Objective Grading Facial Paralysis Severity Using a Dynamic 3D Stereo Photogrammetry Imaging System

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Abstract

Facial paralysis is a loss of facial movement due to nerve damage. It is essential for clinicians to diagnose the severity of the facial paralysis to treat patients, assess progresses and evaluate outcomes. Subjective assessments are common in clinical practices but have their limitations regarding the intra-observer and inter-observer reproducibility. We utilised the dynamic 3D stereo photogrammetry technology for the objective grading of facial paralysis by measuring regional facial asymmetries. The correlations between the measured asymmetries and scores of a modified Sunnybrook facial paralysis grading were evaluated to identify the region of interests of objective measurements closely related to the subjective grades. Categorical classifiers were trained to quantify the severity of the facial paralysis. Preliminary results showed that the objective asymmetry measurements were highly correlated to the subjective assessments of facial paralysis except the eye region. Machine learning approaches showed a potential of improving the accuracy of severity assessments.

Keywords: Facial paralysis, dynamic 3D imaging, facial asymmetry, machine learning, correlation

Introduction

Facial paralysis is a loss of facial movement due to nerve damage, and facial muscles may appear to droop or become weak. Facial paralysis is commonly caused by infection or inflammation of the facial nerve, head trauma, head or neck tumour and stroke etc. Although facial paralysis is a non-life-threatening condition it can cause significant cosmetic deformities, and if the protective closure is lost, it can also put the eye at risk. There is a clinical need to quantify the morphological and functional abnormalities associated with facial muscle movements to improve the diagnosis and management of facial paralysis. Most methods of assessing facial paralysis in clinical practices are subjective, this introduces significant variability in the diagnosis of facial paralysis. Objective assessments approaches were proposed to assist clinician to quantify the severity of facial paralysis. So far, no objective assessments are widely accepted in clinical practices. Review papers of assessment approaches can be found in [1, 2]. Here, we aim to develop an objective facial paralysis diagnosis approach based on the analysis of dynamic 3D stereo photogrammetry.

Subjective assessments

In clinical practices, the clinicians detected facial abnormalities through a systematic visual inspection of facial morphology and muscle movements. Patients are asked to perform specific voluntary expressions such as smile, eye closure, cheek pucker and puff etc, and the global grading of their facial muscle movements provided an overall measure of the function of the seventh cranial nerve [3, 4]. The regional grading of facial muscle movements is usually related to the five main branches of the facial nerve [5, 6], and based on the coordination of a group of muscles of each facial expression [7, 8]. There has always been a debate regarding the intra-observer and inter-observer reproducibility when subjective indices are used for the analysis facial paralysis [9-11].

Fattah et al [12] identified 19 facial nerve grading scales, only the Sunnybrook Facial Grading Scale satisfied all criteria: convenience of clinical use, regional scoring, static and dynamic measures, features secondary to facial palsy (e.g., synkinesis). However, the interobserver and intra-observer reproducibility of the subjective assessments was low with limited sensitivity and specificity.

Objective assessments

Objective assessments are usually achieved by quantifying facial movements of facial images [13-16], videos [17, 18], 3D facial expressions [19-22]. These imaging devices are more accessible than those obtrusive physical interventions devices such as electroneurography [23] and electromyography [24], or motion tracking of facial markers [25, 26]. The Moire pattern [27] was used to detect facial motions and laser speckle images [28] were applied to detect facial blood flow for the diagnose facial paralysis. Since facial asymmetry is a significant feature of facial paralysis, it is the most frequently used dysmorphology pattern for the objective scoring of facial paralysis. Facial asymmetry is measured by compared the motion or blood flows [28] between the left and right sides. The key point/landmark based facial asymmetry measurements heavily relied on the accuracy of landmarking and tracking. The 2D image analysis could only evaluate the lateral and vertical movements and could not reflect the facial asymmetry in depth. On the other hand, 3D imaging offered comprehensive details of facial movements, but the large volume data throughput took time to process.

Most objective assessment approaches of facial paralysis focused on quantify the associated asymmetries. There was a gap between the quantifying the facial asymmetry and the clinical needs of diagnosis of the severity of the facial paralysis. A few studies [18, 29-32] applied machine learning techniques to quantify the severity based on facial asymmetry measurements from videos or static images. An Artificial Neural Network [ANN] took relevant extracted information from the video feed and quickly estimated a score of the current facial nerve damage [18]. He et al [29] further improved the performance by computing the optical flow and applying the radial basis function (RBF) neural network for assessing facial nerve function. Videos of 197 subjects were used. The correlations between the detected asymmetries and the House-Brackmann scale were in 0.70 to 0.83 to different facial regions. Storey et al [30] transferred learning from a 3D CNNs pre-trained on the Kinetics data set to provide A Facial Palsy Grading with a classification accuracy of 82%. Their database consists of 593 sequences generated from 113 subjects, while the facial palsy data set consists of 696 different sequences with 17 subjects collected from online sources. Wang et al [31] proposed model utilizing a cascaded encoder structure, which explored the advantages of the facial semantic feature for facial spatial information extraction, and then benefited the facial paralysis assessment. They had collected around 25000 facial images with the facial attribute markup ground truth, around 12000 facial paralysis images to form up a facial paralysis dataset, and manually marked up the facial features in the images. Most recently, Xu et al [32] designed a new network model with the combination of dual-path LSTM and deep differentiated network to evaluate the severity of facial paralysis automatically. Their dataset consists of videos of 103 facial paralysis patients are obtained, and 40 normal volunteers are involved for video collection. Their experimental results showed an accuracy of 73.47% which were better than the other networks. A common issue of these approaches is that large patient samples are required for train and test the models, because of the heterogeneous symptoms of facial paralysis and the volunteer facial expressions required for clinical diagnosis.

In this paper, we intended to utilize facial asymmetry measurements from the Di4D image system for objective facial paralysis severity quantification. The asymmetry measurements pre-processing from the sequences of 3D models would simplify the complexity of machine learning that shallow networks can be applied for quantifying the severity of facial paralysis. We made use of a dynamic 3D stereo photogrammetry imaging system to measure the facial asymmetry of 16 patients; 7 clinical assessors graded the severity of their facial paralysis based a modified Sunnybrook facial grading system. The correlations between the asymmetry measurements and the subjective grades were analysed. The highly correlated regions to the subjective grades were identified and categorical classifiers were trained to quantify the severity. Lacking a gold standard of subjective assessment was still an issue for our study and a modified Sunnybrook grading system was used based on the previous published data [12].

Material and method

Ethical approval

Ethical approval was obtained from the UK Research Ethics Committee (Reference 17/SC/0541) and the R&D department of NHS Greater Glasgow and Clyde Health Board (Reference GN17OD401).

Dynamic facial movement tracking

16 patients of facial paralysis were recruited. Their voluntary facial expressions were imaged using a dynamic 3D stereophotogrammetry device, the Di4D capture system (Dimensional Imaging, Hillington Park, Glasgow, UK). The Di4D imaging system captures the voluntary expressions at a rate of 60 frames/second, which are maximal smile, cheek puff, lip purse, eyebrow raise and eye closure. Their rest facial expressions were captured as well.

The system consisted of 2 grey-scale cameras (Model aVA 1600-65km/kc; resolution 1600x1200 pixels; Basler, Germany) and 1 colour camera that captures images at a rate of 60 image frames/second using a light source (Model DIV401-DIVALITE; Kino Flo Corporation, Burbank, CA).

Di4D has a combination of passive stereo photogrammetry to recover a sequence of 3D facial models from a stereo pair of synchronised video streams and dense optical flow tracking to track every pixel from one image frame to frame through the video streams with sub-pixel precision. The stereo matching and optical flow tracking relied area based correlations depending on the natural facial skin texture of the high resolution images. A high resolution stereo photogrammetry system based on skin texture can be found in [33], further texturing methods on wrist skin and tiny coin were described in [34, 35], and the evaluation of the method can be found in [36, 37].

A landmark to be placed on the surface of the first 3D model in the sequence, then projected to an image location in the first stereo pair of images. The optical flow tracking information was then used to locate automatically the same point in the second stereo pair of images, which was then projected onto the surface of the second 3D model, and so on for subsequent frames. For facial asymmetry measurements, a generic mesh was utilised to generate landmarks over the whole face.

Facial asymmetry measurements

For the analysis of asymmetry of facial expressions, a generic face mesh was applied. The generic mesh is a universally applicable facial surface representing morphological information of a perfect symmetry face. The generic mesh consists of more than 7000 triangulated vertex “points”, whose 3D coordinates at left and right side of the face are symmetrical.

This generic mesh was elastically deformed in a process known as mesh conformation to represent the patients/participants underlying facial morphology, thus creating a conformed mesh specific to each patient [38]. This process of conformation was started by manually identifying and digitizing a few facial landmarks on the generic mesh as well as on the 3D facial model on the resting frame at the beginning of the expressions. The landmarks initiated the 3D mapping of the generic mesh on the face first, and then the mapped mesh was deformed to the shape of the face by a computerised elastic deformation. The accuracy of this process (<1.0mm) was validated [39]. The vertices of the conformed face mesh was tracked along the subsequent frames of the voluntary expressions. The accuracy of the tracking (<0.55mm) was validated [40].

The conformed 3D model at each frame was aligned by the Partial Procustes Alignment [41] onto its own mirrored model to detect the discrepancies between the left and right sides of the face model and this approach has been applied on static [42] and dynamic [43] facial asymmetry studies. A perfect symmetry face would show no difference between the left and right sides. The difference between the sides of the face was due to the asymmetry. The distances between the left and right sides of the face could be measured at an individual point or averaged from a group of points which would be the regional measurements.

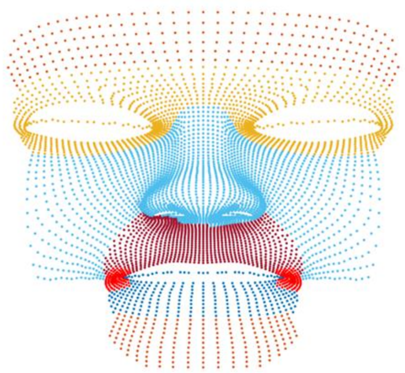

Figure 1. Facial regions defined for asymmetry measurements: 1 – Full Face, 2-Forehead, 3-Eyes, 4-Nose, 5-Cheek, 6-Nasolabial, 7-Upper lip, 8-Lower lip, 9- Chin, 10-Corner of mouth.

The facial regions were defined into 10 groups as illustrated on the Fig 1. The conformed facial mesh aligned to its mirrored model. The distance between an individual point in the model to its corresponding point at the mirrored model is the asymmetry measurement. The regional asymmetry is calculated as an averaged asymmetry of the region, where the summer of the distances of all points at the region is divided by the number of the points in the region. The *max, min, mean, median, range* and *standard deviation (std)* were extracted from the regional asymmetries in the time sequence from the rest posture to the maximal expression and returning to the rest posture. We would think that these six values were representative to the static and dynamic nature of the regional asymmetry. The procedure of the data processing is illustrated in Fig 2.

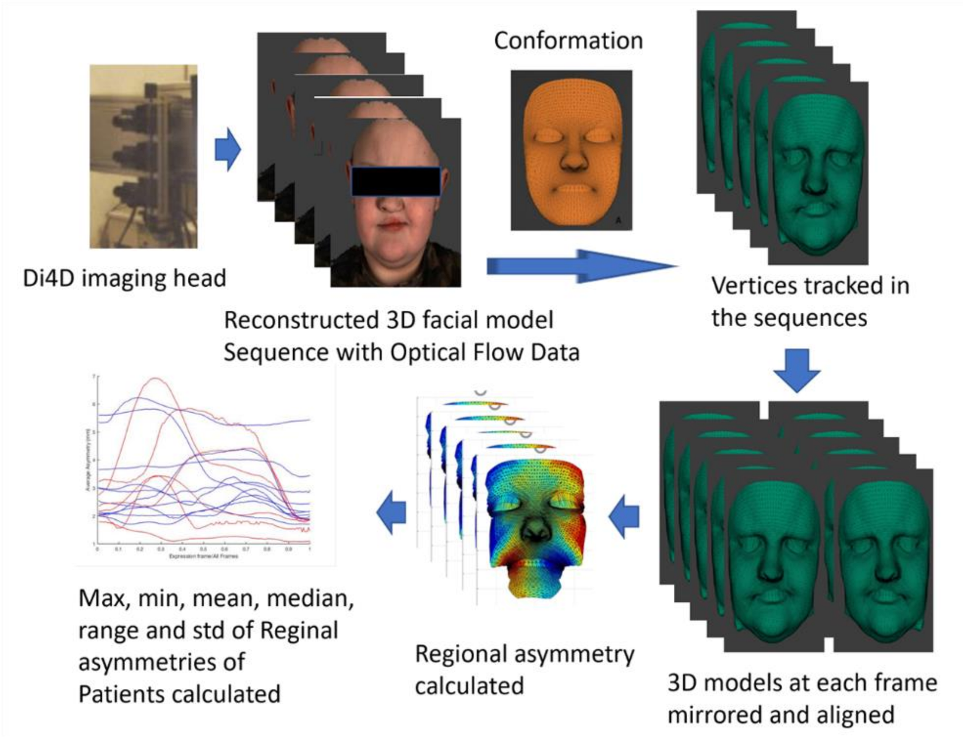

Figure 2. Illustration of the procedure of the data processing

Modified Sunnybrook Grading

After a comprehensive calibration process, 7 assessors assessed the severity of the facial paralysis from the recorded videos of the front and side views of 3D expressions (silver shape model as shown in Fig 3) of the 16 patients; the assessors graded the 8 parameters of modified Sunnybrook grading system (Table 1). The first three parameters are assessed at rest posture and the other five parameters assessed in the five volunteer expressions respectively.

Table 1. A modified Sunnybrook Grading System

Sunnybrook Grading System		
Parameter	Finding	Point Value
Resting Symmetry Score		
Eye	Abnormal or normal	1 or 2
Cheek [nasolabial]	Absent, altered, normal	1 or 2 or 3
Mouth [Drooped]	Abnormal or normal	1 or 2
Voluntary movement Score		
Forehead wrinkle	No movement to normal	1 to 5 points
Gentle eye closure	No movement to normal	1 to 5 points
Open mouth smiling	No movement to normal	1 to 5 points
Cheek puff	No movement to normal	1 to 5 points
Lip pucker	No movement to normal	1 to 5 points

Correlation analysis and machine learning

The *max, min, mean, median, range* and *std* values of the regional asymmetry measurements in the sequence of the 3D models of 16 patients were calculated. Also, the 8 parameters of the modified Sunnybrook grading were assessed by the 7 clinical assessors twice in 45 days. The modes of 8 parameters of 16 patients out of 7 assessors' assessments (twice) were extracted as the consensus grades of the severity of the facial paralysis.

Pearson correlation coefficients were calculated between the regional measurements to the individual parameters of the consensus grades with a significant level of 0.05 to investigate the relationships between the regional asymmetry measurements to the 8 subjective parameters of 6 facial expressions.

Statistics and Machine Learning Toolbox of Matlab (MathWorks®) was used in this study. Machine learning techniques were applied to train on the data set to quantify the Sunny Brook grades. Three machine learning methods of the Matlab classifiers were selected: Supported Vector Machines (SVM), Decision Tree (Tree) and Ensemble Learning (Ensemble), with a five-fold cross-validation. The regional asymmetry measurements were the severity predictors, and the grades of the modified Sunnybrook grading were the responses.

Results and discussions

3D Image sequences of facial expressions

The expressions of the patients were captured in 60 frames per second. Each expression from start to end took about 5 seconds to capture that about 300 frames of 3D facial model were captured. The Fig 3 showed a few frames of 3D facial models of the maximal smile of a patient. Due to area based correlation stereo matching and optical flow tracking, there were artifacts in the areas of reflective or hairy surfaces such as the surfaces of eye balls, eye brows and teeth. Also, there was only one stereo pod used for facial image capture that the reliable facial shape reconstruction was limited to the central facial area. Taking account of the facial surface coverage of the image system and the clinical assessment of the facial expressions, we defined 10 facial regions (Fig 1) for asymmetry grading where we limited the regions of interest to the central of face and regions related to facial muscle movements.

Figure 3. Illustration of the captured 3D models of maximal smile

A generic mesh (Fig 4 left) was conformed into the shapes of the first frame of the 3D models (Fig 4 right); then the vertices of the mesh were tracked in the expression sequences. The motions data of all the vertices were exported for further asymmetry analysis. The asymmetry scores were calculated by comparing the differences between the mirrored 3D model and its original at each frame. The *max, min, mean, median, range and std* were extracted from the regional asymmetries in the expression sequence. Fig 4 illustrated an example of the mean asymmetry scores in x, y and z directions of the eyebrow raise of a patient. In x direction, the red colour means that the asymmetry biased to the left and the blue to the right. In y direction, the red colour shows that the asymmetry biased to the upward and the blue to the downward. In z direction, the red colour shows that the asymmetry biased to the front and the blue to the back. This example showed that the patient had significant asymmetries in the regions of eye and forehead due to nerve malfunctions and also had significant asymmetries in the regions of mouth and chin caused by the compensation movements. We believe that the videos of the colour maps of patients would enhance the grading of the facial paralysis and a further study is required to confirm this.

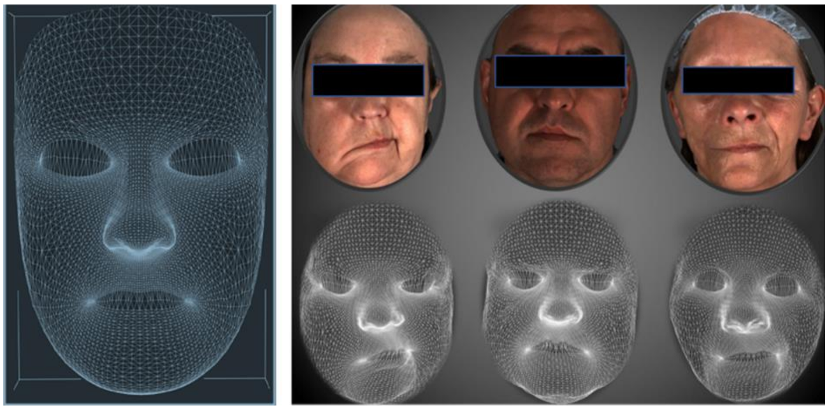

Figure 4. The generic mesh (left) conformed to individual patients (left) for full face motion tracking

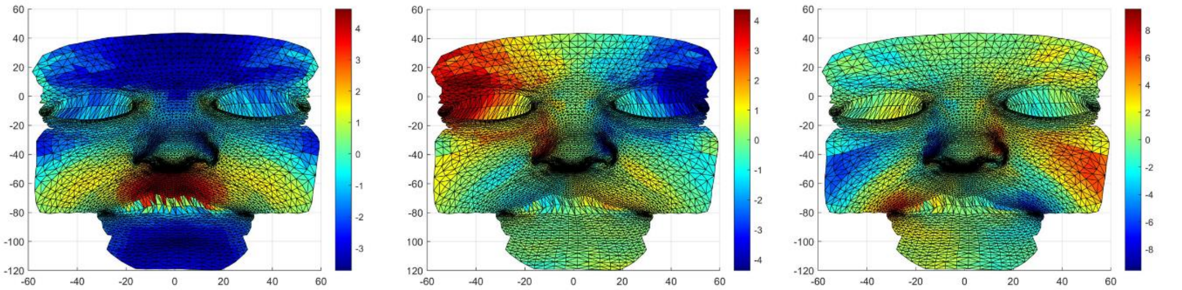

Figure 5. The mean asymmetry scores of the eye brow raise of a patient in x, y and z directions

Reproducibility of subjective assessments

Linear mixed-effects model has been applied on the subjective grades, where the assessors and repeated times were fixed effects, and grading parameters and patients random effects. The results showed no significant effects of repeated subjective assessments on the grades ($p = 1.0$; estimated coefficient 0.00); there was a significant effect of assessors on the grades ($p = 0.0329$; estimated coefficient -0.02). The results indicated that the modified Sunnybrook grading method was repeatable of individual assessors but there were differences in between the assessors.

Correlation analysis of Sunny Brook Grades in 6 facial expressions to the objective measurements

Pearson correlation analysis has been applied on the *max, min, mean, median, range* and *std* of the regional asymmetry and the subjective grades. The correlation coefficients indicated if the subjective assessments had coincided with the asymmetry measurements of the different facial regions. The results showed all negative correlation coefficients. This makes sense because the Sunnybrook grading marked the severer asymmetry at a lower score and the less asymmetry at a higher score, while the subjective asymmetry measurements increased as the asymmetry increased.

The *min* regional asymmetries at rest posture had consistent significant correlations ($p<0.05$) to the first three subjective parameters (Table 2). The *min* value of the facial asymmetries of session represented the rest posture without eye or lip twitching or the other facial movements. The region numbers please refer to the Fig 1. The parameter 2 (Cheek) was highly correlated to the *min* value of the full face, cheek and nasolabial regional asymmetries of the rest; and the parameter 3 (Mouth) highly correlated to the *min* values of full face, upper lip and corner of mouth regional asymmetries of the rest. There were no significant correlations detect in the parameter 1 (Eye). This might be caused by poor 3D shape reconstruction from the regions of the hairy eyebrows and reflective eyeball that the accuracy of asymmetry measurements in the eye region were deteriorated.

Three regional asymmetry measurements (*min* in Table 2, *mean* in Table 3) which had higher correlation coefficients to the individual subjective grades were selected in machine learnings, as the predictors and the corresponding individual subjective grades were the responses.

Sunny Brook Parameter 1-3 of rest expression

Table 2: Correlation coefficients of the **minimal** regional asymmetries and the parameter 1-3

Parameter 1			*Parameter 2*			*Parameter 3*		
Region	CC	p-value	Region	CC	p-value	Region	CC	p-value
1	-0.45	0.0799	1	-0.74	**0.0009**	1	-0.61	**0.0124**
2	-0.48	0.0592	5	-0.77	**0.0005**	7	-0.70	**0.0026**
3	-0.43	0.1005	6	-0.77	**0.0005**	10	-0.61	**0.0126**

The *mean* and *median* asymmetries at volunteer expressions had consistent significant correlations ($p<0.05$) to the 4th to 8th subjective parameters (Table 3). The *mean* and *median* had higher correlations in motions may coincide with the general impression of the facial appearance in motions, while max value represented the worst facial appearance, but the worst facial appearance only existed in a fractional time in the whole session; also, the maximal asymmetry at various facial regions might not appear simultaneously in the session. There was no significant correlation detected in the parameter 4 (Eyebrow raise) due to the same issue of 3D shape reconstruction, we thought. The other parameters showed highly or moderate correlations in relevant regions. In [29], correlated with HB grade around 0.83 in the forehead and around 0.7 in the rest of the region. The tracking approach can be improved in the dynamic 3D imaging system by adopting the method in [29].

We expected that there were significant correlations of the *range* and *std* values to the subject grades, where the *range* and *std* values were representative to the dynamic nature of the asymmetries, but this was not the case.

Sunny Brook Parameter 4-8 of volunteer expressions

Table 3: Correlation coefficients of the **mean** and **median** regional asymmetries and the parameter 4-8

	Region	*CC to Mean*	*p-value*	*CC to Median*	*p-value*
Eyebrow raising, parameter 4	1	-0.40	0.1278	-0.42	0.1063
	2	-0.41	0.1103	-0.43	0.0991
	3	-0.40	0.1201	-0.42	0.1089
Eye closure parameter 5	1	-0.52	**0.0368**	-0.51	**0.0457**
	2	-0.67	**0.0043**	-0.65	**0.0064**
	3	-0.60	**0.0147**	-0.58	**0.0196**
Maximal smile parameter 6	1	-0.66	**0.0051**	-0.66	**0.0052**
	5	-0.67	**0.0043**	-0.67	**0.0048**
	7	-0.66	**0.0055**	-0.67	**0.0042**
Cheek puff parameter 7	1	-0.44	0.0864	-0.48	0.0569
	5	-0.69	**0.0031**	-0.67	**0.0049**
	10	-0.52	**0.0378**	-0.58	**0.0187**
Lip pucker parameter 8	1	-0.52	**0.0375**	-0.50	**0.0462**
	7	-0.65	**0.0057**	-0.61	**0.0124**
	8	-0.62	**0.0110**	-0.60	**0.0136**

Accuracy of subjective and objective assessments

The accuracies of assessments of individual parameters of the modified Sunny Brook grades were analyzed. 7 assessors graded 16 patients twice on 8 parameters of the modified Sunny Brook grades twice. Mode of the grades was calculated from 14 observations on each patient, that there were 8×16 modes of grades for the Sunny Brook grades. Further number of occurrences of the corresponding modes was obtained. The accuracy of each subjective parameter was calculated as the number of its occurrences divided by 14. The average accuracy of each mode was shown in the table 4 for the modified Sunny Brook grades.

Table 4: Accuracies of three machine learning methods comparing to that of the subjective assessments.

Parameters	1	2	3	4	5	6	7	8
Subjective assessments	79.5%	70.1%	84.8%	74.1%	79.9%	65.2%	73.2%	73.2%
SVM	81.2%	**79.5%**	**86.2%**	80.8%	**87.1%**	**66.5%**	**91.1%**	**77.7%**
Tree	**81.7%**	78.6%	**86.2%**	**81.7%**	**87.1%**	62.4%	90.2%	77.2%
Ensemble	**81.7%**	78.1%	84.4%	80.4%	86.6%	62.9%	90.2%	**77.7%**

The accuracy of quantification on each parameter of the modified Sunny Brook grades was shown in table 4. Comparing to the subjective assessment, the accuracies were improved on individual parameters 2, 4, 5, 7 by applying the machine learning methods on the data sets, while the accuracy on the parameter 7 was improved from 73.2% to 91.1%. We think that the accuracy depends on the regional asymmetry measurement and the voluntary expression. The cheek regional asymmetry was highly correlated to the subjective parameter 7; also, there was a larger area in the cheek region and a higher asymmetry magnitude due to the cheeks were further away from the central line of the face. In our previous study [44], we found that facial expressions of lip purse, cheek puff, and raising of eyebrows were reproducible; facial expressions of maximum smile and forceful eye closure were not reproducible. This may partially explain low accuracy of the parameter 6, which was the grade assessing the maximal smile. It is expected that the accuracies of machine learning are better than that of the subjective assessments, because the measurements from the dynamic 3D models are consistent and there are differences in the assessments between the assessors. The values are not comparable to the other studies due to lacking a gold standard. The improvement of accuracy comparing to the subjective assessment is encouraging. Further studies are required to recruit more patients to increase the spectrum of the symptoms in the dataset that accuracy of quantification of the severity can be improved further, and an alternative tracking approach in the eye region is required for the dynamic 3D imaging. Many images and point cloud data were measured in this work, we can consider making fuller use of these data. For further study, we can use multimodal analysis to further improve the reliability and accuracy.

Automated assessment of facial asymmetry is an interesting computer vision topic. We are trying to translate the advancement of computer vision to the bedside. The facial asymmetry must be transferred into clinical criteria to assist the clinicians, rather than asking the clinicians to interpret the asymmetry measurements for the diagnosis of the facial paralysis. In this paper, we are trying to translate the asymmetry measurements to the bedside with limited patient samples. The area correlation based facial tracking system had shortcomings in the regions of reflective and hairy surfaces which had adverse effects on asymmetry analysis; these can be improved with feature based tracking.

Conclusion

We attempted to make use of a dynamic 3D stereo photogrammetry imaging system for the severity of facial paralysis in order to assist clinicians in the diagnosis and treatment. Preliminary results showed that the objective asymmetry measurements were highly correlated to the subjective assessments with the exception of the eye region. Machine learning approaches showed a potential to improve the accuracy of severity assessments, but more data were required for a throughout study. Further rigorous validation is still needed to obtain a reliable and accuracy quantification of the severity of facial paralysis.

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