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Reduced-reference image quality assessment based on distortion families of local perceived sharpness

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A R T I C L E I N F O

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A B S T R A C T

Previous research on reduced reference (RR) image quality assessment (IQA) suggested that appropriate RR features should provide efficient summaries of reference images and be sensitive to a variety of image distortions. The multi-scale local sharpness maps are effective RR features because they can capture smooth, edge, and textured areas of the reference image, and they are affected differently by different distortion types. Motivated by this observation, in this paper, we propose an efficient RR IQA algorithm using local sharpness. Our method, called S4RR, employs four sharpness maps (two FISH maps and two local standard deviation maps) to assess image quality via two main stages. The first stage soft-classifies the distorted image into eight distortion families based on an analysis of the different scatter-plot shapes of the sharpness map values of distorted image vs. reference image. The second stage performs distortion-family-specific quality assessment based on measuring the local sharpness variations between reference and distorted images by using seven types of local statistics and six distance measures. Finally, the soft-classification probabilities computed from the first stage are combined with the distortion-family-specific quality scores to yield a class-weighted average, which serves as the final S4RR quality index. Experiment results tested on various databases show that with less than 5% RR information, the proposed S4RR algorithm achieves better/competitive performance as compared to other state-of-the-art FR/RR IQA algorithms.

1. Introduction

The ability to assess image quality in a manner that is consistent with human subjective ratings of quality is an important task for many image processing systems. Over the last several decades, algorithms for image quality assessment (IQA) have been intensively researched and developed. An IQA algorithm can be classified into three main categories: (1) full-reference (FR), in which the algorithm's inputs are the reference and distorted images; no-reference (NR), in which the algorithm needs only the distorted image; and (3) reduced-reference (RR), in which partial information about the reference image is made available and compared to the input distorted image. IQA research has recently been shifting more towards the NR/RR categories, due to the often impractical requirement of providing the full reference image, particularly in streaming applications. Although NR IQA algorithms have yet to outperform state-of-the-art FR IQA algorithms, modern RR IQA algorithms have begun to approach the performance of FR IQA.

Research on RR IQA has primarily focused on finding appropriate *RR features* that can summarize the reference image while being sensitive to a variety of image distortions. Although it is challenging to determine the type and amount of information to use for RR features, many effective RR algorithms have been developed. These approaches can be roughly classified as those which: (1) use changes in natural-scene-statistics (NSS) [1–3]; (2) calculate differences in transform domain coefficients [4–8]; (3) calculate differences in other features [9–11]; or (4) those which create reduced versions of FR algorithms [12–16].

Despite the difference of the NSS models, image transforms, and the RR features employed, previous approaches to RR IQA have generally been limited in two ways: they are either limited by the number of distortion types on which they can operate (typically up to four common distortion types such as additive white Gaussian noise, Gaussian blur, JPEG, and JPEG2000), or limited in their ability to achieve high quality estimate performance because of the small number of features/scalars used as the reduced information. These distortion-specific RR [9–11] and some other NR algorithms [17,18] have attempted to be generic by combining techniques for analyzing more distortion types. However, they have not been tested on a wide variety of distortion types, such as the numerous distortion types in the TID2008 [19] and TID2013 [20] databases.

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Some other RR algorithms employ from a few to a hundred scalars for the reduced information, and yet can achieve performances only at the level of MSE/PSNR. More recently, Soundararajan et al. [16], and Liu et al. [21] provided two RR algorithms, RRED and SPCRM, respectively. These algorithms have been reported to achieve better performance by increasing the amount of reduced information. When utilizing 2.8% and 3.1% (in terms of scalar numbers) reduced information (for RRED and SPCRM, respectively), these algorithms are nearly as good as current state-of-the-art FR algorithms such as MS-SSIM [22], VIF [23], MAD [24], or FSIM [25] on many large image databases (TID2008 [19], LIVE [26], CSIQ [27]). However, we believe that with appropriate features, RR algorithms can be even better than FR algorithms, particularly considering that humans often do not require full information about the reference image to assess the quality of a distorted image. Therefore, we seek an RR approach that can (1) operate on a wider range of distortion types; (2) be competitive and/or outperform state-of-the-art FR/RR IQA algorithms; and (3) require equal/less amount of reduced information.

In this paper, we present a new RR IQA algorithm that estimates quality based on an analysis of the local sharpness differences between the reference and distorted images. Previous work on image sharpness has focused on developing a sharpness index, a single value that quantifies the overall sharpness of an image (e.g., [28–33] etc.) Some algorithms also generate sharpness maps that quantifies the perceived sharpness of different local areas within an image, and these maps have been used for NR IQA of Gaussian blurred images [32,33] and JPEG2000 compressed images [34]. In our work, the sharpness features are employed for RR IQA of images that contain more general distortion types.

The proposed algorithm, which we called S4RR, employs four sharpness maps for feature extraction: (1) the luminance-based Fast wavelet-based Image SHarpness (FISH) map, (2) the downsampled local lightness distance based (LLD-based) FISH map, (3) the original-scale local standard deviation (LSD) map, and (4) the downsampled-scale LSD map. We argue that changes in these sharpness maps can effectively capture the perceived distortions as long as such changes are quantified in a manner that adapts to different *distortion families*. What makes this approach a good candidate for RR IQA is the fact that sharpness maps can provide efficient summaries of the reference images and are sensitive to a variety of image distortions. This notion is demonstrated in Figs. 1 and 2. As shown in Fig. 1, the reference image and four distorted images are shown in Row (a) with four common distortion types: additive Gaussian noise, Gaussian blur, JPEG compression, and JPEG2000 compression. Rows (b)-(e) show the four sharpness maps for each of the five images, respectively. Fig. 2 shows the luminance-based FISH maps for the four distortion types at three different levels of distortion. Observe that different distortion types and levels produce different sharpness maps. Therefore, it is possible to estimate the quality degradation by measuring the deviations in these distorted sharpness maps from the reference sharpness maps.

Based on the four sharpness maps, S4RR operates via two main stages. The first stage performs distortion identification. Unlike many of the previous NR IQA works (e.g., [17,35,18], etc.) that treat individual distortions as separate classes, we propose in this paper the concept of *distortion families* and each distortion family consists of one or more distortion types that display considerable similarity regarding to certain properties (for example, different types of the noise-corrupted images can be clustered into one distortion family, as they are all distorted by the noise). Consequently, in this stage, 30 classification features are extracted from the two FISH maps (luminance-based and LLD-based) and are fed into a classifier, which estimates the probability that the image is afflicted by one of the multiple distortion families. To be more specific, we build eight distortion families from the 24 distortion types in the TID2013 database [20] based on the scatter plots of the sharpness

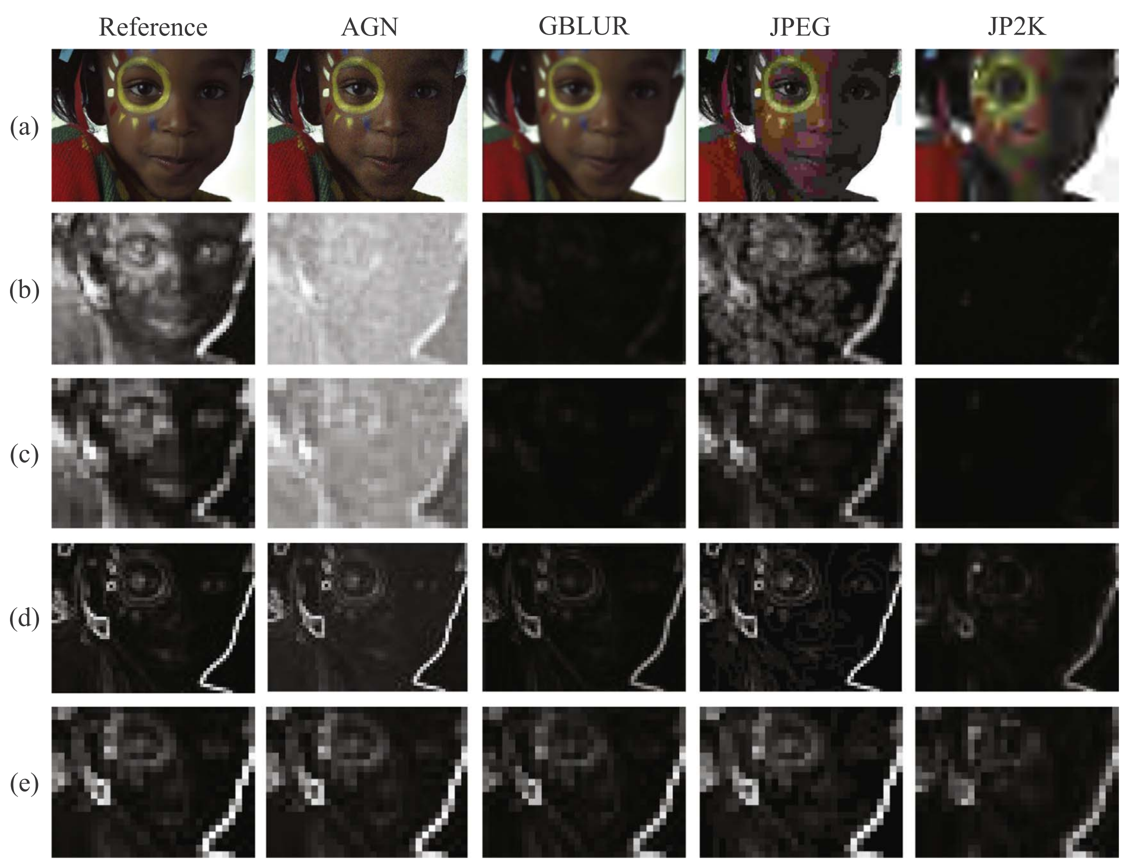

Fig. 1. One reference image ("I15.bmp") and its four distorted versions (row *a*) from the TID2013 database [20] used to demonstrate that sharpness maps are sensitive to different distortion types. Rows *b*, *c*, *d*, and *e* show the four sharpness maps respectively.