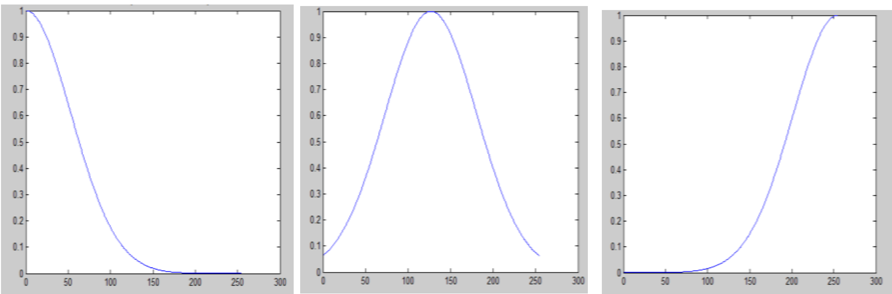
Because of the images do not have linear behavior, it is proposed nonlinear membership functions, so Gaussian membership functions solve this problem (Eq. 1), to take into account the mean and the variance values of the sample processed in the image. This allows adaptability of the algorithm to texture changes, and produce good interpolation results.

$$f(x) = ae^{-\frac{(x-b)^2}{2c^2}}, \tag{1}$$

where

$$a = \frac{1}{c\sqrt{2\pi}} \qquad b = \mu \qquad c = \sigma.$$

The Fig. 4 shows the three groups were formed (small, medium and large) where the ***x-axis*** represents the luminance and the ***y-axis*** represents the fuzzy value.



(a) (b) (c)

Fig. 4 Membership Functions (a) small, (b) medium, (c) big

The equations (2) and (3) show us how we can find the weight of ELA 3+3 and ELA 5+5 algorithms. For ELA 3+3 algorithm [5]:

$$\begin{aligned} &\propto_1 = min[\mu medium_a(h), \mu big_b(h), \mu big_c(h)],\\ &\propto_2 = min[\mu big_a(h), \mu big_b(h), \mu medium_c(h)],\\ &\propto_3 = min[\mu small_a(h), \mu big_b(h), \mu small_c(h)],\\ &\propto_4 = 1 - \propto_1 - \propto_2 - \propto_3, \end{aligned} \tag{2}$$

where for ELA 5+5 algorithm [5],

$$\begin{aligned} &\propto_1 = prod[\mu medium_{a\prime}(h), \mu big_a(h), \mu big_b(h), \mu big_c(h), \mu big_{c\prime}(h)],\\ &\propto_2 = prod[\mu big_{a\prime}(h), \mu big_a(h), \mu big_b(h), \mu big_c(h), \mu medium_{c\prime}(h)],\\ &\propto_3 = prod[\mu big_{a\prime}(h), \mu medium_a(h), \mu big_b(h), \mu big_c(h), \mu big_{c\prime}(h)],\\ &\propto_4 = prod[\mu big_{a\prime}(h), \mu big_a(h), \mu big_b(h), \mu medium_c(h), \mu big_{c\prime}(h)],\\ &\propto_5 = min[\mu small_a(h), \mu big_b(h), \mu small_c(h)],\\ &\propto_6 = 1 - \propto_1 - \propto_2 - \propto_3 - \propto_4 - \propto_5. \end{aligned} \tag{3}$$

The defuzzification processes of algorithms ELA 3+3 and ELA 5+5 are illustrated in equations (4) and (5):

$$X = \propto_1 \left(\frac{A+F}{2}\right) + \propto_2 \left(\frac{C+D}{2}\right) \propto_3 \left(\frac{A+F+C+D}{4}\right) + \propto_4 \left(\frac{B+E}{2}\right), \tag{4}$$

$$X = \propto_1 \left(\frac{A\prime+F\prime}{2}\right) + \propto_2 \left(\frac{C\prime+D\prime}{2}\right) + \propto_3 \left(\frac{A+F}{2}\right) + \propto_4 \left(\frac{C\prime+D\prime}{2}\right) \propto_5 \left(\frac{A+F+C+D}{4}\right) + \propto_6 \left(\frac{B+E}{2}\right). \tag{5}$$

3 Evaluation of Results

3.1 Pick Signal to Noise Ratio (PSNR)

The PSNR criterion used to compare the performance of different algorithms Eq. 6:

$$PSNR = 10 * log\left[\frac{(255)^2}{MSE}\right]. \quad \textbf{(6)}$$

3.2 Mean Absolute Error (MAE)

The MAE is the criterion for assessing the preservation of contours and fine details because of this was suggested for the correlation with the human visual system; Eq. 7 computes the MAE:

$$\text{MAE} = \frac{\sum_{i,j}(|Iin(i,j) - Iorg(i,j)|)}{M\ x\ N}, \quad \textbf{(7)}$$

where *Iin(i, j)* represents the values of the original image, and *Iorg(i, j)* represents the values of the restored Image.

3.3 Mean Square Error (MSE)

The MSE is the approach that presents an objective measure of the average square deviation to find the estimate of the true value and it's calculated by the equation (8) (it is the most common objective measure to compare the quality of the filter between the original image and the filtered one).

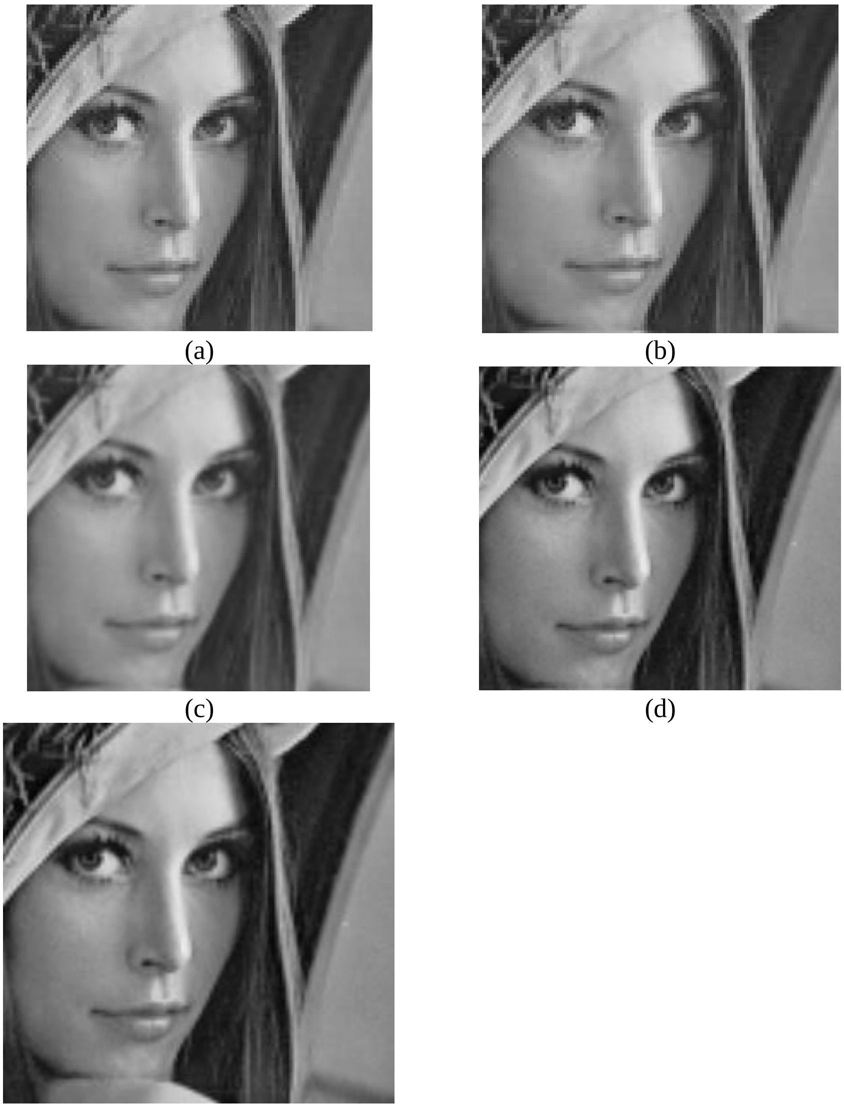
$$\text{MSE} = \frac{\sum_{i,j}\left(Iin(i,j) - Iorg(i,j)\right)^2}{M\ x\ N}, \quad \textbf{(8)}$$

where *Iin(i, j)* represent the values of the original image planes, and *Iorg(i, j)* represent the values of the pixels for the restored image [12].

Criteria evaluation results are achieved using original image dimensions the same as the interpolated one, that mean that we must have original non interpolated image and the same original non interpolated image but with the double in its size to compare pixel by pixel with the interpolated image.

4 Results

The algorithms described before (ELA 3 + 3 and ELA 5 + 5) were applied to well-known images as "Lena", "Peppers" and "Baboon" see Fig. 5, 6, and 7, because they emulate different environments like colors changes, textures etc.



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

Fig. 5. Lena (a) Original image 256x256, (b) KNN 512x512 interpolated image, (c) Bilinear 512x512 interpolated image, (d) ELA 3 + 3 Interpolated Image. (e) ELA 5 + 5 Interpolated Image.

The Lena, Baboon and Peppers images had a good preservation in details and edges. The images show a significant improvement results in a qualitative and quantitative way, due to the algorithm ELA. It delivers better results compared with other methods because of nonlinear membership functions applied to identify edges and details in interpolation algorithm to preserve them.

In Table 3 we can see the quantitative results of the suggested interpolations, the image “Peppers” delivers the highest peak signal to noise ratio because the image contains large homogeneous areas, Baboon image deliver the highest mean absolute error due to the color changes in a sharply way.

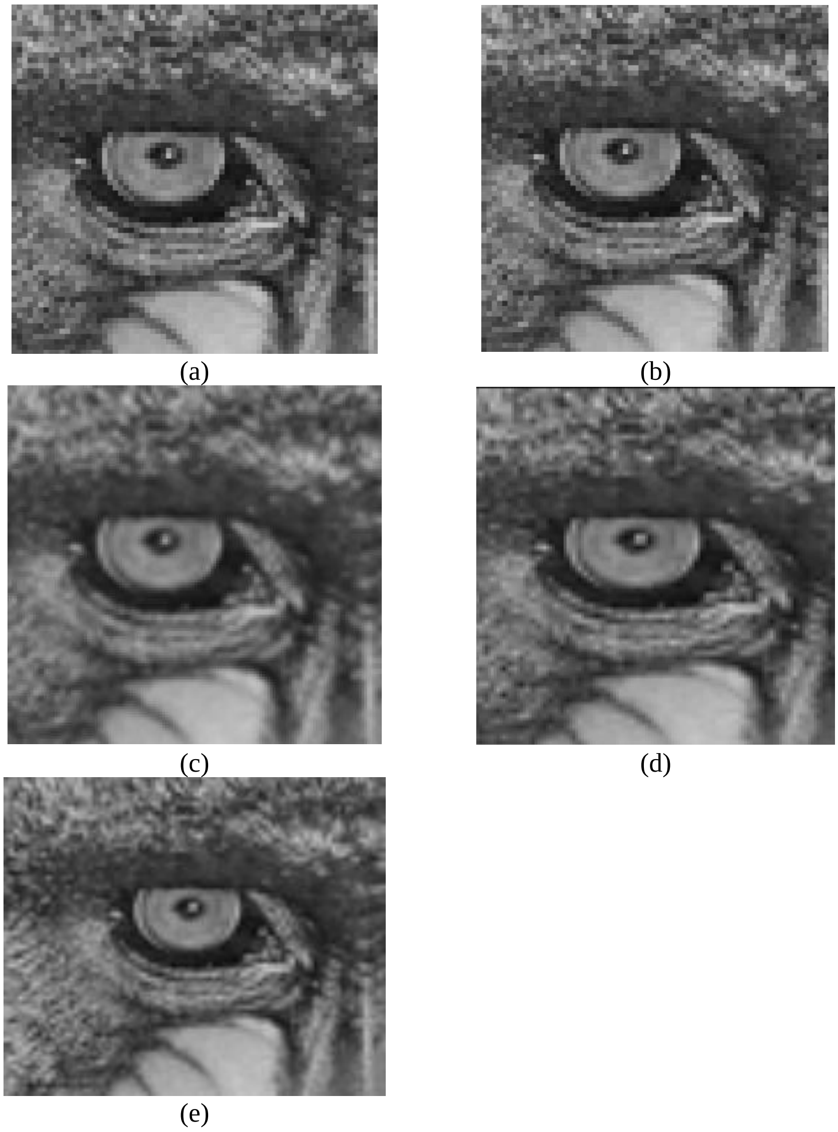


Fig. 6. Baboon (a) Original image 256x256, (b) KNN 512x512 interpolated image, (c) Bilinear 512x512 interpolated image, (d) ELA 3 + 3 Interpolated Image, (e) ELA 5 + 5 Interpolated Image.

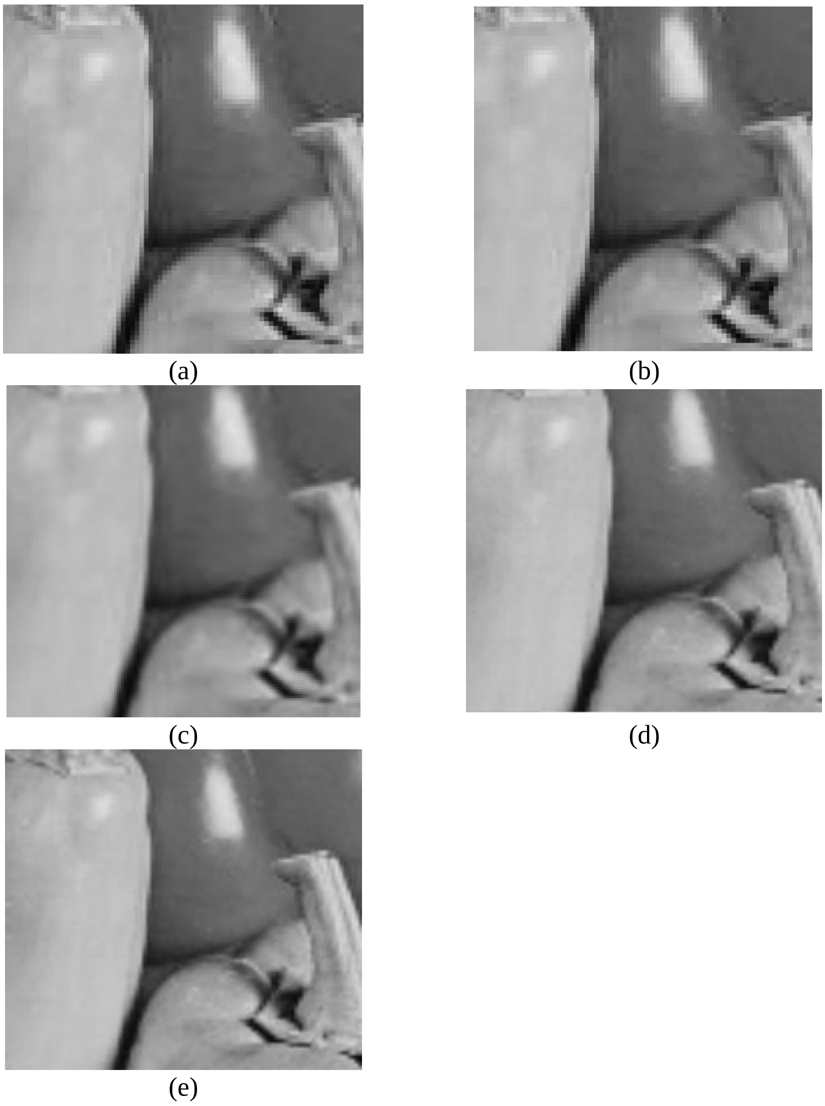


Fig. 7. Peppers (a) Original image 256x256, (b) KNN 512x512 interpolated image, (c) Bilinear 512x512 interpolated image, (d) ELA 3 + 3 Interpolated Image, (e) ELA 5 + 5 Interpolated Image.

The Figures 8 and 9 show an application of the algorithms ELA 3 + 3 and ELA 5 + 5 in video surveillance images, where the image resolution increases in the way that the fine details do not lose as well as the preservation of edges and details.

Table 3. Criteria results for Lenna, Baboon and Peppers.

KNN Interpolation				Bilinear Interpolation		
Judgments	Lena	Baboon	Peppers	Lena	Baboon	Peppers
MAE	3.73	4.74	2.55	3.39	4.60	2.45
MSE	98.49	143.96	68.28	72.86	129.45	48.96
PSNR (db)	28.20	26.55	29.79	29.51	27.00	31.57
ELA 3+3 Interpolation				**ELA 5+5 Interpolation**		
Judgments	Lena	Baboon	Peppers	Lena	Baboon	Peppers
MAE	2.85	4.03	2.16	2.84	4.04	2.14
MSE	44.75	117.43	32.25	44.70	158.09	30.25
PSNR (db)	31.62	27.16	33.04	31.63	26.15	33.24

(a)

(b)

(c)

Fig. 8. Image Video surveillance, (a) Original Image, (b) Interpolated Image by ELA 3+3, (b) Interpolated Image by ELA 5+5.

Performing zoom of the face of the robber we can identify the details and edges preserved agree to the interpolated techniques used.

5 Conclusions

Different interpolation Methods were analyzed, where the method of nearest neighbor interpolation is a basic method that require a low time processing compared to the other methods used because only is considered one a pixel, which is the closest to the interpolated point. Disadvantage with this method, is the loss of the image details such as preserving edges.

(a) (b) (c)

Fig. 9. Image Video surveillance (a) Original Image zoom 400%, (b) Interpolated Image by ELA 3+3 zoom 400%, (c) Interpolated Image by ELA 5+5 zoom 400%.

Contrary to this, the bilinear algorithm takes into account the pixel values surrounding the pixel to be interpolated, a window of 2x2 pixels is used, the result is an image with soft edges, but it requires more processing time compared to the nearest neighbor interpolation.

Algorithms that use fuzzy logic techniques (ELA 3 + 3 and ELA5 + 5) waste more processing time, due to the steps that must be performed to fuzzify and defuzzify the values to interpolate pixels, the main advantage presented is to have an image with more edges delineated and defined.

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References

1. H. Demirel, G. Anbarjafari, S. Izadpanahi: Improved motion-based localized super resolution technique using discrete wavelet transform for low resolution video enhancement. In: Proc. 17th EUSIPCO, Edinburgh, U.K., pp. 1097–1101 (Aug. 2009)
2. T. Celik, C. Direkoglu, H. Ozkaramanli, H. Demirel, M. Uyguroglu: Region-based super-resolution aided facial feature extraction from low-resolution video sequences. In: Proc. IEEE ICASSP, Philadelphia, PA, vol. II, pp. 789–792 (Mar. 2005)
3. H. Demirel, G. Anbarjafari: Satellite image resolution enhancement using complex wavelet transform. IEEE Geosci. Remote Sens. Lett., 7(1), 123–126 (Jan. 2010)
4. L. Yi-bo, X. Hong, Z. Sen-yue: The wrinkle generation method for facial reconstruction based on extraction of partition wrinkle line features and fractal interpolation. In: Proc. 4th ICIG, Aug. 22–24, pp. 933–937 (2007)
5. Y. Rener, J. Wei, C. Ken: Downsample-based multiple description coding and post-processing of decoding. In Proc. 27th CCC, Jul. 16–18, pp. 253–256 (2008)
6. C. B. Atkins, C. A. Bouman, J. P. Allebach: Optimal image scaling using pixel classification. In: Proc. ICIP, Oct. 7–10, vol. 3, pp. 864–867 (2001)

7. Nancy G. La Vigne, Samantha S. Lowry: Evaluating the uses of public surveillance camerasfor crime control and prevention. Urban Institute (September 2011)
8. E.E. Kerre, M Nachtegael: Fuzzy Techniques in Image Processing. 3 ed, Editorial Alfaomega Ra-Ma, Mexico (June 2011)
9. Transactions D: Computer Science & Engineering and Electrical Engineering, Scientia Iranica, International Journal of Science and Technology (February 2011)
10. H. H. Hsiao, J. H. Jeng: Modified De-interlacing method based on edge Direction. (2006)
11. P. Brox: Progressive scan conversion based on edge-dependent interpolation using fuzzy logic. (2007)
12. A. Rosales, F. Gallegos: Procesamiento de Imágenes y Video Multiespectrales y Multicanales. (2011)