Deblurring Filter Design Based on Fuzzy Regression Modeling and Perceptual Image Quality Assessment

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***Abstract* — Images captured by digital cameras are generally not perfect as image blurring is usually generated by camera motion through long hand-held exposure. Deblurring filters can be used to improve image quality by removing image blur. Prior to develop a deblurring filter, a simulator for image quality assessment is essential to optimize filter parameters. Although subjective image quality assessment (subjective IQA) is commonly used for evaluating the visual effect of digital images for a wide range of image processing applications, it is inconvenient to be implemented in real-time. Generally, statistical regression is used to generate a functional map to correlate the subjective IQA and the objective image quality metrics. However, it cannot address the uncertainty caused by human judgment during the subjective IQA. This paper first proposes a fuzzy regression method to develop the functional map that overcomes the limitation of statistical regression that cannot account for uncertainty introduced through human judgment. Based on the fuzzy regression models, the deblurring filter parameters can be optimized. Experimental results show that the satisfactory deblurring can be achieved on blurred images captured by a smartphone camera.**

Keywords— Fuzzy regression, image quality evaluation, objective image quality metric, image deblurring, filter design.

I. INTRODUCTION

In these days, digital cameras and smartphones are very popular among people to capture digital photographs. Blur of photographs often occurs in poor lighting conditions and through long hand-held exposure. This is one of the most common reasons for degraded structure of sharp images. To evaluate the image quality, subjective image quality assessment (subjective IQA) can be conducted by a group of interviewers in scoring image qualities, since humans are users for digital images products [4,5,16]. However, subjective IQA is complicated and inconvenient to be implemented in real-time or as a systematic evaluator for embedding on image enhancement algorithms. Therefore, it is essential to develop a functional model in order to correlate subjective IQA with objective image quality metrics that can automatically predict perceived image quality. Those objective image quality metrics include simple numerical measures on images [6] such as signal-to-noise ratio and bit error rate [17] and complex models which simulate human visual system for evaluating visual image qualities [13,19,24].

Statistical regression [21] is commonly used based on experimental data of subjective IQA in order to develop these image quality prediction models. However, subjective image quality experiments are involved with human opinion judgments which are inherently imprecise. Hence, human uncertainty is generally neglected by statistical regression in predicting image qualities. Also, the regression models may not be performed accurately, as they can only be applied accurately in the range in which they are developed. They can only be applied if the given experimental data is normally distributed according to the developed regression model [9].

In this paper, we propose a fuzzy regression approach which attempts to account uncertainty of human judgment for subjective IQA, as fuzzy regression has a distinct advantage over statistical regression [2,3,7,26]; it can address fuzziness in subjective judgment and it can perform effectively in a small or incomplete data set [10,22]. The fuzzy regression model is developed based on an image quality database particularly for blur distortion [25]. Numerical results show that better fitting capability and generalization capability can be obtained compared with the commonly used statistical regression method. The developed fuzzy regression model is implemented on the design of an image deblurring filter, which is used to remove image blur caused by out of focus settings, camera motion and movement within the scene. The fuzzy regression model is used to evaluate the images which are processed by the deblurring filter. Results indicate that the fuzzy regression model is able to assist the development of deblurring filter.

II. FUZZINESS IN SUBJECTIVE IQA

In IQA, interviewers judge the quality of blurred images based on *n*-point psychometric scales [1]. The images are scored from the integer between *n*-points 1 to 5; and here we consider the lowest and the highest image quality is scored at 1 and *n*, respectively [11]. The image score can be represented by a fuzzy number, $\tilde{y}=\left(y^c,y^r,y^l\right)$, as human judgment is fuzzy, where y^c is the center, y^l is the left spread; y^r is the right spread; and the fuzzy membership function, $\mu_{\tilde{y}}\left(y\right)$ given in (1), represents the membership of $\tilde{y}$.

$$\mu_{\tilde{y}}(y)=\begin{cases}1 & y=y^c\\ \dfrac{y-y^c}{y^c-a^l} & y^l\le y<y^c\\ \dfrac{y^r-y}{y^r-y^c} & y^c\le y<y^r\\ 0, & \text{otherwise}\end{cases} \quad (1)$$

The difference between y^l and y^r represents the fuzziness of the image score of the blurred images. In the IQA experiment, a database of N_I blurred images and with N_c candidates is involved. Given that the image score for the *i*-th blurred image evaluated by the *k*-th candidate as $\left(y_i^c(k), y_i^l(k), y_i^r(k)\right)$, the mean opinion score (MOS) for the *i*-th image, namely $\bar{y}_i$, can be computed as (2) by accounting only the center of the fuzzy number, $y_i^c(k)$,

$$\bar{y}_i=\frac{1}{N_c}\sum_{k=1}^{N_c} y_i^c(k), \quad (2)$$

and the fuzzy MOS, $\tilde{y}_i$, for the *i*-th blurred image is defined by (3) as

$$\tilde{y}_i=\left(y_i^c, y_i^l, y_i^r\right) \quad (3)$$

where $y_i^c=\sum_{k=1}^{N_c} y_i^c(k)\Big/N_c$, $y_i^l=\sum_{k=1}^{N_c} y_i^l(k)\Big/N_c$ and $y_i^r=\sum_{k=1}^{N_c} y_i^r(k)\Big/N_c$.

Here the *m* objective image quality metrics are used to give the objective scores to the blurred images and we define x_q^i as the *q*-th objective score for the *i*-th blurred image. Using $\tilde{y}_i$ with $i=1,2,...,N_I$ and the *m* objective scores to the N_I images, the subjective IQA model formulated in (4) can be developed in order to correlate the fuzzy MOS and the *m* objective IQA metrics,

$$\tilde{y}=f_r\left(x_1, x_2, ..., x_m\right) \quad (4)$$

where x_p with *p* =1,2..,*m* is the *p*-th objective image quality metric and the correlation model f_r attempts to correlate all x_p to $\tilde{y}$. To address the fuzziness of subjective IQA for blurred images, the fuzzy regression presented in Section III is proposed in order to develop f_r.

III. Fuzzy Regression for Subjective IQA Modeling for Blurred Images

The fuzzy regression [10] formulated in (5) can be used to predict the fuzzy MOS, $\hat{\tilde{y}}_i=\left(\hat{y}_i^c, \hat{y}_i^l, \hat{y}_i^r\right)$, for the *i*-th blurred image as:

$$\hat{\tilde{y}}_i=\left(\hat{y}_i^c, \hat{y}_i^l, \hat{y}_i^r\right)=\tilde{A}_0+\tilde{A}_1\cdot x_1^i+\tilde{A}_2\cdot x_2^i+...++\tilde{A}_M\cdot x_M^i \quad (5)$$

where $\tilde{A}_q=\left(a_q^c, a_q^l, a_q^r\right)$ with $q=0,1,2,...,M$ is the *q*–th fuzzy coefficient; a_q^c, a_q^l and a_q^r are center, left spread and right spread of the fuzzy coefficient, and $\hat{y}_i^c$, $\hat{y}_i^l$ and $\hat{y}_i^r$ are given respectively as:

$$\hat{y}_i^c=a_0^c+\sum_{q=1}^{M} a_q^c\cdot x_q^i;\ \hat{y}_i^l=a_0^l+\sum_{q=1}^{M} a_q^l\cdot x_q^i;\ \hat{y}_i^r=a_0^r+\sum_{q=1}^{M} a_q^r\cdot x_q^i$$

The fuzzy regression accounts fuzziness of the fuzzy MOS based on $\hat{y}_i^l$ and $\hat{y}_i^r$. The fuzzy regression assumes that the residual of the MOS estimates are caused by human fuzzy judgments. Hence, the fuzzy coefficients, $\tilde{A}_q$ with $q=0,1,2,...,M$, in (5) address possible distribution corresponding to the human fuzziness [7,10]. All $\tilde{A}_q$ are determined by minimizing the total sum of residual errors, *Error*, given in (6) [3]:

$$E=\sum_{i=1}^{N_I}\left(\hat{\tilde{y}}_i-\tilde{y}_i\right)^2=\sum_{i=1}^{N_I}\left(\tilde{A}_0+\sum_{q=1}^{M}\tilde{A}_q\cdot x_q^i-\left(y_i^c, y_i^l, y_i^r\right)\right)^2 \quad (6)$$

where *E* evaluates the sum of squared differences between the real fuzzy MOS, $\tilde{y}_i$, and the estimated fuzzy MOS, $\hat{\tilde{y}}_i$, with $i=1,2,...,N_I$ of which $\hat{\tilde{y}}_i$ are generated based on (5). (6) can be elaborated as (7), based on the weighted fuzzy arithmetic operations with asymmetric triangular membership [3].

$$E=\frac{1}{12}\sum_{i=1}^{N_I}\left[\left(a_0^r+\sum_{q=1}^{M}a_q^r x_q^i-y_i^r\right)^2+\left(a_0^l+\sum_{q=1}^{M}a_q^l x_q^i-y_i^l\right)^2\right]$$
$$+\sum_{i=1}^{N_I}\left(a_0^c+\sum_{q=1}^{M}a_q^c x_q^k-y_i^c\right)^2+\frac{1}{3}\sum_{i=1}^{N_I}\left[\left(a_0^r+\sum_{q=1}^{M}a_q^r x_q^i-y_i^r\right)\right. \quad (7)$$
$$\left.-\left(a_0^l+\sum_{q=1}^{M}a_q^l x_q^i-y_i^l\right)\right]\left(a_0^c+\sum_{q=1}^{M}a_q^c x_q^i-y_i^c\right)$$

To minimize *E*, (7) is derived with respect to each component of the fuzzy coefficients, a_q^c, a_q^l and a_q^r, with $q=1,2,...,M$. All a_q^c, a_q^l and a_q^r, are determined by solving the derivatives set to zeros. The derivatives of (7) with respect to a_q^c are given by the equation set (8).

$$\frac{\partial E}{\partial a_0^c}=M\cdot a_0^c+\left(\sum_{i=1}^{N_I}x_1^i\right)\cdot a_1^c+\left(\sum_{i=1}^{N_I}x_2^i\right)\cdot a_2^c+...$$
$$+\left(\sum_{i=1}^{N_I}x_M^i\right)\cdot a_M^c-\sum_{i=1}^{N_I}y_i^c=0,\ \text{with } q=0 \quad (8.1)$$

$$\frac{\partial E}{\partial a_1^c}=\left(\sum_{i=1}^{N_I}x_1^i\right)\cdot a_0^c+\left(\sum_{i=1}^{N_I}\left(x_1^i\right)^2\right)\cdot a_1^c+\left(\sum_{i=1}^{N_I}x_1^i\cdot x_2^i\right)\cdot a_2^c+$$
$$...+\left(\sum_{i=1}^{N_I}x_1^i\cdot x_M^i\right)\cdot a_M^c-\sum_{i=1}^{N_I}\left(x_1^i\cdot y_i^c\right)=0,\ \text{with } q=1 \quad (8.2)$$

: : :

$$\frac{\partial E}{\partial a_M^c} = \left(\sum_{i=1}^{N_I} x_M^i\right)\cdot a_0^c + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_1^i\right)\cdot a_1^c + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_2^i\right)\cdot a_2^c + \dots + \left(\sum_{i=1}^{N_I}\left(x_M^i\right)^2\right)\cdot a_M^c - \sum_{i=1}^{N_I}\left(x_M^i \cdot y_i^c\right) = 0, \text{ with } q = M \qquad (8.M)$$

The derivatives of (7) with respect to a_q^r and a_q^l are given by the equation sets (9) and (10) respectively.

$$\frac{\partial E}{\partial a_0^l} = M\cdot a_0^l + \left(\sum_{i=1}^{N_I} x_1^i\right)\cdot a_1^l + \left(\sum_{i=1}^{N_I} x_2^i\right)\cdot a_2^l + \dots + \left(\sum_{i=1}^{N_I} x_M^i\right)\cdot a_M^l - \sum_{i=1}^{N_I} y_i^l = 0, \text{ with } q = 0 \qquad (9.1)$$

$$\frac{\partial E}{\partial a_1^l} = \left(\sum_{i=1}^{N_I} x_1^i\right)\cdot a_0^l + \left(\sum_{i=1}^{N_I}\left(x_1^i\right)^2\right)\cdot a_1^l + \left(\sum_{i=1}^{N_I} x_1^i \cdot x_2^i\right)\cdot a_2^l + \dots + \left(\sum_{i=1}^{N_I} x_1^i \cdot x_M^i\right)\cdot a_M^l - \sum_{i=1}^{N_I}\left(x_1^i \cdot y_i^l\right) = 0, \text{ with } q = 1 \qquad (9.2)$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$\frac{\partial E}{\partial a_M^l} = \left(\sum_{i=1}^{N_I} x_M^i\right)\cdot a_0^l + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_1^i\right)\cdot a_1^l + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_2^i\right)\cdot a_2^l + \dots + \left(\sum_{i=1}^{N_I}\left(x_M^i\right)^2\right)\cdot a_M^l - \sum_{i=1}^{N_I}\left(x_M^i \cdot y_i^l\right) = 0, \text{ with } q = M \qquad (9.M)$$

and

$$\frac{\partial E}{\partial a_0^r} = M\cdot a_0^r + \left(\sum_{i=1}^{N_I} x_1^i\right)\cdot a_1^r + \left(\sum_{i=1}^{N_I} x_2^i\right)\cdot a_2^r + \dots + \left(\sum_{i=1}^{N_I} x_M^i\right)\cdot a_M^r - \sum_{i=1}^{N_I} y_i^r = 0, \text{ with } q = 0 \qquad (10.1)$$

$$\frac{\partial E}{\partial a_1^r} = \left(\sum_{i=1}^{N_I} x_1^i\right)\cdot a_0^r + \left(\sum_{i=1}^{N_I}\left(x_1^i\right)^2\right)\cdot a_1^r + \left(\sum_{i=1}^{N_I} x_1^i \cdot x_2^i\right)\cdot a_2^r + \dots + \left(\sum_{i=1}^{N_I} x_1^i \cdot x_M^i\right)\cdot a_M^r - \sum_{i=1}^{N_I}\left(x_1^i \cdot y_i^r\right) = 0, \text{ with } q = 1 \qquad (10.2)$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$\frac{\partial E}{\partial a_M^r} = \left(\sum_{i=1}^{N_I} x_M^i\right)\cdot a_0^r + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_1^i\right)\cdot a_1^r + \left(\sum_{i=1}^{N_I} x_M^i \cdot x_2^i\right)\cdot a_2^r + \dots + \left(\sum_{i=1}^{N_I}\left(x_M^i\right)^2\right)\cdot a_M^r - \sum_{i=1}^{N_I}\left(x_M^i \cdot y_i^r\right) = 0, \text{ with } q = M \qquad (10.M)$$

Determination of all a_q^c, a_q^l and a_q^r with $q = 1, 2, \dots, M$ are identical to solve the least square regression formulations given in the equation sets (8), (9) and (10) respectively. With the fuzzy coefficients, $\left(a_q^c, a_q^l, a_q^r\right)$, the fuzzy regression formulated in (5) can be used to predict the fuzzy MOS $\hat{\tilde{y}} = \left(\hat{y}^c, \hat{y}^l, \hat{y}^r\right)$. Based on the fuzzy MOS, $\left(\hat{y}^c, \hat{y}^l, \hat{y}^r\right)$, the MOS crisp can be defuzzificated by [3]:

$$\Im\left(\hat{\tilde{y}}\right) = \hat{y}^c + \frac{1}{6}\cdot\left(\hat{y}^r - \hat{y}^l\right) \qquad (11)$$

IV. Fuzzy IQA modeling for deblurring filter design

A. *IQA for blurred images*

We used Zaric's database [26] to develop a fuzzy regression model which attempts to address the blur distortion. The fuzzy regression model is developed based on 161 images including 23 original color images and 138 distorted images which are corrupted with each of the six blur levels from the weakest to the strongest blur distortion respectively. The image scores for both the original images and the distorted images were collected by 118 naïve candidates between 20 and 30 years of age. These image scores were scored 20 times in average. A 5-point psychometric scale was used with the labels: 1=bad, 2=poor, 3=fair, 4=good and 5=excellent. These labels can be represented by five fuzzy numbers [12]: (0,0,0.25), (0.25,0.25,0.25), (0.50,0.25,0.25), (0.75,0.25,0.25), and (1.00,0.25,0). These fuzzy numbers are defined based on the five questionnaire scorings [25]. The fuzzy MOS observation of each image is computed based on (3) with respect to the image scores collected from the interviewers.

The fuzzy regression model is developed by correlating the fuzzy MOS, $\hat{\tilde{y}}_i$, with five image quality objective metrics namely block boundary differences x_1, edge smoothness x_2, edge-based image activity x_3, gradient-based image activity x_4, and image histogram statistics x_5. These five metrics are selected as they are correlated to the blur distortion on an image [5]. The fitting capability and the generalization capability of the fuzzy regression model are compared with those of the statistical regression model [11, 21]. For the fuzzy regression model, the MAE mean, e^{FR} is used to evaluate the difference between the real MOS, $\bar{y}_i$, of the i-th image and the crisp estimates of the MOS, $\Im\left(\hat{\tilde{y}}_i\right)$, where the defuzzication, $\Im$, in (11) is used to transform the fuzzy number $\hat{\tilde{y}}_i$ into a crisp value, and the i-th image in the image set, I, is considered:

$$e^{FR} = \sum_{\exists i \in \mathrm{I}} \left| \Im\left(\hat{\tilde{y}}_i\right) - \bar{y}_i \right|. \qquad (12)$$

For the statistical regression model, the MAE, e^{SR}, in (13) is used to evaluate the difference between $\bar{y}_i$ and the estimates, $\hat{\bar{y}}_i$ of the statistical regression model.

$$e^{SR} = \sum_{\exists i \in \mathrm{I}} \left| \hat{\bar{y}}_i - \bar{y}_i \right| \qquad (13)$$

The fuzzy regression model and the statistical regression model are developed as (14) and (15) respectively as:

$$\begin{aligned}\hat{\tilde{y}} = {} & (0.69, 0.13, 0.08) + (-0.80, -0.07, 0.21)\cdot x_1 \\ & + (-0.00, 0.21, 0.16)\cdot x_2 + (0.262, -0.12, -0.16)\cdot x_3 \\ & + (0.03, 0.03, 0.03)\cdot x_4 + (0.19, 0.06, -0.03)\cdot x_5\end{aligned} \qquad (14)$$

and

$$\hat{y} = 0.69 - 0.80x_1 - 0.00x_2 + 0.26x_3 + 0.03x_4 + 0.19x_5 \qquad (15)$$

where the centers of the fuzzy coefficients of the fuzzy regression is same as the coefficients of the statistical regression. The left and right spreads are introduced on the fuzzy coefficients. The MAE for the fuzzy regression model in (14) and the statistical regression model in (15) are given as 0.118 and 0.120 respectively. Hence, these results indicate that the fitting capability of the fuzzy regression model is slightly better than that of the statistical regression model. Hence, slightly improvement can be obtained by the fuzzy regression model in term of the fitting capability, but fuzzy information due to IQA can be indicated by the fuzzy regression model while the statistical regression cannot generate the fuzzy information. As an illustration, an original image in the image database and its distorted version in the sixth blur level are given as Figures 1(a) and (b) respectively. Figure 2 shows the actual fuzzy MOS and predicted fuzzy MOS for the original and the distorted images. They exemplify that the fuzziness caused by human judgment can be illustrated by the spreads depends on the distortion type of the respective image. This fuzziness is an artifact of the quality scale limits that is taken into account in fuzzy regression but not statistical regression.

Fig. 1a Original image

Fig. 1b Blurred image

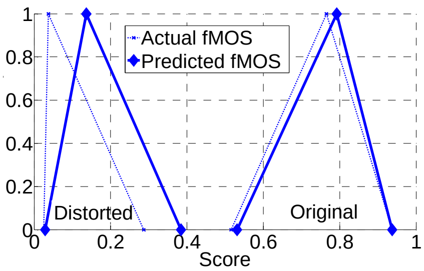

Fig. 2 Fuzzy MOS for the original and blurred images.

The generalization capabilities of both modelling approaches are evaluated based on Leave-one-out cross-validation (namely LOOCV). In the LOOCV, the MOS of 22 original images and their corresponding blurred images are used for training and the remaining original image and its corresponding blurred images are used for validation. The MAEs obtained for the LOOCV for the fuzzy regression and the statistical regression are given as 0.175 and 0.205. Hence, small MSE is obtained by the fuzzy regression and thus the generalization capability of the fuzzy regression is better than that of the statistical regression.

B. *Deblurring filter design*

The fuzzy regression developed in (14) is used to design the deblurring filter which attempts to improve the image quality of the distorted image contaminated with blur noise. The fuzzy regression is used as the generalization capability of the fuzzy regression is better than that of the commonly used statistical regression.

1) Problem formulation of the debluirring filter

Based on the camera motion data captured by the IMU in the smartphone, The camera motion at time *t* with the sampling time T_s is given by (16a), (16b) and (16c) with respect to *x*, *y* and *z* axis to the visual scene:

$$D_x(t)=D_x(t-T_s)+l\cdot\left(w_y(t)-w_y(t-1)\right)\cdot T_s +a\cdot\left(w_z(t)-w_z(t-1)\right)\cdot T_s, \quad (16a)$$

$$D_y(t)=D_y(t-T_s)-l\cdot\left(w_x(t)-w_x(t-1)\right)\cdot T_s -b\cdot\left(w_z(t)-w_z(t-1)\right)\cdot T_s, \quad (16b)$$

$$D_z(t)=D_z(t-T_s)-a\cdot\left(w_x(t)-w_x(t-1)\right)\cdot T_s +b\cdot\left(w_z(t)-w_z(t-1)\right)\cdot T_s. \quad (16c)$$

where $w_x(t)$, $w_x(t)$ and $w_x(t)$ are the angular velocities captured by the IMU for *x*, *y*, and *z* axes respectively; and *a*, *b*, and *l* are the alignment parameters corresponding between the IMU which are illustrated in Figure 3.

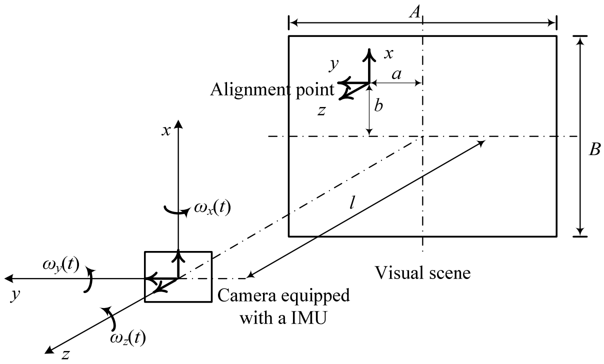

Fig. 3 Illustration of the camera and IMU installed in the smartphone.

Based on $D_x(t)$, $D_y(t)$ and $D_z(t)$, the deblurring kernel namely $\overline{\tau}=\left[\tau_{i,j} \text{ with } i=1,2,..,n_x^{\Gamma} \text{ and } i=1,2,..,n_y^{\Gamma}\right]$, can be determined, where n_x^{Γ} and n_x^{Γ} are are given as,

$$n_x^{\Gamma}=\frac{\max\limits_{i=1,2,\ldots,N_s}\left(D_x(i\cdot T_s)\right)}{p_s} \text{ and } n_y^{\Gamma}=\frac{\max\limits_{i=1,2,\ldots,N_s}\left(D_y(i\cdot T_s)\right)}{p_s}; \quad (17)$$

of which p_s is the number of image pixels; $\tau_{i,j}$ is given as

$$\tau_{i,j}=\frac{\sum_{k=1}^{N_s}F_{i,j}(k)}{\sum_{i=1}^{n_x^{\Gamma}}\sum_{j=1}^{n_y^{\Gamma}}\sum_{k=1}^{N_s}F_{i,j}(k)}, \quad (18)$$

with

$$F_{i,j}(k)=\begin{cases}1, \text{ if } i=\text{round}\left(\dfrac{D_x(k\cdot T_s)}{p_s}\right) \text{ and } j=\text{round}\left(\dfrac{D_y(k\cdot T_s)}{p_s}\right)\\ 0, \text{ otherwise.}\end{cases}$$

Given a distorted image, $\bar{I}^D$, from the smartphone camera, the enhanced image, $\bar{I}^E$, can be generated as:

$$\bar{I}^E = \Theta_F\left(\bar{I}^D, \Theta_\tau\left(\bar{w}, \bar{\phi}\right)\right) \quad (19)$$

where $\Theta_\tau\left(\bar{w}, \bar{\phi}\right) = \bar{\tau}$ correlates the blur kernel, $\bar{\tau}$, with the alignment parameter set, $\bar{\phi} = (a, b, l)$, and the sequence of camera motion namely $\bar{w}$ which is given as:

$$\bar{w} = \left[\left(w_x(0), w_y(0), w_z(0)\right), \left(w_x(T_s), w_y(T_s), w_z(T_s)\right), \ldots, \left(w_x(N_s \cdot T_s), w_y(N_s \cdot T_s), w_z(N_s \cdot T_s)\right)\right]$$

with N_s samples, and Θ_F represents the deblurring filter which generates an enhanced image, $\bar{I}^E$, when the deblurring kernel, $\bar{\tau}$, is engaged with.

After the enhanced image, $\bar{I}^E$, is generated, the predicted fuzzy MOS namely $\tilde{y}\left(\bar{I}^E\right)$ with respect to $\bar{I}^E$ is evaluated based on the fuzzy regression model given in (20)

$$\tilde{y}\left(\bar{I}^E\right) = (0.69, 0.13, 0.08) + (-0.80, -0.07, 0.21) \cdot x_1\left(\bar{I}^E\right) + (-0.00, 0.21, 0.16) \cdot x_2\left(\bar{I}^E\right) + (0.262, -0.12, -0.16) \cdot x_3\left(\bar{I}^E\right) + (0.03, 0.03, 0.03) \cdot x_4\left(\bar{I}^E\right) + (0.19, 0.06, -0.03) \cdot x_5\left(\bar{I}^E\right) \quad (20)$$

where $x_1\left(\bar{I}^E\right)$ represents the metric of block boundary differences with respect to $\bar{I}^E$; $x_2\left(\bar{I}^E\right)$, $x_3\left(\bar{I}^E\right)$, $x_4\left(\bar{I}^E\right)$, and $x_5\left(\bar{I}^E\right)$ represent those for edge smoothness, edge-based image activity, gradient-based image activity and image histogram statistics respectively. The enhanced image can be optimized based on (21) with respect to the alignment parameter set, $\bar{\phi}$, where $\bar{\phi}$, is the only one that can be tuned, as the camera motion, $\bar{\omega}$, is captured by the IMU, and it cannot be tuned.

$$\min_{\bar{\phi}} \tilde{y}\left(\bar{I}^E\right) = \min_{\bar{\phi}} \tilde{y}\left(\Theta_F\left(\bar{I}^D, \Theta_\tau\left(\bar{w}, \bar{\phi}\right)\right)\right). \quad (21)$$

2) Implementation and results

Solving (21) is a nonconvex problem, since the deblurring filter, Φ_F, is a nonlinear function. Hence, particle swarm optimization (PSO) [16], which is effective in solving hard optimization problems, is used to determine the alignment parameter set $\bar{\phi}$. In PSO, the particle is coded with a parametric representation for the three alignment parameters $\bar{\phi} = (a, b, l)$. The following PSO parameters were used: the particle population is 100; the maximum number of iterations is 50. For deblurring filter design, the number of alignment parameters is three. When these two PSO parameter settings are used, the number of computational evaluations is 100x50=5000 which is considered to be large enough for this deblurring filter design problem with three alignment parameters. The PSO is terminated when the maximum number of iterations is reached; the maximum and minimum inertia weights are 0.9 and 0.2 respectively; the cognitive parameter and the social parameter are both set as 2 which are defaulted in [18].

In this research, the Sony Xperia TX smartphone equipped with a camera and an IMU was used to capture the image and the angular velocities associated with the camera motion respectively, where the sampling time of capturing the angular velocities was 5ms and 14 samples of angular velocities are captured for an image exposure. The three alignment parameters with the following domains are considered: $a \in [-1.5..1.5]$, $b \in [-1.5..1.5]$ and $l \in [3.1..4.9]$. Here the computationally simple Lucy deblurring filter is used to perform the deblurring [8]. The convergence plot for the PSO is given in Figure 6. We can see from the plot that the PSO progressed gradually from 0.74 to 0.84. Then it saturated about 0.842. The following parameters are determined by the PSO: $a = -0.308$, $b = 1.413$, and $c = 3.434$. Based on these alignment parameters, an image with better quality can be generated, where Figure 7 shows the distorted image contaminated with blur noise of which the noise is generated by camera motion through long hand-held exposure. Figure 8 shows the enhanced image which is processed by the deblurring filter engaged with the determined alignment parameters. The deblurred image shows that the blurred effect is removed from the original image and the object edges are clearer. This application demonstrates how the debluring filter design can be incorporated with the fuzzy regression model which evaluates fuzzy MOS of an image.

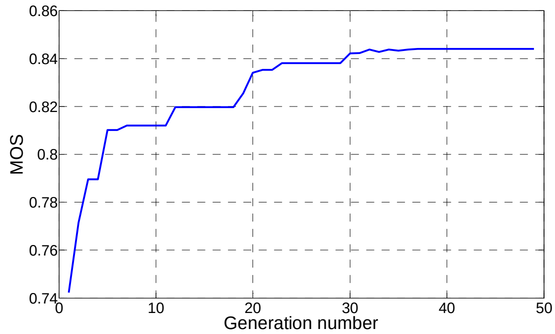

Figure 6 Convergence plot for the PSO.

Fig. 7 Original image **Fig. 8** Deblurred image

The image quality metrics for measuring the amount of blur on an image, namely no-reference blur [15], and two image activity measures based on edge gradients and the amount of edge [20] were used to evaluate the amount of blur in the original image and the image enhanced by the deblurring filter. Table 1 shows the blur degrees given by the no-reference blur for both images. It shows that blur degree obtained by the enhanced image is smaller compared with the original image. The measures based on gradients and edges show that the image activity obtained by the deblurring filter is higher compared with the original image. They further validate the effectiveness of the deblurring filter which is designed based on the fuzzy regression model.

Table I Comparison between original image and deblurred image.

	No-reference blur measure (Smaller value means less blur)	**Gradient measure (Larger value means less blur)**	**Edge measure (Larger value means less blur)**
Original image	4.53	0.008	10.11
Deblurred image	3.52	0.023	10.59

V. Conclusion

In this paper, we presented a fuzzy regression method to address uncertainty in-subjective IQA, where the uncertainty is caused by human judgment and is generally ignored by the commonly used statistical regression in generating image quality models. Using blurred images from an image database, we compared the effectiveness of the fuzzy regression against the commonly used statistical regression. The results showed that more accurate predictions and fitting capability can be achieved by the fuzzy regression for modelling subjective IQA for those blurred images. The developed fuzzy regression model was used to optimize deblurring filter and the results showed that satisfactory deblurring can be achieved on blur images captured by smartphone camera.

In future work, further evaluation of the proposed approach will be conducted by modelling different image distortions.

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