FAST BLIND QUALITY EVALUATOR FOR SCREEN CONTENT IMAGES VIA ANALYSIS OF STRUCTURE

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Motivation

- Existing blind evaluators for screen content images (SCIs) are mainly learning-based and require a number of training images with co-registered human opinion scores. Some weakness exists: 1) The size of existing databases is small, and it is labor-, time-consuming and expensive to largely generate human opinion scores. 2) Utilizing the scores of FR methods as training labels, the performance of the generated NR model is directly determined by the effectiveness of the selected FR methods. 3) Most methods require too much running time.
- We design a fast blind quality assessment method for SCIs by simple analysis of structural characteristics without any training operation.

Observation

Fig. 1 (a) is the reference image and (b)-(d) are its corrupted versions processed by Gaussian blur, Motion blur and JPEG compression, respectively.

- ✓ Different distortions induce diverse appearance changes over the reference image, e.g., blockiness, blurriness, etc.
- ✓ These distortions corrupt the image major edges (where the gradient magnitude is large) on both text and picture regions, as shown in Fig. 2.

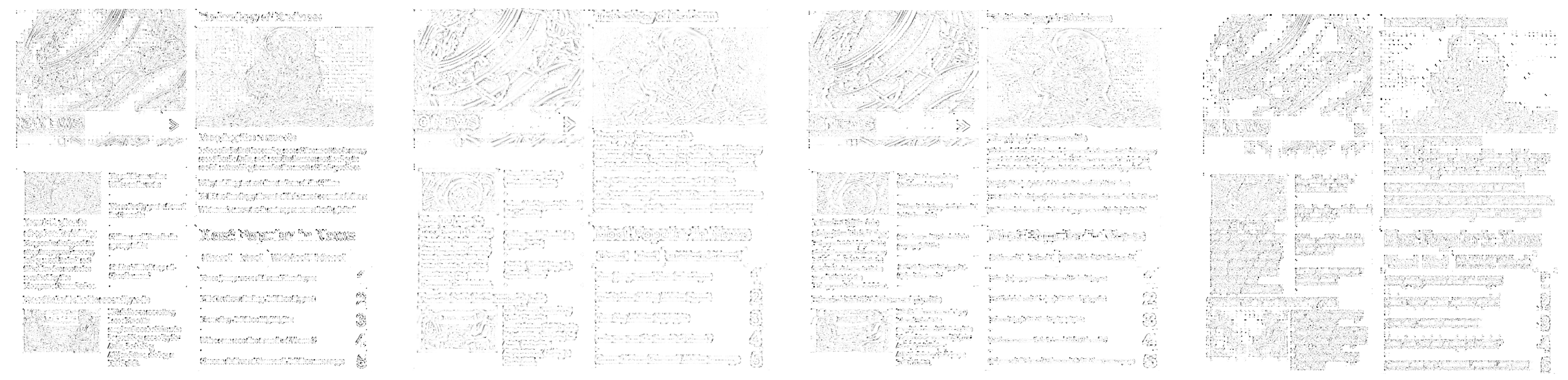

Fig. 2 Illustration of the structure variation map and weighting map. (a)-(d) are the structure variation maps of Figs. 1(a)-1(d).respectively. A higher gray value denotes to higher gradient similarity.

Proposed Method

Given an image I, the gradient similarity G_n^s between I and its translated version I_n (generated by shifting I with 2 pixel along one of four directions, i.e., horizontal, vertical, main-diagonal and secondary-diagonal directions) is calculated by:

$$G_S^n(x,y) = \frac{2\cdot G_0(x,y)\cdot G_n(x,y)+T_1}{G_0(x,y)^2+G_n(x,y)^2+T_1} \quad (1)$$

T_1 is a constant. Here, it is set as 600 empirically. G_0 and G_n are the gradient magnitude of I and I_n. By Eq. (1), we can totally obtain four gradient similarity maps along different directions. Then, we generate the structure variation map by selecting the maximum value among the gradient similarity responses over all directions:

$$G(x,y) = \max(G_S^n(x,y)),\ n = \{1,2,3,4\}. \quad (2)$$

Fig. 2(a)-2(d) present the structure variation maps of Figs. 1(a)-1(d). Next, we propose to utilize the weighting pooling by considering the distortion characteristics of SCIs. Specifically, we first process the I with a Gaussian blur operation. Then, the gradient similarity G_f between I and the Gaussian-blurred version I_2 is computed by:

$$G_f(x,y) = \frac{2\cdot G_0(x,y)\cdot G_b(x,y)+T_2}{G_0(x,y)^2+G_b(x,y)^2+T_2} \quad (3)$$

Here, T_2 is set as 1 empirically. G_b is the gradient magnitude of I_2. To emphasize the importance of the edge surrounding region, the weighting map G_w is calculated as $G_w = 1\text{-}G_f$. Fig. 4(a)-4(d) present weighting maps of Figs. 1(a)-1(d). In the end, the quality of a test SCI can be estimated by pooling the structure variation map with the weighting map:

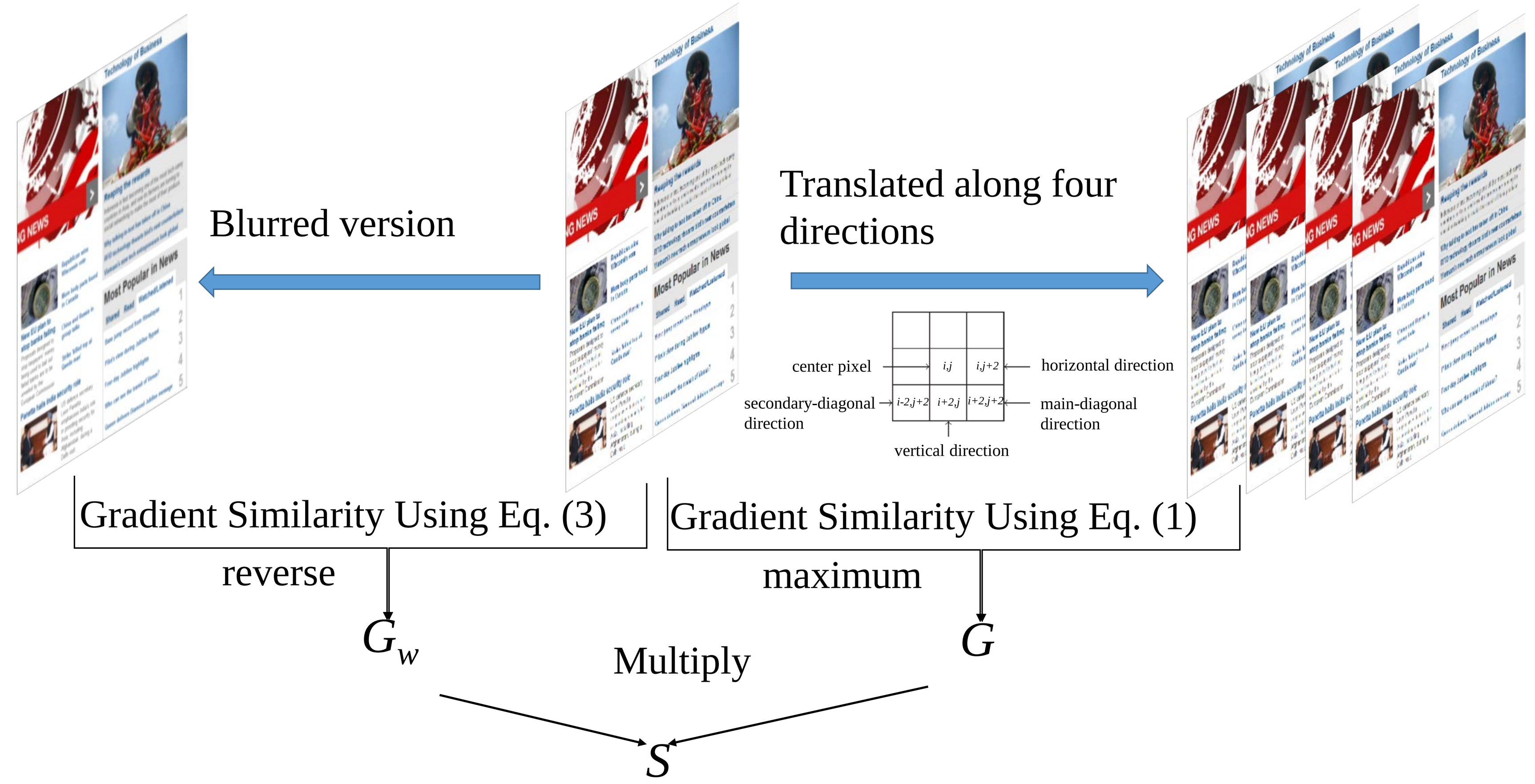

Fig. 3 Framework of the proposed method.

$$S = \frac{\sum_{(x,y)\in A} G(x,y)\cdot G_W(x,y)}{\sum_{(x,y)\in A} G_W(x,y)} \quad (4)$$

where A is the pixel coordinate set of the test SCI.

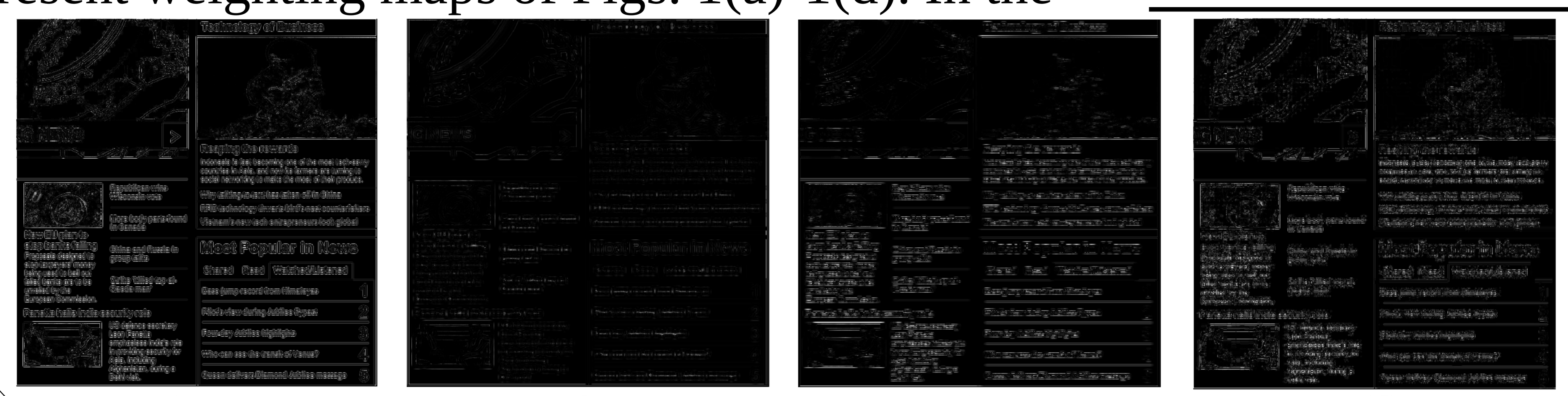

Fig. 4 Illustration of the weighting map. (a)-(d) are the weighting maps of Figs. 1(a)-1(d), respectively. As seen, the edge surrounding region is arranged with high importance. A higher gray value denotes to higher gradient similarity.

Results on SIQAD database

Table 1. Performance Comparisons.

Method	Type	PLCC	SRCC	KRCC	RMSE	Time (s)
FSIM [19]	FR	0.591	0.582	0.425	11.551	0.762
MAD [23]	FR	0.619	0.607	0.461	11.241	0.718
GSIM [15]	FR	0.569	0.548	0.405	11.775	0.117
GSS [5]	FR	0.846	0.836	0.639	7.631	1.168
SFUW [17]	FR	**0.891**	**0.880**	-	**6.499**	-
SIRR [6]	RR	0.754	0.729	-	9.403	-
Wang [22]	RR	**0.801**	**0.766**	0.576	**6.802**	-
NIQE [24]	NR	0.341	0.370	0.255	13.467	0.070
IL-NIQE [25]	NR	0.388	0.322	0.228	13.206	20.994
BQMS [13]	NR	0.755	0.722	0.530	9.304	9.038
Proposed	NR	**0.768**	**0.734**	**0.545**	**9.173**	**0.016**