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Illumination preprocessing for face images based on empirical mode decomposition

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ABSTRACT

The Empirical Mode Decomposition (EMD) can adaptively decompose a complex signal into Intrinsic Mode Functions (IMFs) that are relevant to intrinsic physical significances, therefore is a powerful tool for multi-scale analysis of non-stationary signals. Towards restoring a frontal-illuminated face from a single image, in this paper we study the usage of EMD for manipulating the illumination issue on face images. We propose an EMD-based algorithm to extract the illumination-insensitive facial features. We also come up with an EMD-based scheme to detect the shadows and to reduce the effects of shadows on face images. By preserving the intrinsic facial features as well as lessening the shadows, it is more likely to restore the frontal-illuminated face image with good visual quality from a single image. Experiments verify the effectiveness of the proposed methods.

1. Introduction

It is a well-known fact that the variations in illumination could seriously affect the performance of face recognition and face image processing algorithms. Therefore, illumination normalization is a central issue in face recognition and face image processing. In this paper, we are interested in the issue of restoring a frontal-illuminated face image, which is a very difficult mission since it is hard to remove the person-specific shadows.

A good face restoration algorithm should retain facial features meanwhile should preserve the identity of a subject. To achieve these properties, an effectual approach is to extract and keep the intrinsic facial features separately. To get the illumination-insensitive facial representation, variant time-frequency analysis methods are often employed, including the wavelet transform [1,2], the weighted Gaussian filtering [3], the Gabor transform [4], the total variation model [5], the discrete cosine transform [6], the contourlet transform [7], the discrete Fourier transform [8], and the independent component analysis (ICA) [9]. Most of these methods use the frequency filters that heavily rely on the pre-determined basis functions designed artificially (e.g., for the Fourier transform, the wavelet transform, the Gabor transform, and the cosine transform) or learned from a dataset (e.g., for the ICA). While these pre-determined basis functions are in very limited modalities and are not adaptive to the signal to be analyzed, they are not optimal for discovering different physical components from a face image. Especially, the reflectance and the illumination implied in a face image seem to be non-stationary. In order to address this problem, we have developed the Empirical Mode Decomposition (EMD) based feature extraction algorithm for grasping the ever-changing light factor on images. Superior to other frequency filters, EMD can adaptively decompose a complex signal into intrinsic mode functions (IMFs) that are relevant to intrinsic physical significances.

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Many methods have been proposed for the restoration of the frontal-lit face image from a single image, such as the Spherical Harmonic Basis Morphable Model (SHBMM) [10], QI relighting algorithm [11,12], and the Illumination Transition Image (ITI) based method [13]. Existing methods often work under the assumption of a Lambertain surface with no shadows. For the image with shadows, the performances of existing algorithms may drop obviously. Therefore, it is better to eliminate shadows before synthesizing the frontal-illuminated face image. However, completely separating shadows from facial features based on a single face image is still an unsolved problem. In this paper, we come up with an EMD-based scheme to detect shadows and to weaken the shadow effect.

The EMD was first introduced by Huang et al. [14]. It shares with wavelets the quality of being a multi-scale technique, but one in which information at different scales is captured by so-called intrinsic mode functions (IMFs) that are constructed in an adaptive (i.e., data-driven) manner. Due to the non-parametric and data-driven advantages, EMD has been found many successful applications in a diverse collection of subjects, ranging from biological and medical sciences to geology, astronomy, engineering, and others [15–17].

EMD has also been suggested to address the illumination variation problem in a face recognition system [18–21]. Zhang et al. apply the EMD on a face image directly and then select the most high-frequency IMF [19] and the phase congruency [21], respectively, as facial features for recognition. Bhagavatula et al. proposed a method to determine the IMF responsible for the effects of shadowing, and then to reconstruct the image by discarding that IMF so as to remove the illumination artifact [18]. Sun et al. proposed combining the EMD and the Dual-Tree Complex Wavelet Transform (DT-CWT) to remove the illumination [20]. In this paper, we will show that the direct application of EMD in the image domain cannot grasp the illumination effect very well since this manner is not consistent with the physical imaging model.

Based on the Lambertain reflectance model, we will present an effective method of using EMD for light analysis on face image in the logarithm domain. As our observations, the facial features are almost kept in the two most high-frequency IMFs while the shadows always appear in the remaining IMFs and residue. Accordingly, we propose extracting facial features, detecting and lessening shadows on different sub-bands respectively. Note that our illumination-preprocessing method works towards preserving facial features as well as reducing the effects of shadows rather than restoring a frontal-illuminated face images directly. We will demonstrate the help of the proposed preprocessing method for existing face restoration algorithms, especially on the face images with extreme variations in illumination.

The rest of this paper is organized as follows. In Section 2, the EMD is reviewed. In Section 3, we describe how to extract the illumination-insensitive facial representation by using the proposed logarithmic EMD algorithm. In Section 4, we introduce the method of reducing the effect of shadows on face images based on EMD. In Section 5, two representative methods of restoring the frontal-illuminated face images are presented. The experimental results are shown in Section 6 and the conclusion is shown in Section 7.

2. Review of the Empirical Mode Decomposition (EMD)

In this section, we briefly introduce the EMD. The EMD was first introduced by Huang et al. [14] as a tool to adaptively decompose a signal into a collection of Intrinsic Mode Functions (IMFs). It relies on a fully data-driven mechanism that does not require a priori known basis. Therefore, EMD is especially well suited for analyzing non-linear and non-stationary signals like biometric signals.

A function is defined as an IMF if the number of its extreme equals the number of zero-crossings and if it has a zero local mean. What is important is that IMFs may stand for different intrinsic physical significances hided in the original signal. The EMD is to decompose a signal into such a set of IMFs. In mathematical, the EMD for a signal f can be formulated as

$$f = \sum_{k=1}^{K} d_k + r \tag{1}$$

where $\{d_k\}$ are the IMFs of different frequencies (from higher to lower frequency with respect to the increasing of k), and r is the residue. An EMD may be implemented by using the following algorithm [14]:

(i) Find all local extrema of f;
(ii) Interpolate between all minima (maxima) to get an envelope $e_{\min}$ ($e_{\max}$) and compute the mean envelope $m(t) = (e_{\min}(t) + e_{\max}(t))/2$;
(iii) Extract detail $d(t) = f(t) - m(t)$;
(iv) Check if $|m(t)| < \varepsilon$ for all t; if so, d is an IMF; else, repeat steps (i)–(iii) via replacing f by d;
(v) Calculate residual $r(t) = f(t) - d(t)$;
(vi) Go to step (i) with using r as f;
(vii) Repeat until signal has no extrema.

An illustration of steps (i)–(iii) is shown in Fig. 1. An example of EMD on the electrocardiogram signal is shown in Fig. 2. As shown, the EMD gives a fairly good breakdown of different causation parts of the total composite heartbeat, especially in the 3rd IMF, where each heartbeat has been identified as a single entity.[2]

While the EMD is originally come up with to process a 1-D signal [14], some 2D EMD algorithms have also been proposed to handle 2D signals [22–24]. Specially, authors in [24] present a 2D EMD based on Delaunay triangulation and cubic interpolation. This algorithm takes into account the geometry while preserving a low computational cost. In our experiments, we decompose the image in two ways, respectively, (1) rearranging the image as a 1-D vector and then employing the 1-D EMD algorithm; (2) using the direct 2D EMD algorithm in [24]. Fig. 3 illustrates the results of EMD for a face image by using different methods.

[2] The raw data is downloaded from https://www.clear.rice.edu/elec301/Projects02/empiricalMode/code.html.