Int. J. Electron. Commun. (AEÜ) 69 (2015) 75–81

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

Monogenic signal theory based feature similarity index for image quality assessment

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ARTICLE INFO

Article history:
Received 12 December 2013
Accepted 24 July 2014

Keywords:
Image quality assessment (IQA)
Monogenic phase congruency (MPC)
Human visual system
Feature similarity index

ABSTRACT

Image quality assessment (IQA) aims to establish generic metrics consistently with subjective evaluations using computational models. Recent phase congruency, which is a dimensionless, normalized feature of a local structure, is used as the structure similarity feature. This paper proposes a novel feature similarity index that is Riesz transform based monogenic phase congruency feature similarity index (RMFSIM). RMFSIM is based on monogenic signal theory for full reference IQA. Monogenic phase congruency (MPC) map, instead of phase congruency map, is constructed utilizing the local phase, the local orientation and the local energy information of the 2D monogenic signal. The corresponding 1st-order and 2nd-order coefficients of the MPC map are obtained by Riesz transform. The local feature coefficients similarities are computed by the similarity measure, and then a final single quality score is derived from weighting feature coefficients similarities. Experimental results demonstrate that the proposed similarity index is highly consistent with human subjective evaluations and achieves good performance with the existing state-of-the-art methods in terms of prediction monotonicity and accuracy.

1. Introduction

Digital image suffers inevitably from a wide variety of distortions in the process of collection, processing, compression, storage, and transmission. Due to the different levels of image quality decline, it is hard to obtain real image. Numerous applications, such as image acquisition, image transmission, image compression, image restoration, and image enhancement, are severely affected. Therefore, image quality assessment (IQA) plays a major role in numerous computer vision and image process applications.

In general, there are two categorizations of IQA methods: subjective method and objective method. According to human visual system (HVS), subjective IQA metric, which is the most reasonable IQA metrics, estimates image quality by many observers to participate in image manually interpretation. However, it is not suitable for some important scenarios such as real-time and automated systems. Objective IQA measurement uses a mathematical model to calculate the similarity index by quantizing the distortion image and the reference image to obtain the evaluation results, which is a simple and easy IQA metric. There are some distinct advantages, for instance, embedding real time image processing system. According to the degree of dependence on the reference image, there are three categorizations of objective IQA methods: full reference (FR), reduce reference (RR) and non-reference type (NR).

Mean squared error (MSE) and peak signal-noise ratio (PSNR) are two general kinds of traditional algorithms for full reference image quality assessment. Since these algorithms do not consider the interdependence of pixels, the structure correlation between pixels and the characteristics of human visual perception, evaluation results of which are not consistent with subjective evaluation results, their results are unreliable for objective image quality assessment.

In order to achieve metrics conform to human visual evaluation, a lot of evaluation methods based on visual features were proposed, depending on sensitivity of the visual signals (such as brightness, contrast and spectrum) of the human visual system. Representative metrics are visual signal to noise ratio (VSNR) [1] and visual information fidelity (VIF) [2]. Although these methods accord with the result of subjective evaluation, it is still very limited to human understanding of HVS. The most widespread method for FR-IQA is structural similarity index [3] (SSIM) by the luminance, contrast and structure comparison images obtained from the reference and distortion images. Experimental results from [3] show that it is

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http://dx.doi.org/10.1016/j.aeue.2014.07.015
1434-8411/

more consistent with HVS than PSNR and MSE but less effective for badly blurred and noisy images. Recently, numerous extensions of SSIM have been developed, such as multi-scale SSIM (MS-SSIM) index [4], complex wavelet structural similarity (CW-SSIM) index [5] and four-component SSIM [5], which to some extent improve the performance of the measure. Feature-similarity (FSIM) index is proposed by Zhang et al. [6], which used the phase congruency (PC) as the primary feature and the gradient magnitude (GM) as the secondary feature to obtain the local quality map and weighted by PC to derive a single quality score. Due to invariance to lighting conditions of PC [14], the performance of FSIM is superior to the performance of SSIM and the other variants by experimental results using six databases.

However, for this reason PC is highly sensitive to noise, it results in lowering precision of the localization of feature derived from phase congruency. FR-IQA using PC based image features is booming as the traditional PC algorithm used some noise removal technique is less sensitive to noise to some extent. But the remaining noise still has negative effects on localization of features. This drawback has a strong impact on performance of FR-IQA, for instance, FSIM.

In this paper, a novel feature similarity (RMFSIM) index for full reference IQA is proposed based on monogenic signal theory by FSIM inspired. Firstly, a MPC map that is relatively insensitive to noise is presented. Then the corresponding 1st-order and 2nd-order feature coefficients of the MPC map are obtained by Riesz transform. The local amplitude, phase and orientation feature similarities of monogenic signal of image and corresponding 1st-order and 2nd-order Riesz transform feature coefficients similarities are computed by a similarity measure, and a single final quality score is derived from weighting similarities finally. Experimental results demonstrate that the proposed similarity index is highly consistent with human subjective evaluations and achieves good performance in terms of prediction monotonicity and accuracy.

2. Monogenic signal theory

We now briefly describe the important theoretical basis, namely, Riesz transform and the monogenic signal, and expatiate on a novel measure of PC called monogenic phase congruency. These are described in the following section.

2.1. Riesz transform

The Hilbert transform of a 1-D function has been widely used in signal processing since Gabor proposed the analytic signal. The Hilbert transform $H[g(t)]$ of a signal $g(t)$ is defined by the following convolution integral [7]:

$$H[g(t)] = g(t) * \frac{1}{\pi t} \xrightarrow{FT} -j\,\mathrm{sgn}(\omega)G(\omega) \tag{1}$$

where * stands for the convolution, *FT* means Fourier transform, $G(\omega)$ is the Fourier transform of $g(t)$ and $\mathrm{sgn}(\omega)$ is the sign function.

However, problems occurring in image processing applications based on 2-D signal processing cannot be solved by Hilbert transform. Therefore, the Riesz transform, which is the natural multidimensional signal representation of the 1-D Hilbert transform [8], was proposed. It is the scalar-to-vector signal transformation whose frequency response is $-j\omega/\|\omega\|$. In 2-D space, given the input signal $f(\boldsymbol{x})$ with $\boldsymbol{x} = \{x_1, x_2\}$, by using the well-known property that $G\{1/\|x\|\}(\omega) = 2\pi/\|\omega\|$ and performing a partial differentiation with respect to x_1 or x_2, we readily derive the corresponding impulse responses $R_{x_1} = x_1/2\pi\|x\|^3$ and $R_{x_2} = x_2/2\pi\|x\|^3$; the 1st-order and 2nd-order Riesz transform of $f(\boldsymbol{x})$ can be expressed as

$$\begin{pmatrix} R_{x_1}(f) \\ R_{x_2}(f) \end{pmatrix} = \begin{pmatrix} R_{x_1} * f(x) \\ R_{x_2} * f(x) \end{pmatrix} = \begin{pmatrix} \dfrac{x_1 f(x)}{2\pi(x_1^2+x_2^2)^{3/2}} \\ \dfrac{x_2 f(x)}{2\pi(x_1^2+x_2^2)^{3/2}} \end{pmatrix} \tag{2}$$

$$\begin{cases} R_{x_1x_2}(f) = R_{x_1} * R_{x_2}(f) \\ R_{x_1x_1}(f) = R_{x_1} * R_{x_1}(f) \\ R_{x_2x_1}(f) = R_{x_2} * R_{x_1}(f) \end{cases} \tag{3}$$

Since higher order Riesz transforms are beneficial to analyze 2-D image structures [9], the coefficients of the 1st-order and the 2nd-order Riesz transforms are utilized to obtain important features of MPC in our metric. The 1st-order Riesz transform $R_{x_1}(f)$ and $R_{x_2}(f)$ can be obtained with Eq. (2), the 2nd-order Riesz transform $R_{x_1x_1}(f)$, $R_{x_1x_2}(f)$ and $R_{x_2x_2}(f)$ can be obtained with Eq. (3).

2.2. The monogenic signal

The monogenic signal which is the third generalization of the analytic signal was introduced by Felsberg in 2001 [10]. It is considered to be a multi-dimensional extension of the analytic signal. The monogenic signal $\mathbf{f}_m$ of an image $f(\boldsymbol{x})$ is defined as the combination of f and its Riesz transform.

$$\mathbf{f}_m(x) = \{f(x), R_{x_1} * f(x), R_{x_2} * f(x)\} \tag{4}$$

The local amplitude (energy) and the local phase of $f(x)$ over scale s can be expressed by Eqs. (5) and (6)

$$\mathbf{A}_s(x) = \left\|\mathbf{f}_m(x)\right\| = \sqrt{f_s^2(x) + (R_{x_1} * f_s(x))^2 + (R_{x_2} * f_s(x))^2} \tag{5}$$

$$\varphi_s(x) = -sign(R_{x_1} * f_s(x))a\tan^2(f_s(x), R) \tag{6}$$

where $R = \sqrt{(R_{x_1} * f_s(x))^2 + (R_{x_2} * f_s(x))^2}$.

The local orientation over scale s can be calculated as

$$\theta_s(x) = a\tan\left(\frac{R_{x_2} * f_s(x)}{R_{x_1} * f_s(x)}\right) \tag{7}$$

The monogenic signal has a representation that is invariant and equivalent with respect to energetic and structural information, which is the orthogonal decomposition of the 2-D image by quadrature (mirror) filters. Since energy and structure are independent information, the local phase only changes if the local structure varies and structural information is invariant with respect to the local energy of the signal [10].

2.3. Phase congruency

Phase congruency (PC) is a perceptually significant image feature detection method that is dissimilar to the method based on gradient in spatial domain. Step features can only be detected using gradient, but phase congruency correctly detects features for all kind of phase angle, and not just step features having a phase angle of 0 or 180°. Features of signals are consistent with those points where phase congruency or similarity is maximum using the phase information of signals. It is immune to illumination and contrast for feature detector.

Denote by M_s^e and M_s^o the even- and odd-symmetric filters on scale s, and they form a quadrature pair [9]. Responses of each quadrature pair to the signal will form a response vector at position x on scale s: $[e_s(x), o_s(x)] = [f(x) * M_s^e, f(x) * M_s^o]$, so the local amplitude $A_s(x)$ can be obtained by $\sqrt{(e_s(x)^2 + o_s(x)^2)}$, and