

# Real-time No-Reference Image Quality Assessment based on Filter Learning: Supplementary Material

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## 1 Supervised Filter Learning

Suppose we have  $n$  training images and the  $k$ -th training image is denoted as  $X_k$ . The corresponding feature vector of  $X_k$  is  $Z_k = \phi(X_k, B)$  where  $B = [b_1, \dots, b_K] \in R^{d \times K}$  represents a set of filters. The supervised filter learning method jointly optimizes the prediction model and the set of filters. The objective function of this optimization problem is defined as follows:

$$C(B, w, \{X_k\}_{k=1}^n) = \sum_{k=1}^n L(y_k, f(\phi(X_k, B), w)) + \lambda_1 \|w\|_{l_2}^2 + \lambda_2 \text{avecorr}(B) \quad (1)$$

*subject to*  $\|b_i\| = 1, i = 1, \dots, K$

where  $f$  is the prediction function:  $f(Z_k, w) = \sum_{i=1}^{2K} w_i Z_k(i) + w_0$ ,  $y_k$  is the true quality score of the  $k$ -th image,  $L$  is the  $\epsilon$ -insensitive loss function and  $\text{avecorr}(B) = \frac{1}{K-1} \sum_{i=1}^K \sum_{j:j \neq i} < b_i, b_j >$  is the average correlation of one filter with every other filters.

Optimal  $B$  and  $w$  is given by

$$(B^*, w^*) = \text{argmin}_{B, w} C(B, w, \{X_k\}_{k=1}^n)$$

This optimization problem can be solved by optimizing alternatively over  $B$  and  $w$ . The initial set of filters are obtained by performing k-means clustering on a set of local features. When  $B$  is fixed, optimal  $w$  can be found using a standard SVR program. Given  $w$  fixed, we can apply stochastic gradient descent (SGD) to find the optimal  $B$ .

The SGD process requires us to compute the gradient of the objective function  $C$  with respect to a filter  $b_i, i = 1, \dots, K$ . Using chain rule, we can have:

$$\frac{\partial C}{\partial b_i} = \sum_{k=1}^n \frac{\partial L}{\partial f_k} \frac{\partial f_k}{\partial Z_k} \frac{\partial Z_k}{\partial b_i} + \lambda_2 \frac{\partial \text{avecorr}(B)}{\partial b_i} \quad (2)$$

where  $f_k = f(Z_k, w)$  is the predicted quality score for the  $k$ -th training image.

The loss function used in  $\epsilon$ -SVR is non-differentiable, therefore we use the following approximation (Huber loss) for computing gradient

$$L(y, \hat{y}) = \begin{cases} 0 & |y - \hat{y}| \leq \epsilon - h \\ |y - \hat{y}| - \epsilon & |y - \hat{y}| \geq \epsilon + h \\ \frac{(y - \hat{y} - \epsilon + h)^2}{4h} & \epsilon - h < y - \hat{y} < \epsilon + h \\ \frac{(y - \hat{y} + \epsilon - h)^2}{4h} & -\epsilon - h < y - \hat{y} < -\epsilon + h \end{cases} \quad (3)$$

where  $0 < h < \epsilon$ . When  $h \rightarrow 0$ , Eq. 3 is equivalent to the  $\epsilon$ -insensitive loss used in  $\epsilon$ -SVR. The derivative of the above loss function is given by:

$$\frac{\partial L}{\partial f_k} = \begin{cases} 0 & |y_k - f_k| \leq \epsilon - h \\ -1 & y_k - f_k \geq \epsilon + h \\ 1 & y_k - f_k \leq -\epsilon - h \\ \frac{f_k - y_k + \epsilon - h}{2h} & \epsilon - h < y_k - f_k < \epsilon + h \\ \frac{f_k - y_k - \epsilon + h}{2h} & -\epsilon - h < y_k - f_k < -\epsilon + h \end{cases} \quad (4)$$

The derivative of the prediction function with respect to the global feature vector is given by <sup>1</sup>:

$$\frac{\partial f_k}{\partial Z_k} = [w_1, w_2, \dots, w_{2K}] \quad (5)$$

The global feature vector  $Z_k = [Z_k(1), \dots, Z_k(2K)]^T$ , where for  $i = 1, \dots, K$

$$Z_k(i) = b_i \cdot x_{max,i}^k, \quad x_{max,i}^k = \operatorname{argmax}_{x_l \in X_k} (b_i \cdot x_l)$$

$$Z_k(i+K) = b_i \cdot x_{min,i}^k, \quad x_{min,i}^k = \operatorname{argmin}_{x_l \in X_k} (b_i \cdot x_l)$$

where superscript  $k$  is the index of the training image,  $x_l \in X_k$  means  $x_l$  is a local feature vector from image  $X_k$  and  $\cdot$  represents inner product. We therefore have  $\frac{\partial Z_k(i)}{\partial b_i} = x_{max,i}^k$ ,  $\frac{\partial Z_k(i+K)}{\partial b_i} = x_{min,i}^k$  and the derivative of the global feature vector with respect to  $b_i$  is given by:

$$\begin{aligned} \frac{\partial Z_k}{\partial b_i} &= [0, \dots, 0, \frac{\partial Z_k(i)}{\partial b_i}, 0, \dots, 0, \frac{\partial Z_k(i+K)}{\partial b_i}, 0, \dots, 0]^T \\ &= [0, \dots, 0, x_{max,i}^k, 0, \dots, 0, x_{min,i}^k, 0, \dots, 0]^T \end{aligned} \quad (6)$$

The derivative of the correlation penalty term with respect to  $b_i$  is given by:

$$\frac{\partial \operatorname{avecorr}(B)}{\partial b_i} = \frac{1}{K-1} \sum_{j:j \neq i} b_j^T \quad (7)$$

To sum up, when linear  $\epsilon$ -SVR is used, we can compute the derivative of the objective function as follows <sup>2</sup>:

$$\frac{\partial C}{\partial b_i} = \left( \sum_{k=1}^n \frac{\partial L}{\partial f_k} (w_i x_{max,i}^k + w_{i+K} x_{min,i}^k) + \lambda_2 \frac{1}{K-1} \sum_{j:j \neq i} b_j \right)^T \quad (8)$$

## 2 Examples of filter responses

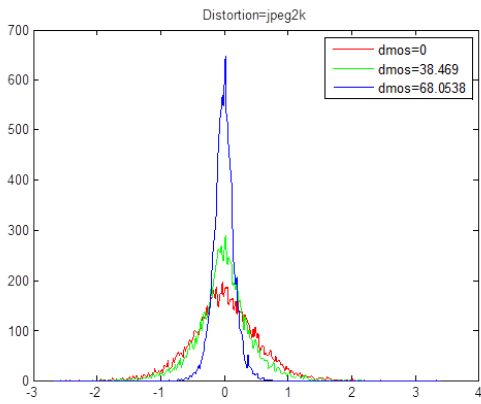
To demonstrate that with properly learned filters, the distribution of filter responses from distorted and non-distorted images are very different, we show filter responses of images with five different types of distortions at three different distortion levels in Fig. 1. The non-distorted reference image is also shown in Fig. 1.

## 3 Doc-IQA Dataset

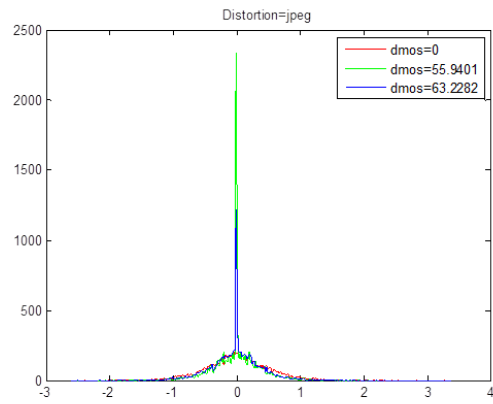
Examples of images from the SOC and the Newspaper dataset are shown in Fig. 2 and Fig. 3 respectively. The histogram of OCR accuracy of images from these two Doc-IQA dataset are shown in Fig. 4. It can be seen that the distribution of the OCR accuracy of images from both Doc-IQA datasets are non-uniform and the SOC dataset is highly imbalanced.

<sup>1</sup>If  $y \in R^m$ ,  $x \in R^n$ , then  $\frac{\partial y}{\partial x} \in R^{m \times n}$

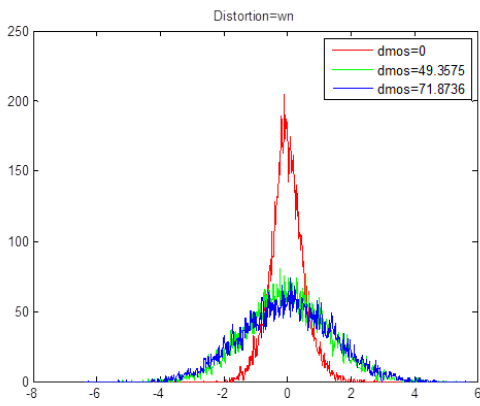
<sup>2</sup>For ease of representation, the transpose sign in Eq. 8 is omitted in the paper.



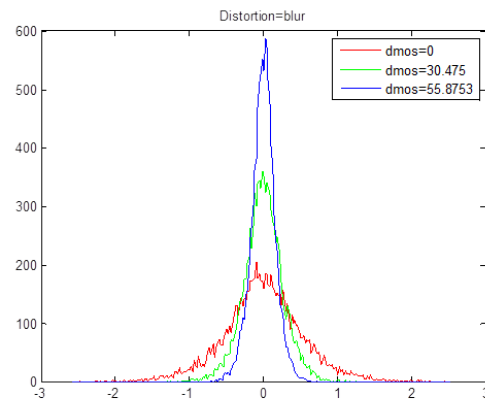
(a) JPGE2K Compression



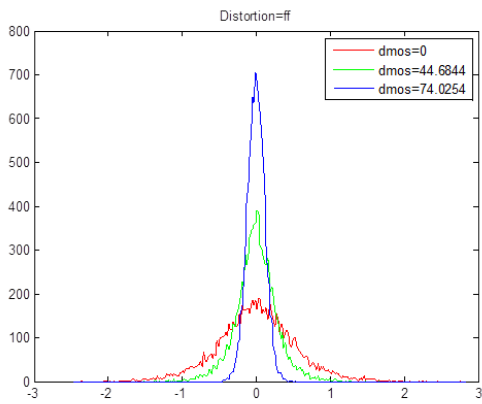
(b) JPEG Compression



(c) White Gaussian Noise



(d) Gaussian Blurring



(e) Fast Fading



(f) Reference Image

Figure 1: Examples of filter responses for different types and levels of distortions. (High DMOS indicates low quality)

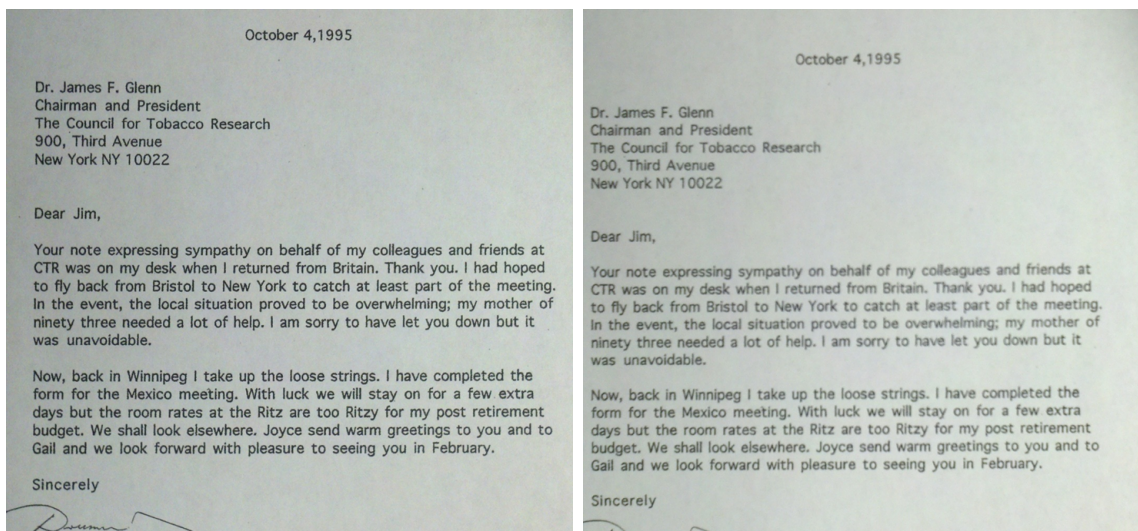


Figure 2: Examples of images from the SOC dataset.

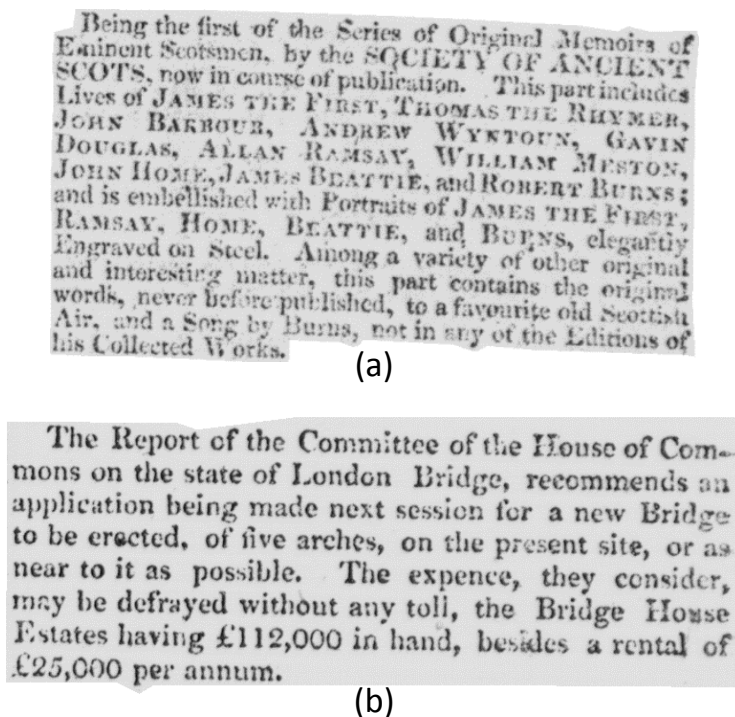
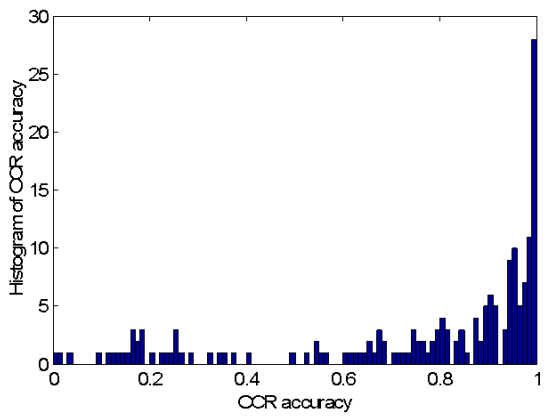
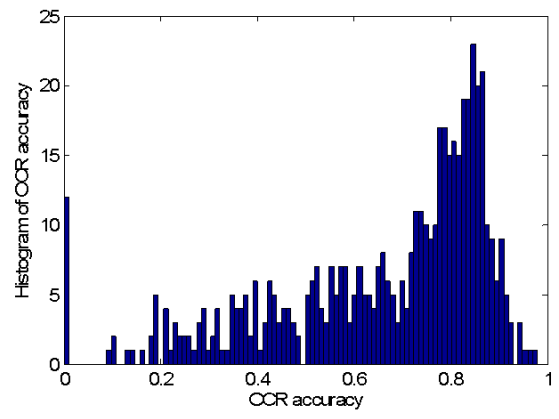


Figure 3: Examples of images from the newspaper dataset. Character level OCR accuracy (a) 0.097 (b) 0.958.



(a) SOC dataset.



(b) Newspaper dataset.

Figure 4: Histogram of OCR accuracy of images from the SOC and the Newspaper dataset.