A Fuzzy Regression Analysis Based No Reference Image Quality Metric

Indrajit De and Jaya Sil

Abstract. In the paper quality metric of a test image is designed using fuzzy regression analysis by modeling membership functions of interval type 2 fuzzy set representing quality class labels of the image. The output of fuzzy regression equation is fuzzy number from which crisp outputs are obtained using residual error defined as the difference between observed and estimated output of the image. In order to remove human bias in assigning quality class labels to the training images, crisp outputs of fuzzy numbers are combined using weighted average method. Weights are obtained by exploring the nonlinear relationship between the mean opinion score (MOS) of the image and defuzzified output. The resultant metric has been compared with the existing quality metrics producing satisfactory result.

1 Introduction

Correlation describes the strength of association between two random variables. Whether the variables are positively or negatively correlated is determined by the slope of the line, representing relation between the variables. Regression goes beyond correlation by adding prediction capabilities. Classical regression analysis is used to predict dependent variable when the independent variables are directly measured or observed. However, there are many situations where observations cannot be described accurately and so an approximate description is used to represent the relationship. Moreover, the classical regression analysis deals with precise data while the real world data is often imprecise. In classical regression model, the

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difference between the measured and expected values of the dependent variable is considered as random error, which can be minimized using different statistical methods. However, the random error may occur due to imprecise observations and in such a situation the uncertainty is due to vagueness, not randomness [1] and so statistical methods fail to provide accurate results.

Uncertainty in image data has been modeled in this paper using fuzzy regression technique where quality of the test image is evaluated as fuzzy number. To quantify the subjective quality class labels of the test image represented by interval type 2 fuzzy sets, corresponding membership functions are modeled by best fitted polynomial equations. The random error is mapped as *residual error*, defined as the difference between observed and estimated output. The residual error is used to calculate spreads of the fuzzy number that defuzzifies the outputs. The crisp outputs are fused by weighted average method to reduce human biasness in assigning quality class labels to the training images. The resultant quality metric has been compared with the existing quality metrics producing satisfactory result.

2 Modeling Image Quality Classes by Fuzzy Regression

Fuzzy regression analysis involves fuzzy numbers and the general form is described by equation (1) [4].

$$\check{Y} = \widetilde{A_0} + \widetilde{A_1}x_1 + \cdots \widetilde{A_n}x_n \tag{1}$$

Where $\check{Y}$ is the fuzzy output, $\widetilde{A_i}$, i = 1,2,….n are fuzzy coefficients and X = (x_1,…., x_n) is non fuzzy input vector. The fuzzy coefficients are assumed triangular fuzzy numbers (TFN) and characterized by membership function $\mu_{A_i}(x_i)$ as defined in figure 1.

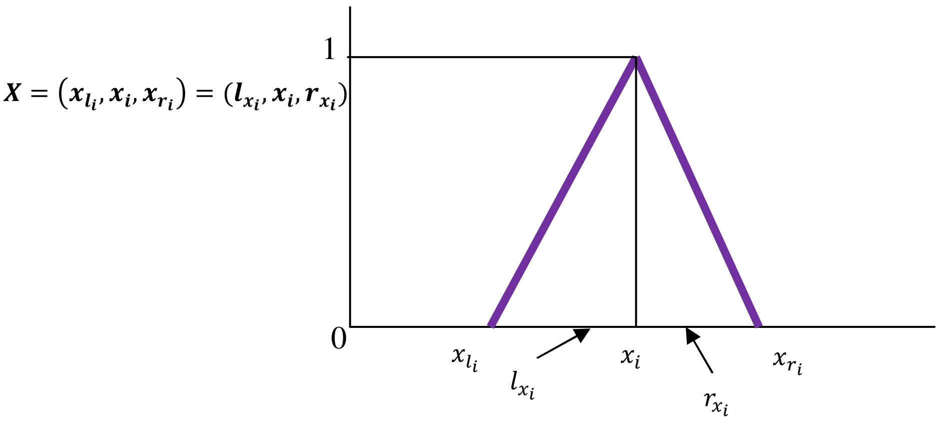


Fig. 1 Membership function Illustrating Triangular Fuzzy Number

When the left spread l_{x_i} and right spread r_{x_i} are equal then the TFN reduces to symmetrical triangular fuzzy number (STFN).

No reference image quality metric designed using fuzzy regression analysis (FRANRIQA) has been described in figure 2.

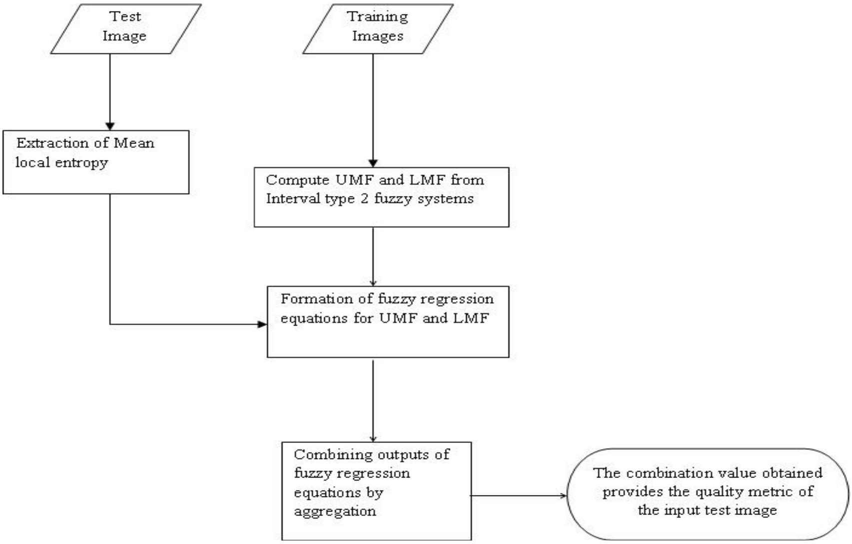


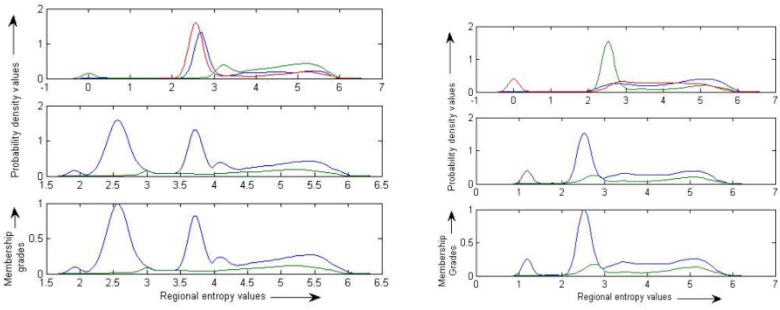
Fig. 2 Flow diagram of Fuzzy Regression Analysis based image quality metric computation

To design the proposed metric for assessing image quality, different training images of BIOIDENTIFICATION Image Database [5] are considered. Upper and lower membership functions (UMF and LMF) of interval type 2 fuzzy sets representing quality classes (*good* and *bad*) of the images (see, figure 3) are obtained using entropy of visually salient regions [10] and kernel density function [11], as shown in figure 4.

(a) *good* quality

(b) *bad* quality

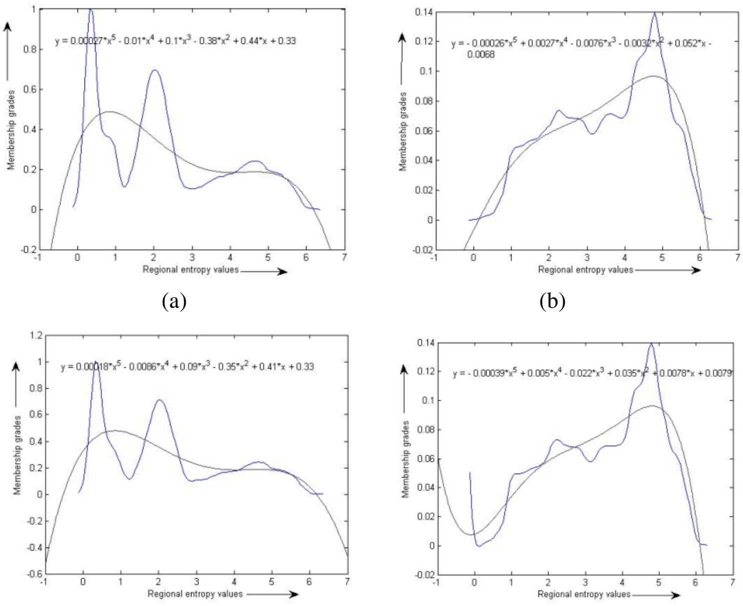
Fig. 3 Sample training images taken from BIOIDENTIFICATION database



(a) (b)

Fig. 4 (a) UMF and LMF for (a) *good* quality class and (b) *bad* quality class

The membership functions of quality classes are modeled to fifth degree polynomial equations (illustrated in figure 5) and used as fuzzy regression equations.



(c) (d)

Fig. 5 Fuzzy Regression Equations Modeled (a) UMF and (b) LMF for *good* quality Images; (c) UMF and (d) LMF for *bad* quality Images

3 Fuzzy Regression Analysis Based Image Quality Metric

Fuzzy regression technique has been applied to quantify the quality metric of an image from the quality class label evaluated by interval type 2 fuzzy based no reference image quality assessment method. Average entropy of visually salient regions [6] of the test image is computed, denoted as *Mean_local_ entropy* of the test image. The symmetrical triangular fuzzy number (STFN) is represented by the triangle in figure 6. The value of UMF and LMF corresponding to *Mean_local_ entropy* of the test image is evaluated as illustrated in figure 6 and used as centre of the respective symmetrical triangular fuzzy number (STFN) representing estimated output of the image quality class. The total spread of a symmetrical fuzzy number is twice the *average norm of residual error* calculated considering 100 sample images.

Quality of the test image represented by STFN is defuzzified and for each class four crisp values ($centre_{UMF}$ + $left\_spread_{UMF}$, $centre_{UMF}$ + $right\_spread_{UMF}$, $centre_{LMF}$ + $left\_spread_{LMF}$, $centre_{LMF}$ + $right\_spread_{LMF}$) are obtained. Eight crisp values are fused to assess quality of the test image, which is free from human biasness.

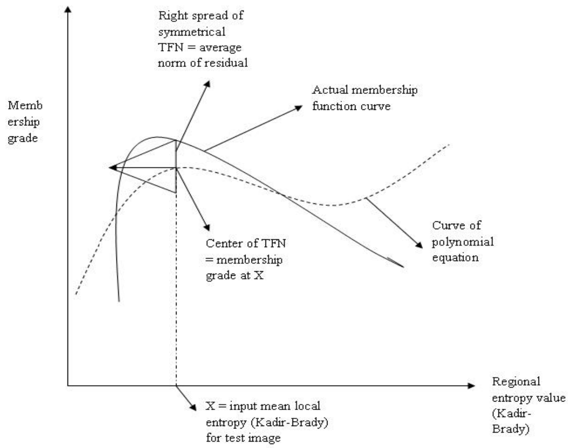


Fig. 6 Symmetrical Triangular Fuzzy Number using Fuzzy Polynomial Regression and Membership function of a particular quality class considering 100 training images

The proposed system is validated using different types of test images taken from TOYAMA image database[7] (Fig.7) having different Peak Signal to Noise Ratio (PSNR), Mean Opinion Score (MOS) and Mean Structural Similarity Index (MSSIM)[8].

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

Fig. 7 Sample test images from TOYAMA database- (a) kp0837, (b) kp2320, (c) kp22, (d) kp1315

Example:

Evaluation of quality metric of the test image (Fig. 7(b)) has been explained below.

Say, fifth order polynomial equation which is best fitted with figure 5 (a) given as:

$$y = 0.00027x^5 - 0.01x^4 + 0.1x^3 - 0.38x^2 + 0.44x + 0.33$$

Mean_local_entropy of the test image (kp2320) is used as input *x* for which respective *y* value is calculated representing centre of a STFN. Defuzzified outputs Y_{TFN} = (-0.0174, *y*, 0.0174) are obtained by adding left spread and right spread to *y,* where 0.0174 is the *average residual norm* for the image.

4 Combination of Fuzzy Numbers

Output of fuzzy regression equation is a fuzzy numbers with left and right spread therefore, for each membership function two crisp values are evaluated. Thus for an image in a particular quality class, four crisp values are emerged (UMF and LMF), which are fused to remove human biasness in assigning quality classes to the training images.

4.1 Weight Computation

Evaluation of combined image quality metric using defuzzified outputs of fuzzy numbers are presented here considering the test image of TOYAMA database (Fig. 7(b)). Eight defuzzified crisp values of fuzzy numbers are combined by weighted average method where the weights are determined using a cubic polynomial equation as plotted in figure 8. Nonlinearity between defuzzified values and the normalized MOS of the test image is best fitted with the cubic polynomial equation and therefore, the coefficients of the equation are considered as weights for the particular test image (kp2320). The weighted average value is computed using equation (3).

$$W = \frac{\sum_{i=1}^{N} \prod_{i=1,j=1}^{N/2,M/2} w_{jj} \times F_{ij}}{\sum_{i=1}^{M} w_i} \tag{3}$$

Where W is the weighted average, w_{jj} is respective weight of F_{ij} which is the concerned fuzzy number, *N* is the no. of fuzzy numbers (eight here) and *M* is the number of weights equal to the number of coefficients (four here).

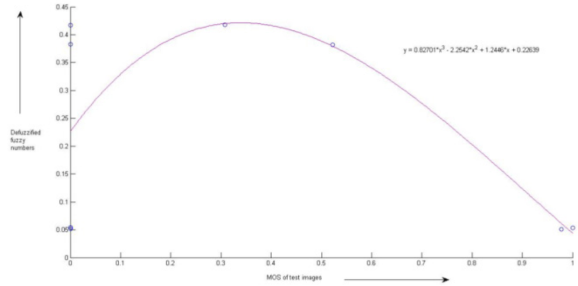


Fig. 8 Polynomial equation for computing weights of image kp2320

Using the coefficients of the equation given in figure 8, which are weights: 0.8270, -2.2542, 1.2446, 0.2263, the quality metric is computed below.

$$\frac{\sum_{i=1}^{8}\prod_{i=1,j=1}^{8/2,4/2} w_{jj} \times F_{ij}}{\sum_{i=1}^{4} w_i} = \frac{\begin{bmatrix}0.0505 & 0.0516\\ 0.0535 & 0.0544\\ 0.3823 & 0.3826\\ 0.4177 & 0.4174\end{bmatrix} \times \begin{bmatrix}0.8270 & 1.2446\\ -2.2542 & 0.2263\end{bmatrix}}{0.8270+1.2446-2.2542+0.2263} = 0.8124$$

5 Results of Fuzzy Regression Technique

For sample test images the no reference image quality metrics are evaluated using Fuzzy Regression analysis (FRANRIQA) as shown in table 1. Table 1 provides the normalized values of the FRANRIQA metrics, which is necessary to compare the said metric with others whose scales are different. Table 2 and table 3 provide PPMCC as prediction accuracy [9] and SROCC as prediction monotonicity [9] while comparing with MOS and other quality metrics. From the tables it is evident that the correlation between FRANRIQA metric and MOS of the test images is significantly better compare to other no reference quality metrics and even benchmark objective quality metric, like MSSIM.

Table 1 Comparison between Fuzzy regression based Quality Metric and Other Quality Metrics

Image Name	Normalized FRANRIQA Metric	Normalized MOS	Normalized BIQI	Normalized JPEG QUALITY SCORE	Normalized PSNR	Normalized MSSIM
kp0837	0.9387	0.9778	0.6031	0.8764	0	0.6031
kp22	1.0000	1.0000	0.5067	0.4032	1	0.5067
kp1315	0.8893	0.5222	1.0000	1.0000	0	1.0000
kp 2320	0.8774	0.3079	0.7115	0.8884	0	0.7115

Table 2 PPMCC between MOS and Other Quality Metrics

Pearson product moment correlation coefficient(PPMCC) between Normalized MOS and other quality metrics	Normalized FRANRIQA Metric	Normalized BIQI	Normalized JPEG QUALITY SCORE	Normalized PSNR	Normalized MSSIM
	0.8939	-0.6504	-0.6161	0.5796	-0.6504

Table 3 SROCC values between MOS and Other Quality Metrics

Spearman rank order correlation coefficient(SROCC) values between Normalized MOS and other quality metrics	Normalized FRANRIQA Metric	Normalized BIQI	Normalized JPEG QUALITY SCORE	Normalized PSNR	Normalized MSSIM
	1.0000	-0.8000	-0.8000	0.7746	-0.8000

6 Conclusions

An interval type 2 fuzzy regression analysis based quality metric has been described in this paper to assess quality of distorted images using Shannon entropies of visually salient regions as features. Uncertainty in image features are measured using Shanon's entropy and modelled by Interval type2 fuzzy sets to remove the limitation of selecting type-1 fuzzy membership value. Human perception on visual quality of images are assigned using five different class labels and the proposed method removes human biasness in assigning class labels by combining the crisp outputs of quality metrics. The variation of features are wide enough for capturing important information from the images. The proposed FRANRIQA metric has been compared with the existing quality metrics producing satisfactory result.

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