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Hybrid facial image feature extraction and recognition for non-invasive chronic fatigue syndrome diagnosis

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ABSTRACT

Due to an absence of reliable biochemical markers, the diagnosis of chronic fatigue syndrome (CFS) mainly relies on the clinical symptoms, and the experience and skill of the doctors currently. To improve objectivity and reduce work intensity, a hybrid facial feature is proposed. First, several kinds of appearance features are identified in different facial regions according to clinical observations of traditional Chinese medicine experts, including vertical striped wrinkles on the forehead, puffiness of the lower eyelid, the skin colour of the cheeks, nose and lips, and the shape of the mouth corner. Afterwards, such features are extracted and systematically combined to form a hybrid feature. We divide the face into several regions based on twelve active appearance model (AAM) feature points, and ten straight lines across them. Then, Gabor wavelet filtering, CIELab color components, threshold-based segmentation and curve fitting are applied to extract features, and Gabor features are reduced by a manifold preserving projection method. Finally, an AdaBoost based score level fusion of multi-modal features is performed after classification of each feature. Despite that the subjects involved in this trial are exclusively Chinese, the method achieves an average accuracy of 89.04% on the training set and 88.32% on the testing set based on the *K*-fold cross-validation. In addition, the method also possesses desirable sensitivity and specificity on CFS prediction.

1. Introduction

Chronic fatigue syndrome (CFS) is a persistent weakened condition associated with a variety of somatic and psychological symptoms [1]. The socio-economic impact of CFS is substantial given the chronic nature and seriousness of the illness. Chronic fatigue syndrome (CFS) is a condition characterized by impairment of neurocognitive functions and quality of sleep and of somatic symptoms such as recurrent sore throat, muscle aches, arthralgia, headache, and post exertional malaise [1]. The precise pathophysiology of this condition is currently unknown. In addition, there is no clear consensus with regard to changes in blood composition or genetic factors, such as polymorphisms, which may predispose certain individuals to CFS [2]. Therefore, due to the absence of reliable biochemical markers, currently, the diagnosis of CFS is based on clinical symptoms alone [3]. As this diagnostic procedure relies on the experience and skills of the individual making the judgment, CFS can be accurately diagnosed by only a limited number of skilled medical practitioners [3]. The most commonly used criteria for CFS is defined by the Centres for Disease Control and Prevention (CDC) [1] and is often criticized for being too inclusive and putting insufficient emphasis on cognitive dysfunction, abnormal fatigability and post exertion malaise [4]. Consequently, an additional non-invasive diagnostic method that enables objective judgment to be made is urgently needed [3].

Roberts et al. [5] found that CFS patients had a lower cortisol response to awakening and used the salivary cortisol response to awakening to assess hypothalamic–pituitary–adrenal (HPA) axis to form a non-invasive diagnosis method of CFS, but there are several diseases that can cause cortisol response decrease, such as hypothyroidism. Hence, it is more suitable for this method to play a role as a non-invasive screening method for CFS.

Li et al. [6] found that essential qi and spirit, colour and texture of the face, eye and lip have distinct differences after they had observed 1169 patients in chronic fatigue. Xu et al. [7] analysed the skin colour of the forehead, two cheeks and the nose, chin and lips based on CFS patients' face images. They concluded that the visual difference between the faces of CFS patients and healthy people can be used to diagnose CFS.

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Actually, image processing technology has been used to recognize driver fatigue. However, most existing methods focus on analysing blink [8–10], gaze [8], yawn [11–13] and a combination of such factors [8,14,23]. Features that identify driver fatigue include percentage of eye lid closure over the pupil over time (PERCLOS), Average Eye Closure Speed (AECS), Gaze distribution (GAZEDIS), Percentage of Saccade (PERSAC) and Yawn Frequency (YawnFreq). Some researches have been done on drowsiness related facial expressions [15–17]. The method proposed in [17] represents a class of main methods. They extract the features of the entire face, decrease the dimensionality of the features and recognize fatigue by machine learning algorithms. In the researches mentioned above, outstanding facial behaviours, like eye blinking and yawning, etc., are regularly used as indicators for fatigue detection. However, these features do not present so obviously in a chronically fatigued person [2], so there is a need to find other facial features to substantially represent chronic fatigue and to develop a new method to detect CFS with these features.

The facial appearances of a chronically fatigued individual and a fatigued driver have both similarities and differences. Most fatigued drivers' faces appear to be drowsy. However, facial appearance of a chronically fatigued individual seems to be in long-term and chronic change according to the opinions of physicians and Chinese medicine experts.

Neu et al. [18] found that, in addition to fatigue, CFS patients presented with higher affective symptom intensity and worse perceived sleep quality. Polysomnography shows more slow-wave sleep and micro-arousals in CFS but similar sleep time, efficiency and light-sleep durations compared to controls.

In improving recognizing accuracy, fusion of hybrid facial features performs more effectively than unimodal system [25,35,36]. Sim et al. [35] combined face and iris biometric traits with the weighted score level fusion technique to deal with non-ideal scenarios such as off-angles, reflections, expression changes, variations in posing, or blurred images. Eskandari et al. [36] applied particle swarm optimization (PSO) and backtracking search algorithm (BSA) to select optimized features and weights, achieved a robust recognition system by fusion of the multimodal biometric system and optimizing the weights assigned to each sub-system. Therefore, in this paper, we propose a Hybrid Appearance (HA) feature extracting and processing method for computer aided non-invasive diagnosis of CFS. The HA feature consists of colour, texture and shape features of different facial regions. The HA feature comes from observations of traditional Chinese medicine (TCM) experts on faces of CFS patients. We compare our HA feature with the Gabor features from Eye region, lower Eye lid region and Mouth region (EEM) presented in [8]. The cross-validation results on the training set demonstrate that HA feature obtained a more ideal error rate than EEM features. Based on the same HA feature and score level fusion approach, we compare principal component analysis (PCA) [20], locality preserving projection (LPP) [21] and manifold preserving projections (MPP) on the testing set. The results also show that the proposed method possesses benefits of excellent sensitivity, specificity and accuracy.

Table 1
Facial appearance features of CFS patients and healthy people.

Facial regions	Chronic fatigued individual	Healthy individual
Forehead	More grey	Less grey
	Vertical striped wrinkles	No vertical striped wrinkles
Lower eye lid	Puffiness	Less puffiness
Cheek and nose	Less reddish	More reddish
Mouth corner	Down	Up or straight

The rest of this paper is organized as follows. Section 2 presents the hybrid features identification procedure and the acquisition methods, including feature identification, image pre-processing, facial region segmenting and feature extraction for each region. Section 3 describes the feature reduction and fusion approach. Section 4 carries out the experimental results of different feature and different method.

2. Hybrid feature identification and extraction

Some CFS people are associated with sleep disorders; however, others are not. This study focuses on the former case.

2.1. Feature identification

After one year's cooperation with several traditional Chinese medicine experts, we found that CFS individuals and healthy ones with yellow skin have the following key differences in facial appearance when they have a neutral expression, as shown in Table 1.

2.2. Image pre-processing and feature extraction

2.2.1. Image pre-processing and adaptive facial region segmenting

The obtained face images are pre-processed through two steps:

1. Image normalization
   The pictures are acquired by a Nikon COOLPIX L21 camera with a fixed distance from the subjects. The subjects are asked to look into the camera, and some extra requests are made to ensure relatively perfect frontal images, such as a decorous pose and a neutral expression. The images are normalized to make the two eyes and the vertical coordinate of the mouth aligned. Then images are cropped to the size of 640×640, after face detecting [22] and feature points locating [26].
2. Illumination calibration

The illumination calibrating operation is based on quotient image, the ratio of different face albedo, which is constant and less sensitive to variable light sources [24]. Suppose I_y and I_a represent two facial images of tested person y and standard person a respectively, the quotient image Q_y is expressed by $Q_y = I_y / I_a$. Given three images (I_1, I_2, I_3) under three different illumination conditions of standard person a, we can reconstruct the image of tested person y under target light source c by $I_y^c = \sum_{i=1}^{3} (I_i * x_i^c) \otimes Q_y$, where I_y^c is an image of person y under the illumination condition c, and I_1, I_2, I_3 are three illuminated images, x_i^c is the projection coefficient under light source c, and $\otimes$ is the Cartesian product.

The estimation of Q_y is described in detail in literature [24], where minimal energy function is used on a training matrix $A = [A_1, A_2, \ldots, A_n]$ to calculate $\overline{A}$, which is used in formula $Q_y = I_y / \overline{A} x$.

After pre-processing of images, the facial regions are selected according to the TCM experts' opinions on which facial regions can reflect appearance changes on CFS individuals. We add 12 active appearance model (AAM) feature points and ten straight lines across those points to ensure an adaptive segmenting of facial regions as can be seen from Fig. 1(a). Consequently, the problems of hair obstacle and face size diversity can be avoided, and the image normalization is simplified. The 12 feature points are selected from the 26 AAM feature points presented in [26], which are also shown in Table 2. The 12 feature points can be detected and tracked using the method proposed by Yi et al. [26]; hence, the ten straight lines can be located based on those points and used as an alignment for boundaries of facial regions. As can be