Automatic Objective Severity Grading of Peripheral Facial Palsy Using 3D Radial Curves Extracted from Point Clouds

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Abstract. Peripheral facial palsy is an illness in which a one-sided ipsilateral paralysis of the facial muscles occurs due to nerve damage. Medical experts utilize visual severity grading methods to estimate this damage. Our algorithm-based method provides an objective grading using 3D point clouds. We extract from static 3D recordings facial radial curves to measure volumetric differences between both sides of the face. We analyze five patients with chronic complete peripheral facial palsy to evaluate our method by comparing changes over several recording sessions. We show that our proposed method allows an objective assessment of facial palsy.

Keywords. Facial Palsy, Point Clouds, Grading

1. Introduction

Peripheral facial palsy originates from underlying damage to the nervus facialis by infections, brain tumors, strokes, or injuries during surgery. The damage to the nerve can vary, resulting in mild to severe symptoms. A comparison between paresis and healthy side or structural changes are the primary evaluation criteria in grading systems like Sunnybrook [1], House-Brackmann [2], or eFace [3]. Such grading systems are prone to a subjective bias introduced by the rater's grading experience and the evaluation environment as stated in [4].

A computer-aided approach [5] uses 2D facial landmarks for precise measurements. However, algorithms for landmark estimation do not include facial palsy patient images in their training data. Thus, placing is unreliable for medical evaluation as such cases are unknown to the algorithm. Deep learning approaches [6,7] recreate existing metrics from 2D images and copy human grading biases. Furthermore, essential surface structures, like the nasolabial fold depth, cannot be reliably estimated from 2D recordings. The use of 3D facial data is promising for fine-grained assessments. One approach [8] proposes sparse 3D landmarks features, which could be used to describe anteroposterior direction changes. However, current applications

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require hand-operated processes for correct execution. In contrast, our method automatically creates a dense, structured 3D facial surface description based on a 3D camera recording. Our method's algorithmic nature decreases the potential for subjective biases as we exclusively use the 3D sensor data.

2. Materials and Methods

Facial radial curves were first proposed by Berretti et al. [9] using geodesic lines as novel face representation. They are used to describe anatomical structures [10] or to achieve presentation attack detection [11]. We provide a novel extraction algorithm for 3D point clouds creating equidistant sampled curves around the nose tip, see Figure 1. These curves allow us to objectively measure the volumetric differences between both sides of the face and should indicate facial nerve damage.

2.1. Acquisition and Pre-processing of the 3D Point Clouds

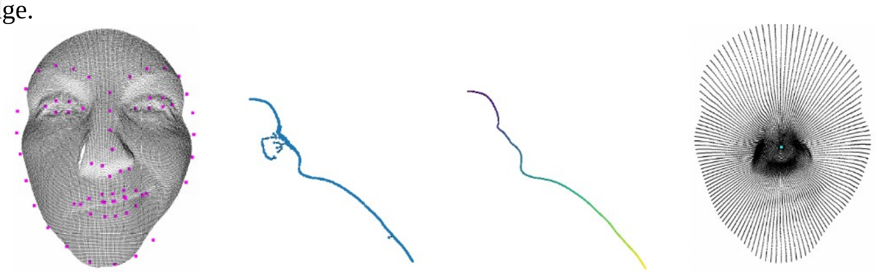
To acquire the data for evaluation, we use a 3D sensor, which provides a color and depth image. The sensor captures a patient's frontal view while following a set of instructions [4] showing different facial movements. The method described in [11] allows us to compute a 3D point cloud including 68 facial landmarks detected in the image. We translate the coordinate system origin to the nose tip for simplified rotation and cropping of the point cloud. We define a cropping sphere with a radius from the nose to the jaw tip and remove all points outside it. This step ensures that unnecessary points, e.g., hair or upper body, are removed. Estimating the facial radial curves requires that the nose points towards the positive *z*-axis. We calculate the required rotation with the method described in [11] using 3D landmarks.

2.2. Robust Estimation of Facial Radial Curves in 3D

We estimate *N* facial radial curves rotating around the nose tip in the *yz*-plane. Each curve describes a path along the face surface originating at the nose tip and ending on the outer radius of the face. A plane *R* defined by its normal vectors (n_1, n_2) is rotated around this *yz*-plane in *360/N* steps. We define the set of possible curve points as

$$P=\left\{ p_i=(x_i, y_i, z_i) : \vee p_i^T n_1 \vee \leq \delta \,;\, p_i^T n_2 > 0 \right\}, \tag{1}$$

where δ is a threshold to ensure small distances to the curve location. Further, we apply a perpendicular transformation for each point in *P* such that they lie on the plane *R*. As all points reside on the same 2D plane, we can efficiently solve the problem in the two-dimensional space. As most points were correctly recorded by the sensor, there must exists a subset of points in *P*, closely describing the facial surface. We propose an extraction algorithm for this path that is resilient towards outliers, e.g., errors during the recording. First, we define a complete graph *G* within *P*. Then we compute the minimum spanning tree (*MST*) of *G*. This process reduces the number of possible paths drastically but ensures consideration of all points during the reconstruction. We extract the path from the nose tip to the outer radius point in the *MST*, and only a single path should exist in G. Outliers cannot be included as they connect to the graph via one edge.



(a) Facial point cloud with estimated landmarks (b) Min. spanning tree inside surface point set (c) Surface Reconstruction (d) Extracted facial radial curves

Figure 1. Facial curves intermediate construction steps

Inside the selected path, we fit a two-dimensional spline. We sample the spline with M equidistant steps to create a discrete curve representation C. The resulting curve points are placed back in the plane R to ensure the correct three-dimensional rotation. After the computation of all curves, we obtained a dense, structured representation of the face in $R^{M \times N \times 3}$, see Figure 1 (d).

2.3. Grading Peripheral Facial Palsy using Facial Radial Curves

To estimate the severity of facial palsy, we compare both sides of the face using the computed facial radial curves. We define corresponding curves as the index pair $(i, N-i)$ with $i=1...N/2$. They share the exact origin, and each point pair describes the same face location. We can use this property to compute the volume difference, see Eq. (2), in the anteroposterior direction between the curves, which is the mean absolute pointwise ($\ominus$) volume difference of the z-coordinate:

$$d_i = \varnothing \left(\left| C_z^{(i)} \ominus C_z^{(N-i)} \right| \right). \tag{2}$$

We further provide a mapping *m()*, see Eq. (3), to simplify usage similar to Sunnybrook [1] with 100 being a perfect symmetric face and 0 a complete asymmetry:

$$m(d_i) = 100 - \frac{\arctan(d_i)}{2/\pi} \times 100. \tag{3}$$

We repeat this process for all curve pairs to obtain an average value for the recording. Symmetric faces would yield a score of 100, and values lower than 100 indicate some asymmetry. However, every human face has some dissymmetry. It is essential to measure unaffected faces to obtain a threshold to understand changes due to facial palsy.

3. Results

We compare t = 3 time points of five long-term patients with chronic complete peripheral facial palsy for two years. For each recording, we extract the facial radial curves with parameters $N = M = 128$. In Table 1 we list for each patient our proposed grading and the average Sunnybrook grading of three independent medical experts. For our grading, we display the average scores of all movements. Furthermore, we use the standard deviation to indicate symmetry among the movements. A small value would indicate high symmetry among all movements, whereas a high value would indicate strong asymmetry. We can see an improvement of patients one to four in terms of the average score, including a decreased standard deviation. However, the results of patient five indicate no symmetry improvement with consistent variance among all movements at the first and most recent session. These improvements correspond with the observations of the medical experts who treat these patients based on their grading scores. However, the deviations for the Sunnybrook score elevate the problem of human bias in the evaluation of facial palsy.

Table 1. Scores of chronic complete peripheral facial palsy patients for two years. Our method shows average score and standard deviation of eleven movements [4]. For Sunnybrook, the average score and standard deviation of three independent raters are shown. Scores written in italic represent incomplete scores.

Patient	Grading	T1	T2	T3
1	Volume Difference	76.56 ± 8.44	83.37 ± 5.47	84.09 ± 3.71
	Sunnybrook	17.67 ± 5.03	28.00 ± 4.36	41.50 ± 6.36
2	Volume Difference	73.51 ± 9.36	76.47 ± 10.66	82.73 ± 5.90
	Sunnybrook	12.33 ± 3.51	25.67 ± 3.06	20.00 ± 3.61
3	Volume Difference	66.44 ± 10.32	71.83 ± 10.81	71.56 ± 7.91
	Sunnybrook	*12.50 ± 2.50*	16.66 ± 2.88	22.67 ± 2.08
4	Volume Difference	66.84 ± 9.42	74.22 ± 6.98	71.92 ± 7.41
	Sunnybrook	*17.50 ± 2.50*	16.33 ± 3.06	18.67 ± 4.93
5	Volume Difference	71.26 ± 10.05	74.92 ± 6.70	70.68 ± 11.77
	Sunnybrook	*13.33 ± 2.88*	24.00 ± 6.24	29.67 ± 11.37

4. Discussion

The results in Table 1 expound that our proposed method is a suitable alternative for grading facial palsy. A significant problem for existing gradings is the variance between raters which obstructs an objective assessment. Our data-driven method requires only a 3D recording of the patient doing different movements. With precise instructions, this process can be completely automated and reduce the time constraints for medical experts. The usage of 3D data further elevates the objective natures of our grading. Using a large set of different facial movements ensures a better understanding of the impact of the nerve damage. Additionally, tracking inter-patient scores might be an indicator of successful treatment.

5. Conclusion

Our proposed data-driven method yields objective, comparable results to existing gradings in the first experiments. The recording process can be fully automated with a photo laboratory and offers medical experts efficient and fast feedback. We plan to evaluate our method on a more extensive and diverse set of patients during the clinical routine. However, our first results indicate that it could be an additional routine during the assessment of facial palsy. We intend to continue this research track by including more dynamic recordings of the patients' facial movements. Lastly, approaches to separate the curves into different regions, like House-Brackmann [2], could further enhance the grading.

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