Sensors and Materials, Vol. 36, No. 5 (2024) 2159–2168
MYU Tokyo

S & M 3659

Facial Paralysis Diagnosis and Treatment Assessment Computational Model

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(Received January 3, 2024; accepted May 2, 2024)

Keywords: asymmetry, computational model, facial paralysis diagnosis and treatment, medical imaging, computer-aided diagnosis

In this study, we introduce an asymmetry calculation model for evaluating the effectiveness of facial paralysis diagnosis and treatment, implemented through a Python and OpenCV algorithm. The algorithm is based on actual images from cases of facial paralysis treatments, and numerical experiments for image comparison and subsequent detailed statistical analysis are conducted. The research findings indicate that the calculated numerical indices provided by this model can relatively accurately assess the effectiveness of facial paralysis diagnosis and treatment on a graded scale. Consequently, in this study, we propose to combine overall facial and specific facial region motion disparity features for a comprehensive facial paralysis grading evaluation. This innovative approach provides a robust tool for the accurate assessment of facial paralysis treatment outcomes, offering significant support for clinical practices and treatment optimization.

1. Introduction

Automated methodologies geared towards evaluating the severity of facial palsy necessitate the utilization of specialized scales designed to quantify nerve damage. Among the recognized scales for this purpose are the House–Brackmann (HB), Sunnybrook, Yanagihara, FNGS 2.0, and eFACE scales. Delving into the intricacies of these grading scales reveals a meticulous categorization of facial nerve damage into discrete levels on the basis of stringent criteria.(1) These criteria delve into the nuanced aspects of facial expression, specifically focusing on the symmetry of the face during both neutral expressions and voluntary facial muscle movements. The scales operate on a set of strict measures that capture the subtle variations in facial muscle coordination and responsiveness. This comprehensive approach allows for a thorough assessment of the extent of nerve damage. Furthermore, the assessment measures extend beyond the primary consideration of facial symmetry, encompassing secondary features such as synkinesis.(1) This

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https://doi.org/10.18494/SAM4894

ISSN 0914-4935 © MYU K.K.
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multifaceted evaluation ensures a more comprehensive understanding of the impact of facial palsy, taking into account not only the primary facial muscle function but also potential secondary manifestations. As such, these scales serve as invaluable tools in providing a nuanced and detailed assessment of the severity of facial nerve damage. Healthcare professionals manually measure specific locations on both sides of a person's face to assess the degree of facial paralysis before recommending suitable therapy. However, these methods are susceptible to errors. Accurate evaluation of the severity level is essential as it guides the selection of the most effective and appropriate medical care. Consequently, there is a need for a quantitative metric to aid in medical diagnosis.(2)

Therefore, in this study, we explore an automatic facial paralysis prediction method. Facial paralysis, commonly referred to in modern Chinese medicine as facial nerve paralysis, is a common condition characterized by obstructed facial muscle movements. Its primary symptoms manifest as difficulty in performing basic facial actions such as raising eyebrows, closing eyes, shrugging, puffing cheeks, and showing teeth. In clinical practice, the severity of facial paralysis is often assessed using the HB grading scale and its modified methods.(3,4) With the HB approach, clinicians primarily evaluate the severity of facial paralysis on the basis of two aspects: the asymmetry of the patient's face at rest and the functional differences in facial muscle movements on the two sides of the face during facial actions. Because of variations in patient cooperation and subjective observation biases among physicians, the final diagnostic accuracy heavily relies on the doctor's experience. This process is slow and prone to misdiagnosis.

In recent years, there has been a continuous focus on computer-aided diagnosis in clinical treatment. This approach involves the use of specialized algorithms to extract diagnostically valuable features from digital images, optimize these features, and perform classification diagnosis. It aids doctors in promptly analyzing diagnoses and assessing the likelihood and severity of diseases and ultimately enhances diagnostic accuracy and efficiency. Numerous scholars both domestically and internationally have conducted research on computer-aided diagnostic methods for facial paralysis and proposed various recognition and evaluation approaches based on different algorithms. For instance, Neely *et al.* introduced a computer-aided analysis method for grading facial movement function.(5) Dong *et al.* proposed an automatic grading method for facial movement function in facial paralysis patients.(6) Lou *et al.* presented an evaluation method for facial nerve movement function that was based on the active appearance model.(7) Ngo *et al.* suggested a quantitative assessment of facial paralysis by combining Gabor features and local binary pattern (LBP) features.(8) Lou *et al.* also introduced a novel method for assessing the severity of facial paralysis by combining static and dynamic features of the patient's face.(7)

Wang *et al.* proposed a facial paralysis grading assessment method based on deep temporal features.(9) Xu *et al.* suggested an automatic assessment method for facial paralysis grades, which was based on video analysis.(10) These studies collectively contributed to the advancement of computer-aided diagnostic techniques for facial paralysis, offering diverse methodologies for recognition and evaluation based on different algorithmic approaches. Taking into account the current state of research on facial paralysis diagnosis and treatment assessment both domestically and internationally, computer-aided diagnosis for facial paralysis offers a relatively rapid and objective means of conducting graded evaluations. Holze *et al.* proposed an automatic grading assessment method for facial paralysis based on video analysis.(11) Existing research methods primarily focus on facial paralysis detection and the assessment of facial asymmetry. Improving the accuracy of these detection methods and asymmetry assessments is crucial, and achieving such improvement requires precise quantification and evaluation of facial features throughout the diagnosis and treatment process for facial paralysis patients. However, current research methods often lack detailed quantification and comprehensive evaluation of facial asymmetry.(10,11) In this study, we aim to construct an asymmetry calculation model and algorithm specifically designed for facial paralysis diagnosis and treatment. The proposed model and algorithm are aimed at quantifying facial asymmetry and will assist physicians to enhance the accuracy and efficiency of diagnosing facial paralysis. By addressing the need for precise quantification and evaluation of facial features, we seek to contribute to the refinement and advancement of computer-aided diagnostic techniques for facial paralysis, which will ultimately benefit the diagnosis and treatment of this condition.

2. Medical Image Asymmetry Calculation Model

Medical images are primarily used for studying human organs as the human body exhibits a considerable amount of symmetry, such as in facial features and certain skeletal structures. Some medical conditions can lead to pathological changes in specific organs, resulting in asymmetry. The degree of asymmetry in organs can be measured by constructing a calculation model, and this model, when applied to the numerical analysis of medical images, can provide clinicians with a more objective diagnostic method. A method for calculating the asymmetry of medical images under affine transformation has been proposed and applied to the diagnosis of cholesteatoma.(12) This method involves traversing points within the region of interest (ROI), utilizing an algorithm based on the calculation of asymmetry with respect to given symmetrical points for each traversed point, and comparing the results. Ultimately, the asymmetry of the entire region is obtained, offering a valuable tool for diagnosing and assessing cholesteatoma.

2.1 Asymmetry calculation model for three-dimensional images(10)

Three-dimensional images can be represented using a ternary function $\xi(x, y, z)$ or $\xi(P)$ [where $P = (x, y, z)$, and x, y, and z are the spatial coordinates of pixels]. Here, $\xi(P)$ denotes the eigenvalue of the three-dimensional image at spatial point P. Assuming that Ω and Ω' are mutually symmetrical ROIs with lesions, and for a point P, let its symmetrical point be $Q(P)$, which is a function $Q(P, P_0, P_1)$ concerning P_0, P_1, and P. Here, P_0 is the initial point in the lesion region Ω, and P_1 is a symmetrical point in the lesion region Ω'. We can define $|\Omega| = \int_{\Omega} d\mu$, where μ is the spatial measurement, where

$$D_{P_1}(\xi)=\frac{\displaystyle\int_{\Omega}\frac{\displaystyle\int_{|P-(x,y,z)|\le d}(\xi(P)-\xi(Q(P,P_0,P_1)))^k\,d\mu}{\displaystyle\int_{|P-(x,y,z)|\le d}(\xi^k(P)+\xi^k(Q(P,P_0,P_1)))d\mu}d\mu}{|\Omega|}. \tag{1}$$

Here, $d > 0$, where d is a local parameter, and k takes values of 2 and 4.

$$D_{P_1}(\xi)=\frac{\left|\displaystyle\int_{\Omega}\frac{\displaystyle\int_{|P-(x,y,z)|\le d}(\xi(P)-\xi(Q(P,P_0,P_1)))^{k'}\,d\mu}{\displaystyle\int_{|P-(x,y,z)|\le d}(\xi^{k'}(P)+\xi^{k'}(Q(P,P_0,P_1)))d\mu}d\mu\right|}{|\Omega|} \tag{2}$$

Here, k' takes values of 1 and 3. $D_{P_1}(\xi)$ is the calculation model for asymmetry, and $D_{P_1}(\xi)$ is necessarily within the range [0, 1]. The operation range in Eq. (1) is $|P-(x, y, z)| \le d$. When traversing through P_1 in the range $Q(\Omega)$, there must exist an optimal P_1^* that satisfies

$$\min_{P_1\in Domain(\xi)} D_{P_1(\xi)} = D_{P_1^*}(\xi). \tag{3}$$

The symmetrical plane determined by P_0 and P_1^* is referred to as the optimal symmetrical plane, and the value of $D_{P_1^*}$ is the quantified measure of asymmetry in this three-dimensional space.

1.2 Asymmetry calculation model for two-dimensional images

The asymmetry calculation model D from Eq. (1) and the calculation model in Eq. (2) in practical computations involve initially selecting and specifying the region Ω corresponding to the left lesion. By searching for the symmetrical points in the corresponding region on the other side and obtaining the corresponding ROI Ω', the asymmetry between the left and right lesion regions is calculated. With k set to 2 and z defined as the image index, this calculation model can be adapted for two-dimensional medical images. The improved calculation expression is as follows.

$$D_{P_1}(\xi)=\frac{\displaystyle\int_{\Omega}\frac{\displaystyle\int_{|P-(x,y)|\le d}(\xi(P)-\xi(Q(P,P_0,P_1)))^2\,d\mu}{\displaystyle\int_{|P-(x,y)|\le d}(\xi^2(P)+\xi^2(Q(P,P_0,P_1)))d\mu}d\mu}{|\Omega|} \tag{4}$$

The improved calculation model Eq. (4) is not only suitable for the computation of two-dimensional medical images but is also designed for algebraic operations, making it amenable to algorithm optimization and speeding up of the calculation process. Furthermore, the improved calculation model Eq. (4) retains the invariant properties under spatial affine transformations, as previously demonstrated.[10]

3. Implementation Method of Asymmetry Calculation Model for Medical Images of Facial Paralysis

Asymmetry is widely present in the natural world, and the assessment of asymmetry often relies on subjective human judgment. In clinical settings, facial paralysis is commonly manifested as unilateral facial muscle paralysis, and the asymmetry of the facial features on the two sides of the face serves as a primary basis for clinicians in diagnosing facial paralysis. As asymmetry is an invariant property under spatial mapping, intuitively, compressing or enlarging a three-dimensional image in both the X and Y axes simultaneously does not affect its symmetry. The proposed model for calculating facial paralysis asymmetry is based on the detection of facial landmarks and the segmentation of facial regions. Firstly, the image undergoes preprocessing and normalization. Subsequently, the facial region is extracted using digital image processing methods, and the facial symmetry axis is identified. The facial region is then divided into left and right symmetric ROI areas along the symmetry axis. Feature information is extracted from the left portion, and the same is done for the right portion after horizontal flipping. The asymmetry of features between the left and right regions is calculated using the method described in Sect. 2.2. Finally, a support vector machine (SVM) classifier is employed to output the classification results for facial paralysis. The implementation steps of the asymmetry model algorithm are as follows.

1. Load images from different diagnosis and treatment stages of facial paralysis cases.
2. Preprocess and correct rotation of facial paralysis images.
   The inclination of the face directly affects the extraction of symmetric features. Therefore, it is necessary to perform rotation correction on the images to align them all to a frontal view. In this study, the inner corner points of both eyes are chosen as the reference for rotation. Assuming the coordinates of the left eye's inner corner point are $E_1(x_1, y_1)$, and the coordinates of the right eye's inner corner point are $E_2(x_2, y_2)$, the rotation angle α is defined as

$$\alpha = \arctan \frac{|y_2 - y_1|}{|x_2 - x_1|}. \tag{5}$$

3. Determine the facial symmetry axis and calculation of the position of symmetric points with respect to the axis.
   Identify the facial symmetry axis by digital image processing methods and determine the coordinates of symmetric points on the basis of facial structural features combined with plane geometry principles. According to plane geometry principles, in a Cartesian coordinate

system, a line on the plane corresponds to the graph of a second-degree equation. If the general form $ax + by + c = 0$ is used to represent the equation of the line, then the coordinates (x', y') of the point (x, y) with respect to the symmetric point about this line are given by

$$x' = -\frac{2aby + (a^2 - b^2)x + 2ac}{b^2 + a^2}, y' = -\frac{(b^2 - a^2)y + 2abx + 2bc}{b^2 + a^2}. \tag{6}$$

4. Obtain symmetry axis parameters and ROI parameters. Use Eq. (6) to calculate the left and right symmetric regions.
5. Calculate asymmetry using Eq. (4).
   Once the symmetry axis is determined, acquire the parameters for the symmetry axis and the left and right ROIs of the face. Split the face into left and right regions along the symmetry axis and extract asymmetry features using Eq. (4).
6. Apply SVM for predictive classification of extracted asymmetry features. Obtain the final facial paralysis level on the basis of the classification results.

4. Analysis of Numerical Results of Asymmetry Calculation in Medical Images of Facial Paralysis

4.1 Experimental data and experimental environment

In the context of research related to facial paralysis diagnosis and assessment, there is currently no publicly available dataset owing to concerns about patient privacy. All experiments conducted in this study were based on medical imaging data provided by the Rehabilitation Department of the Second Hospital of Longyan City, Fujian Province, China. For the experiments, 57 facial paralysis patients were selected on the basis of the HB grading system. The images were captured during the diagnosis and treatment process and included partial images of patients performing facial actions such as raising eyebrows, closing eyes, wrinkling the nose, puffing the cheeks, and showing teeth, as specified by the HB grading system. In accordance with the grading criteria of the HB system, we classified facial paralysis into five levels: zero representing normal (corresponding to grade I in HB), one representing mild facial paralysis (corresponding to grades II and III in HB), two representing moderate facial paralysis (corresponding to grades IV and V in HB), and three representing severe facial paralysis (corresponding to grade VI in HB). The determination of facial paralysis levels was explicitly annotated by three professional doctors, and a qualified medical expert conducted the final review and confirmation of the annotations.

The experiments were conducted using Python along with OpenCV (Python imaging library), Numpy, and Scipy for algorithm calculations and simulations. The specific quantity of experimental image data is presented in Table 1. The utilization of patient-specific medical imaging data from the Rehabilitation Department ensures the authenticity and relevance of the experimental dataset. The classification into different facial paralysis levels aligns with the

Table 1
Data of experimental images.

Facial expression	Zero: normal	One: mild	Two: moderate	Three: severe
Raise eyebrows	11	15	15	16
Close eyes	10	14	15	18
Wrinkle nose	14	16	17	10
Puff cheeks	13	14	14	16
Show teeth	12	15	13	17

established HB grading system, which provides a standardized basis for evaluation. The involvement of multiple medical professionals in the annotation process enhances the accuracy and reliability of the experimental results. The choice of Python-based tools for algorithm implementation facilitates flexibility and accessibility in the computational aspects of the experiments.

4.2 Experimental data preprocessing

The data collection process is often influenced by factors such as the acquisition equipment, shooting angle, shooting distance, lighting conditions, and the cooperation level of the patients. Therefore, in this study, the original experimental images were preprocessed and normalized. Numerous experiments have shown that the tilt of the face can affect the extraction of subsequent features and the discrimination of the final facial paralysis grade. For images with tilt, we applied Eq. (5) for rotation correction. The before-and-after effects of the correction are illustrated in Fig. 1. Figures 1(a) and 1(b) show images before rotation correction. In Fig. 1(a), which is an image of the action showing teeth, a noticeable left tilt is present, and both eyes, including the eyebrows, are not on the same horizontal line. Figure 1(b) shows an image of the action closing eyes, slightly tilted to the right. Figures 1(c) and 1(d) show the images after rotation correction. In Fig. 1(c), both eyes are aligned on the same horizontal line, and Fig. 1(d) shows a significant improvement compared with the image before rotation correction.

4.3 Experimental results and statistical analysis

For preprocessed and normalized images, features corresponding to five facial expressions were extracted, and their asymmetry was calculated. The results are shown in Table 2. In contrast to Table 1, the number of images for each of the five facial expressions in Table 2 is 57. However, the numbers of images for normal individuals (corresponding to grade 0) and facial paralysis patients (corresponding to grades 1, 2, and 3) are not the same. A comparative analysis of the average asymmetry values for the five facial expressions reveals that the asymmetry values for normal individuals typically concentrate within a specific range. In contrast, there is a noticeable difference in the asymmetry values between facial paralysis patients and normal individuals. Moreover, the asymmetry values exhibit a stepwise increase with the severity of facial paralysis, indicating that the more severe the facial paralysis, the higher the asymmetry

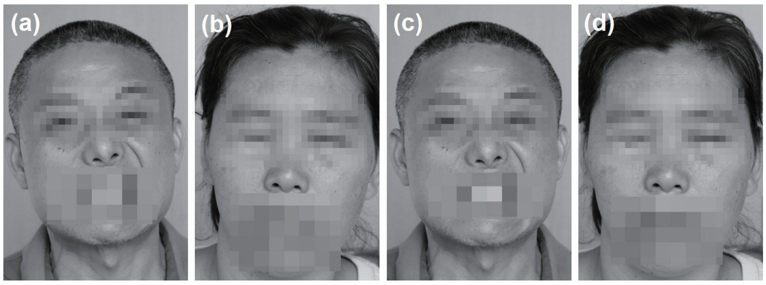

Fig. 1. Images of (a) showing teeth and (b) closing eyes before rotation correction. (c) and (d) Images of respective actions after rotation correction.

Table 2
Comparative results of asymmetry calculation for five facial expressions.

Facial expression	Number of images	Image proportion		Average asymmetry value	
		Normal individuals	Facial paralysis patients	Normal individuals	Facial paralysis patients
Raise eyebrows	57	11	46	0.11	0.35
Close eyes	57	10	47	0.09	0.43
Wrinkle nose	57	14	43	0.12	0.40
Puff cheeks	57	13	44	0.11	0.44
Show teeth	57	12	45	0.12	0.48

value. This suggests that the proposed asymmetry calculation model has good discriminative power for distinguishing between individuals with and without facial paralysis, as well as for assessing the severity of facial paralysis.

To further validate the effectiveness and superiority of our proposed method, we conducted comparative experiments with two classical methods: Gabor + SVM[4] and LBP + SVM.[6] The average accuracies of different methods are presented in Table 3. From Table 3, it is evident that the average accuracy of the two classical methods for the five facial expressions is consistently below 80%. In contrast, our proposed method achieves an average accuracy of over 80% for all facial expressions except for "Wrinkle Nose." Notably, the accuracy for "Puff Cheeks" and "Close Eyes" exceeds 85%. This improvement can be attributed to the fact that the asymmetry of the corners of the mouth and pupils, relative to other facial structures, is visually more pronounced. This aligns with the common clinical practice where physicians often prioritize the asymmetry of the corners of the mouth and pupils when diagnosing facial paralysis. For all five different facial expressions, our proposed method demonstrates a substantial increase in average accuracy. This enhancement underscores the effectiveness and robustness of our approach in capturing and analyzing asymmetry patterns associated with various facial actions. The results suggest that our method outperforms the classical Gabor + SVM and LBP + SVM methods, showcasing its potential for more accurate and reliable facial paralysis diagnosis.

Table 3
Average accuracies of different methods.

Facial expression	Gabor + SVM	LBP + SVM	This study
Raise eyebrows	69.47	75.86	82.71
Close eyes	65.57	79.42	85.43
Wrinkle nose	66.17	64.95	79.56
Puff cheeks	77.46	74.25	87.77
Show teeth	70.27	69.53	83.28

5. Conclusions

In this study, we proposed an asymmetry calculation model for the assessment of facial paralysis diagnosis and treatment. Following the diagnostic process employed by clinical practitioners, the model extracts asymmetry features from image data corresponding to five different diagnostic facial expressions in the course of facial paralysis diagnosis and treatment. Asymmetry is computed for each facial action, and a grading assessment is conducted to ensure that the results reflect the nuanced differences in facial function. Numerical calculations and analysis results indicate that, compared with traditional facial paralysis grading assessment methods, the proposed model exhibits a notable improvement in the average accuracy of facial paralysis grading assessments. Furthermore, the model's results agree well with the diagnostic outcomes of clinical experts. This suggests that our proposed asymmetry calculation model and algorithm hold certain reference values for the diagnosis and assessment of facial paralysis. However, challenges remain owing to factors such as the limited availability of facial paralysis datasets and the lack of unified assessment standards, impacting the practical application of existing research findings. With the continual accumulation and expansion of facial paralysis data, future research could be focused on selecting differentiated features and precisely locating feature regions. Additionally, the integration of deep learning algorithms can enable more in-depth data processing, facilitating faster and more objective facial paralysis diagnosis and grading assessments.

Acknowledgments

This research was supported by the education department of Fujian Province with Grant No. JAT210232, Summit-Tech Resource Corp., and projects under Grant Nos. MOST 111-2221-E-390-018 and NSTC 112-2622-E-390-002.

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