

Wrinkle detection system based on active appearance model

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Abstract

The facial wrinkle is a important feature of facial expression, automatic wrinkle detection has been an important topic in recent most works. Many wrinkle detection works focusing on detecting forehead wrinkle line, which are linear shapes, whereas cheek wrinkle lines has not been deeply studied, because of their shape complexity. In this paper presented an effective algorithm for automatic detection of wrinkle line, which largely consist of active appearance model based on wrinkle structure location. The proposed wrinkle detector is applied for real time application to identify early Stroke symptoms. Using unique initial shape instead of active appearance model mean shape, our experimental result got more accurate results than another shape models methods. Experimental results illustrated the competitiveness of the proposed method in detecting wrinkle lines with 92% accuracy.

Keyword : wrinkle detection, active appearance model, Hessian matrix, Stroke detection.

1. Introduction

Nowadays one of the dangerous disease is Stroke. A stroke occurs when the blood supply in the part of your brain is interrupted or decreases, preventing the brain tissue from receiving oxygen and nutrients. Brain cells begin to die in a few minutes. Stroke is an emergency medical care, and immediate treatment is critical [1]. Early action can reduce brain damage and other complications. According to the American Stroke Association [2] the early symptoms of Stroke are facial asymmetry and motion activities. In our work we focused detecting Stroke using cheek wrinkle line, because of facial asymmetry the wrinkles line of Stroke patient bending. In the past few years, wrinkles have been used in many studies, and researchers have created various methods. However, each method has its own strengths and weaknesses.

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Current wrinkle detection methods focused on detecting active wrinkle positions as forehead wrinkles [3][4], but detecting passive wrinkle position as cheek wrinkles is not effective with previous methods. The cheek wrinkles is more complicated and challenging.

The paper has two main objectives. Firstly, detecting cheek wrinkle line by creating wrinkle model. Secondly, develop Stroke warning application using above model.

The main contribution of this work is summarized as follows: 2. Related Work, 3. Proposed Method. 4. Experimental results.

2. Related Work

The FAST (face drooping, arm weakness, speech difficulty, time to call 911) was developed in the United Kingdom in 1998 by a group of stroke physicians, ambulance personnel, and an emergency department physician and was designed to be an integral part of a training package for ambulance staff. The FAST was created to expedite administration of intravenous tissue plasminogen activator to patients within three hours of acute stroke symptom onset. According to FAST system of detecting stroke: face drooping, arm weakness and speech difficulty.

Face features, defined as the detection and localization of certain characteristic points on the face, is an important intermediary step for many subsequent face processing operations for implement face and face feature detection active appearance model (AAM) is most suitable. Active appearance model introduced by Cootes et al [5]. Active appearance model is a statistics-based pattern matching method in which shape and texture variability is extracted from a representative training set. An analysis of the main components principal component analysis (PCA) according to the shape and texture data allows you to get a parameterized face model that fully describes both trained faces and invisibles with photo realistic quality. Fitting the active appearance model to the target face is a nonlinear optimization task, where the difference in texture between the current model estimate and the target image covered by the model is minimized.

3. Proposed method

The development system architecture comprises from three main parts: image acquisition, wrinkle detection system and output of results [Fig. 1].

The first and most important step is to detect face and face feature points from input image. For this step we created active model for detecting face and face landmarks from 68 points, every point has

3.1 Image acquisition

In this second step involved in the system architecture is the image capture. The user's frontal face image take automatically when user is smiled by acquired using the camera as a standard .jpeg file format. To detect smile and take image automatically was inspired from [6]. In this paper the authors calculated the blink by using facial landmarks, they created eye aspect ratio by equation of six points of eye distance and average of distance. In our case to calculate mouth aspect ratio were used height and weight points of mouth, when user mouth position is smile the ratio aspect is high.

To calculate the mouth aspect ratio were used distance D, between points 48 and 54 using created face detection model, for calculating average A of distance between points 50-58, 51-57, 52-56.

$$MAR = \frac{A}{D} \quad MAR = \frac{\|p_{50} - p_{58}\| + \|p_{51} - p_{57}\| + \|p_{52} - p_{56}\|}{3 \|p_{48} - p_{54}\|} \quad (1)$$

Smiling with the closed mouth position, increases the distance between p48 and p54 and decreases the distance between the top and bottom points, from this calculation see that A will decrease and D will increase. Smiling with open mouth position, leads to D decreasing and A increasing. The testing results show that, wrinkle line more accurate detected when A value is increased. Using above calculation, when user open the camera and smiled the image will captured automatically, if user not smiled in the screen announced about smiling.

3.2 Wrinkle detection system

The proposed algorithm consist of following steps: First, detecting wrinkle position area. Second, ridge detection method is applied. Third, creating unique initial shape, Finally, apply AAM using created initial shape.

3.3 Wrinkle line initial shape position

To good estimate of the wrinkle and localize their position, the cheek area was cropped using points coordinates. The cropping area cover cheek, mouth and nose regions, to remain cheek region another areas was covered with non-zero mask. Because of working with detecting wrinkle position using ridge detection method and adopt it to the AAM, research confront with noise illumination [7] and shadow problems, to remove this problems was used Gaussian blur [8][9] by smoothing the image, which

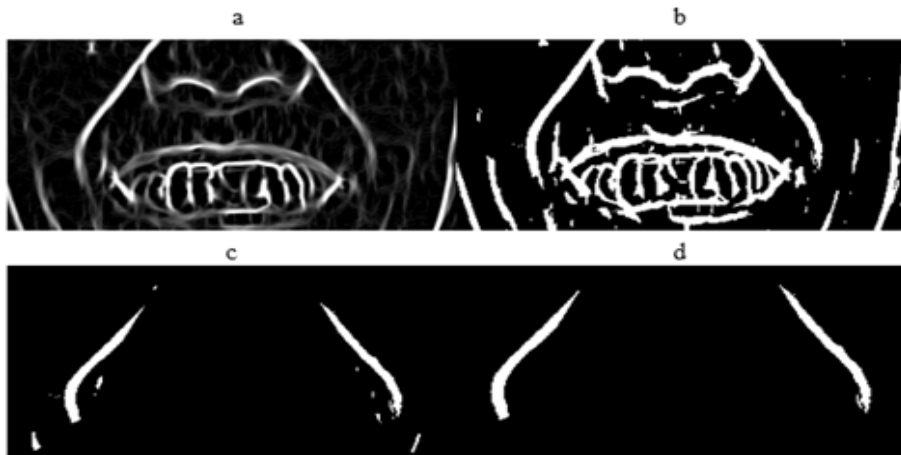
remain only stronger pixel values borders than another pixels. To solve illumination case was used adaptive histogram equalization [10] [Fig. 3].

The [Fig. 3] shows the preprocessing steps, which include cropping the cheek area, blurring by Gaussian blur, grayscale image, than applied histogram equalization.



[Fig. 3] a. original cropping part of face, b. Gaussian blurring, c. gray pattern of image, d. automatic histogram equalization

The [Fig. 4] shows detecting the approximate wrinkle position by ridge detection method.



[Fig. 4] a. wrinkle line position by Hessian matrix, b. binary image, c. region masked image, d. save only long connected lines

To extract initial position of wrinkle lines in cheek area using edge detection operator is not effective, as edge detection operators detect borders between areas of high and low gray values, it could not detect wrinkle position. An edge detector is a first derivative operator, an edge detector measures the steepness of the slope at each point of landscape. Our aim is thin lines are darker or brighter than

their neighbors [Fig. 4], this can be reached using second order derivatives [11]. To localize wrinkles pixels by second order derivatives, we applied a Hessian matrix [12], if image function is in this case for small values x and y :

$$g(x,y) = \frac{1}{2} \begin{pmatrix} x \\ y \end{pmatrix} * \begin{bmatrix} \frac{\delta^2 g}{\delta x^2} & \frac{\delta^2 g}{\delta x \delta y} \\ \frac{\delta^2 g}{\delta x \delta y} & \frac{\delta^2 g}{\delta y^2} \end{bmatrix} * (x,y) + \begin{pmatrix} x \\ y \end{pmatrix} * \begin{pmatrix} \delta g \\ \delta y \end{pmatrix} + g(0,0) \quad (2)$$

3.4 Active appearance model

The wrinkle structure of different persons might appear different and wrinkle line might be weak or strong, as the cheek region is passive part of face in some cases just using second order derivatives is not enough to detect whole line position, in weak wrinkle structure we lose some parts of whole line, AAM is applied for such purpose.

AAM was trained using face images with different emotional expression. The dataset are manually labeled. For detecting nasolabial wrinkles more accurate we used local area features, that is why, faces labeled totally with 88 points [Fig. 3], which 68 is located face landmarks, and 20 points located in wrinkle line. All labeled points represented as nk vector:

$$x = (x_1, y_1, x_2, y_2, \dots, x_{n-1}, y_{n-1}, x_n, y_n)^2 \quad (3)$$

which(7) used to create mean shape of trained dataset by Procrustes :

$$\bar{x}_k = \frac{1}{n} \sum_{i=1}^n x_i \quad (4)$$

Procrustes transformation [13] is applied to remove the difference between labeled shapes by transformation of scaling translation, and rotation. Then, PCA is employed to keep the information of identity of pose and expression:

$$C = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^2 \quad (5)$$

where C represent the eigenvectors of the shape, and is the mean shape of C . By calculating this calculation we take the mean shape of database. To create texture wrapping model we used principal texture variation:

$$InputImage = A_0 + A_c c = A^T(I - A_0) \quad (6)$$

where A_0 present the mean texture value and A is texture database. The disadvantage of AAM in our case is using for every input image only one created initial mean shape of trained database, that brings failings in detecting various shape position of wrinkle line. Nasolabial wrinkle line is not has similar shape structure, that is why was applied second order derivatives Hessian matrix to create unique wrinkle initial line for each input image. For the nasolabial wrinkle region created wrinkle structure, each wrinkle structure contains 20 points, which extracted from edges position coordinates by calculating Hessian matrix. To apply the AAM algorithm for sets of points with unique initial shape under Procrustes transformation and reduce error between input image and model using relationship between the shape and texture model:

$$\min_s \frac{1}{2} \| \overrightarrow{W} - W_s \|^2 + \lambda \| s \|_1 \quad (7)$$

where W is vectorization of wrinkle structure after Procrustes transformation, s is the spars coefficient corresponding to the wrinkle structure database, \overrightarrow{W} is the vectorization of the input shape, and λ is the regularization parameter $1e-6$.

4. Experimental Results

In this research were used 1000 images which included stroke patient face images and normal patient face images. The dataset are manually labeled with totally 88 points, which 68 face landmarks and 20 points for nasolabial wrinkle structure [Fig. 5].

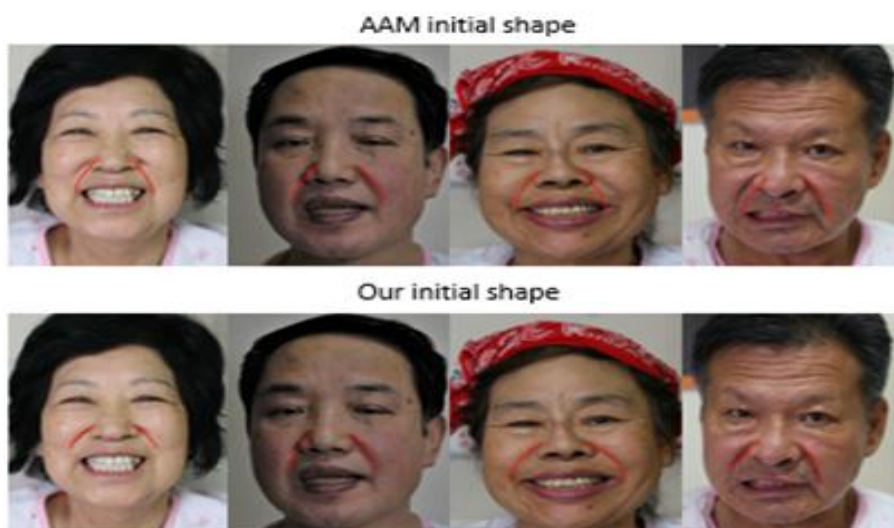
In [Fig 5] shows face landmarks (68 points) and wrinkle position (20 points) manually labeled with points.

In this work, for detect the check wrinkle position was used for each input image unique initial shape based on second order derivatives and AAM initial shape [Fig. 6].

In the [Fig. 6] shows the initial line results taken by AAM and proposed method. In AAM for every input image used the same initial shape, but in proposed method for every input image used unique initial shape from structure of wrinkle.

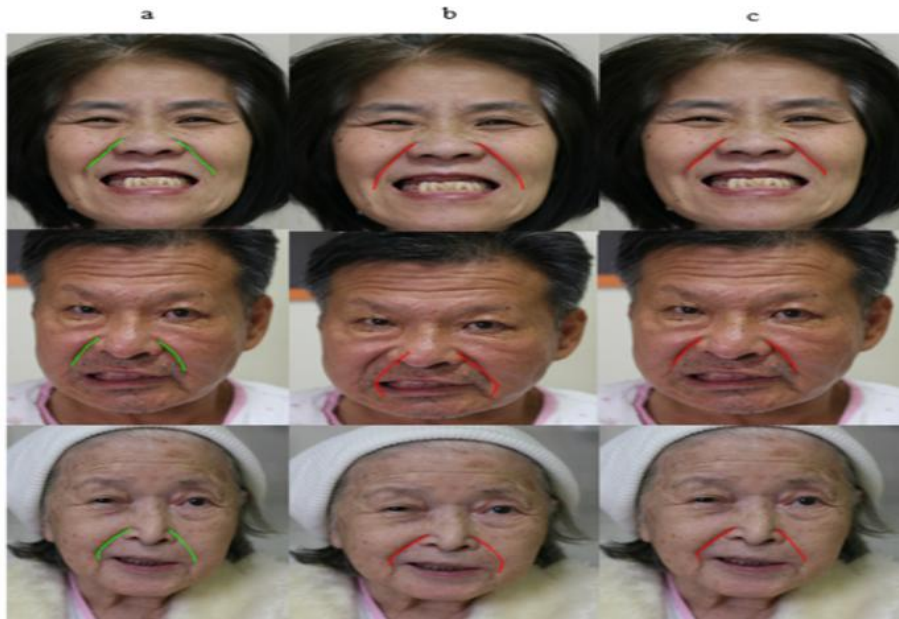


[Fig. 5] The 88 landmarks. 68 landmarks express face features, 20 landmarks express nasolabial wrinkle positions



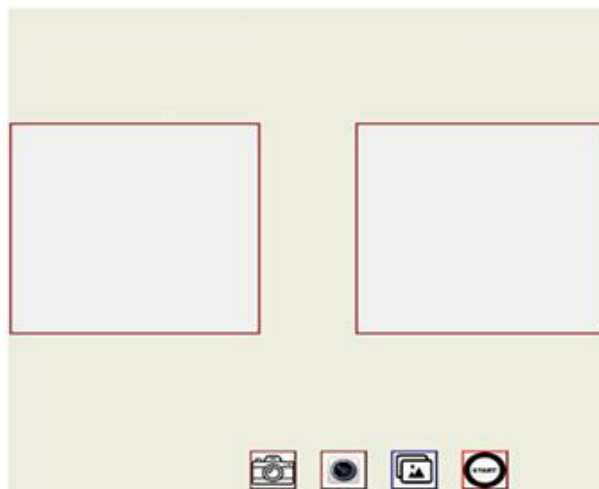
[Fig. 6] AAM initial shape, initial shape token by AAM, Our initial shape, initial shape token by Hessian matrix.

In the [Fig. 7] we compared the proposed work with AAM. The AAM method not suitable detect different type of shape, the algorithm more suitable detect similar shapes. The competitiveness of the proposed algorithm can be proved by the observation [Fig. 6] that are more accurate those of the two methods. Moreover, the proposed algorithm estimated wrinkle line by modified AAM using unique initial shape for each input image, gave results more accurate than other methods, showing the effectiveness of this method.



[Fig. 7] a.the ground truth, b AAM, c. the proposed method.

The interface of detecting cheek wrinkle line consist of input window and the result output window, four buttons. To input data the application has two modes: first, real time using camera, second, choosing data from file [Fig. 8].



[Fig. 8] The main page of user interface.

For using the real time case the user press camera button, after the system detect user face and face landmarks and calculated the mouth aspect ratio. If aspect ratio is low, in the screen user will get

warning in form of text and color of rectangle will be red, if aspect ratio is high the rectangle color will be changed to the blue and warning text is disappeared. After all above condition have done, the image will be captured automatically. To apply wrinkle detection model the user press capture button, than in the next window will be output cheek wrinkle detected result.

The [Fig. 8] shows the main page of user interface, which include two windows, four buttons with own functions. In the first showed automatic captured image, in the second window showed result image with drawn line.

In the second case, the image choose by file, where the user press the file button and opened the needed file path and choose the image. In this case for applying wrinkle detection model the user press start button, which provide the result in the next window [Fig. 9].



[Fig. 9] The user interface design.

The [Fig. 9] shows the process of capturing image using automatic smile detection and the result by detecting wrinkle line using active appearance model.

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