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Augmented reality for botulinum toxin injection

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Summary

Augmented-reality (AR) devices allow physicians to incorporate data visualization into diagnostic and treatment procedures to improve work efficiency and safety and reduce cost. They are also used to enhance surgical training. In this study, we implemented an AR application for Botox injections using a face recognition algorithm based on deep learning, and we evaluated the recognition accuracy of this application using 27 participants. The accuracy was around 3 mm for all parts of the facial region. The method of increasing surgical efficiency with AR is accurate enough to be used for surgery and provides great potential for further development.

KEYWORDS

augmented reality, botulinum toxins, clinical education, face recognition, injection technique

1 | INTRODUCTION

Augmented reality (AR) combines a real-world image of with a virtual image created on a computer. Compared to other technologies, AR falls in the middle of the mixed-reality spectrum. Thus, we can interact with both worlds at the same time. AR takes advantage of existing natural environments and overlays virtual information atop it. Because of its inherent advantages, it brings users experiences they cannot attain with VR, which implies a completely virtual environment. From social media filters to surgical procedures, ARs are rapidly gaining popularity, because they bring the elements of the virtual world to the real world and improve what is seen and felt. In the field of medicine and dentistry, AR has the advantage of making it possible to see ultrasound, computer tomography, radiography, etc, imagery overlaying an actual patient.[1] This reduces surgical risk by allowing anatomical structures of the patient to be seen directly at the time of actual surgery, and improves surgical accuracy by allowing virtual surgery to be viewed with the actual patient. Additionally, operation times can be shortened. Botulinum toxin (Botox) is a neurotoxic protein produced by the clostridium bacterium. It inhibits the release of acetylcholine in synaptic shear membranes, resulting in muscle paralysis. These effects can attenuate the facial muscles, causing dynamic rhytid or paralysis to eliminate wrinkles; induce weakness or degeneration of masticatory bruxism treatment; and improve square jaw.[2] The location of the masticatory muscles and facial expression muscles can be identified through peripheral structures or directly by the surgeon. An AR application that recognizes the actual patient's eyes, nose, and face shape and informs the surgeon of procedure information, such as standard patient entry point, injection depth, and insertion volume, can be a great help for someone with little experience in the treatment of Botox or filler. Additionally, AR can increase the efficiency of procedures by acting as a basic guide in clinical practice. It can be also used as an auxiliary tool to describe the procedure contents to the patient. Furthermore, the reliability of the procedure can be increased. Unlike VR, which consists of virtual world alone, it is essential to analyze and recognize real-world image information in real-time in order to properly implement AR, which should combine virtual images appropriately with real images. This process is done by recognizing the markers three-dimensionally[2-5] or by recognizing the patterns of actual structures.[6-8] Especially in the medical field where accuracy is important, it is important to accurately register actual images and medical images.[9,10] Vogt et al developed a marker based AR system with stereoscopic Head Mount display and additional video camera for tracking.[11] Almhdie et al demonstrate 3D registration using modified Iterative Closest Point (ICP) algorithm based on a comprehensive lookup matrix.[12] Chen et al presented a novel intra-operative dense surface reconstruction framework that is capable of providing geometry information from only monocular MIS videos for geometry-aware AR applications such as site measurements and depth cues using SLAM-based Dense Surface Reconstruction.[13] Medical data recognition is another

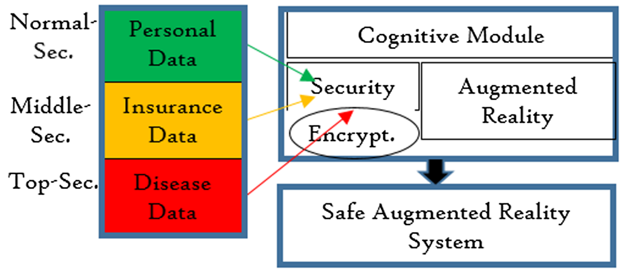

FIGURE 1 Augmented reality system

important challenge. These include some classical algorithms like data processing, analysis procedures, pattern classification, neural modeling, and genetic computation.[14-16] Ogiela et al proposed cognitive semantic interpretation solutions for the analysis of foot bones and palm bones lesions using Extended Understanding Based Image Analysis Systems (E-UBIS).[17] Long et al reported the satisfactory evaluation results on both retinal imaging databases for automatic HE detection, by using dynamic threshold and FCM followed by an SVM for classification.[18] Yan et al suggested multi-Instance multi-Stage deep learning for medical image recognition and achieved better performances than conventional learning approaches using ad-hoc designed image features and the standard deep CNN.[19] For the present study, we developed an AR app for Botox injections for actual patients, student education, and patient counseling. We implemented the app using Unity3D and a face-recognition algorithm based on deep learning. Thus, we can implement AR-based treatments using smartphones or tablets in real clinics. Furthermore, we evaluated the recognition accuracy of soft-tissue markers to confirm the applicability of this capability in clinical practice.

2 | BACKGROUND AND MOTIVATION

2.1 | Secure structure

Because the medical system including dental system contains humans' sensible data, the system has to prepare a security module such as encryption and multiple step's security access.[14] Figure 1 shows the system which consists of Security level, Cognitive Module, and Safe Augmented Reality System. Generally, a patient's information consists of personal information such as a ID number, a phone number, a home address, a work place, etc; insurance information, which is a public insurance from the government and private insurance company; and disease information, which should be treated as top secret.[15] In a hospital, all staff of the hospital share all data from all patients on the server, which has to control as a multi-leveled security following the data state.[13] All patients' leveled data will be stored after finishing an encrypting algorithm; next, some special data like its deceases information of patients has to be done with the high-level security in a cognitive models.[16]

To apply the patient's information specifically in the system, the system does a semantic process. With this process, the system can realize the information security level.[17] If the system has the whole security process for the patients, the system will be down or will decrease the process speed because of mass data such as videos. In addition, this system is based on an augmented reality that generates many data. Also, if it stores the whole data, the storage would be wasted, so the categorization is needed.

2.2 | Motivation

Botulinum toxin (Botox) is a neurotoxic protein produced by the clostridium bacterium. It inhibits the release of acetylcholine in synaptic shear membranes, resulting in muscle paralysis. These effects can attenuate the facial muscles, causing dynamic rhytid or paralysis to eliminate wrinkles; induce weakness or degeneration of masticatory bruxism treatment; and improve square jaw.[20] The location of the masticatory muscles and facial expression muscles can be identified through peripheral structures or directly by the surgeon. An AR application that recognizes the actual patient's eyes, nose, and face shape and informs the surgeon of procedure information, such as standard patient entry point, injection depth, and insertion volume, can be a great help for someone with little experience in the treatment of Botox or filler. Additionally, AR can increase the efficiency of procedures by acting as a basic guide in clinical practice. It can be also used as an auxiliary tool to describe the procedure contents to the patient. Furthermore, the reliability of the procedure can be increased. In particular, the facial muscles that are the target of Botox surgery are based on the shape of the eyes, nose, and face. The detection of facial landmarks has already been studied in various papers. In addition, emotion recognition, face-swap, and face recognition have been widely commercialized and can be used in the vicinity.[21-26] Therefore, we tried to implement AR for Botox Injection using face-swap through detection of facial landmarks.

3 | IMPLEMENTATION

3.1 | Creating a Botox injection guide image

A standard oral maxillofacial model was constructed using medical images of patients who visited Chosun University dental hospital. Computer Tomography (CT) and Magnetic-Resonance Imaging (MRI) were used to segment the facial bone and muscle using Mimics software (Materialize,

FIGURE 2 Facial-muscle 3D model and Botox unit information

Belgium). A segmented model was remodeled for reconstruction to the normalized map using 3D MAX. Finally, a 3-dimensional (3D) facial bone and muscle model was developed. Only the muscular part of the standard oral maxillofacial model was extracted. A standard facial model with size and shape matching with the standard oral maxillofacial model was created and merged so that both types can be seen simultaneously. The frontal view of the merged model was transformed into a 2D image. A Botox Injection Guide Image for each treatment site was created by displaying the injection point of the injection needle and injection capacity for each treatment site. We created a Botox injection guide by adding injection points and a dose of Botox descriptions to the model (See Figure 2).

3.2 | Botulinum toxin injection app

We implemented the AR app for Botox injection on the Android operating system using Unity3D. OpenCV and Dlib libraries were used for face recognition and image conversion,[26] and plugins were used to make each library available in Unity. Face swap was performed using the usual method using OpenCV and Dlib library. Each step is as follows.

- 68 facial landmarks were extracted from the real-time image using the Histogram of Oriented Gradients (HOG) algorithm of the Dlib library (See Figure 2).
- Delaunay triangulation was used to triangulate the facial landmarks of the Botox Injection Guide Image. This process was done using the OpenCV library.
- The triangulation was performed using the facial landmarks extracted from the real-time image according to the facial landmarks and triangulation of the Botox Injection Guide Image. This process was done using the OpenCV library.
- We take the triangles of the Botox Injection Guide Image and we extract them. We also need to take the coordinates of the triangles of the destination face, so that we can warp the triangles of the source face to have the same size and perspective of the matching triangle on the destination face. This process was done using the OpenCV library.

When the patient's face was captured through the camera, the outlines of the eyes, nose, mouth, and facial contours were recognized in real time (See Figure 3). The main anatomical structures of the recognized face were then matched with the Botox injection guide so that the actual Botox injection point for the patient would be displayed on the patient's face.

4 | MATERIALS AND METHODS

The experiment was conducted on 28 people. A studio was set up so that the distance between the location of the mobile phone where the application was installed and the measurement target was 60 cm, which is similar to the distance between the surgeon and the patient during the actual procedure. To measure error value during the experiment, we added auxiliary lines at regular intervals on the basic screen. The subject was asked to sit comfortably in a designated seat, keeping his lips closed. The position of the smartphone was perpendicular to the Frankfort horizontal plane of the subject. Afterwards, the subject naturally rotated the head to the left 45°. Thereafter, the procedure was repeated in the order of right, top, and bottom. Then, all procedures were recorded. The difference between the recognized and the actual marker positions was measured using the recorded image at the front, tilted left, right, up, and down sides (see Figure 4). The statistical significance of the results of frontal recognition and the accuracy of the perceived results from each side were analyzed using a paired T-test using IBM SPSS Statistics v.22.

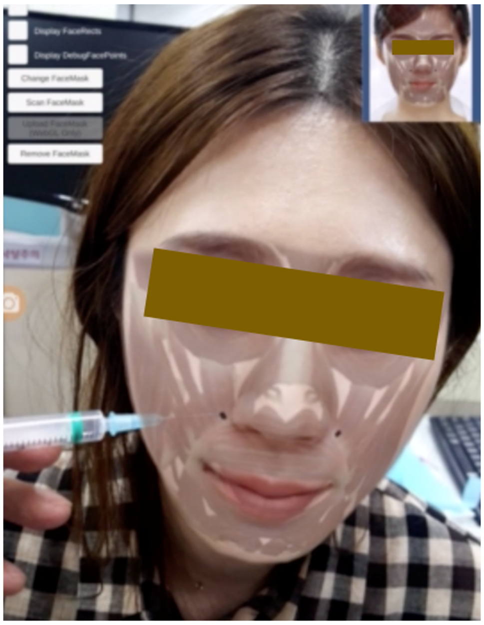

FIGURE 3 Face recognition algorithm using deep learning

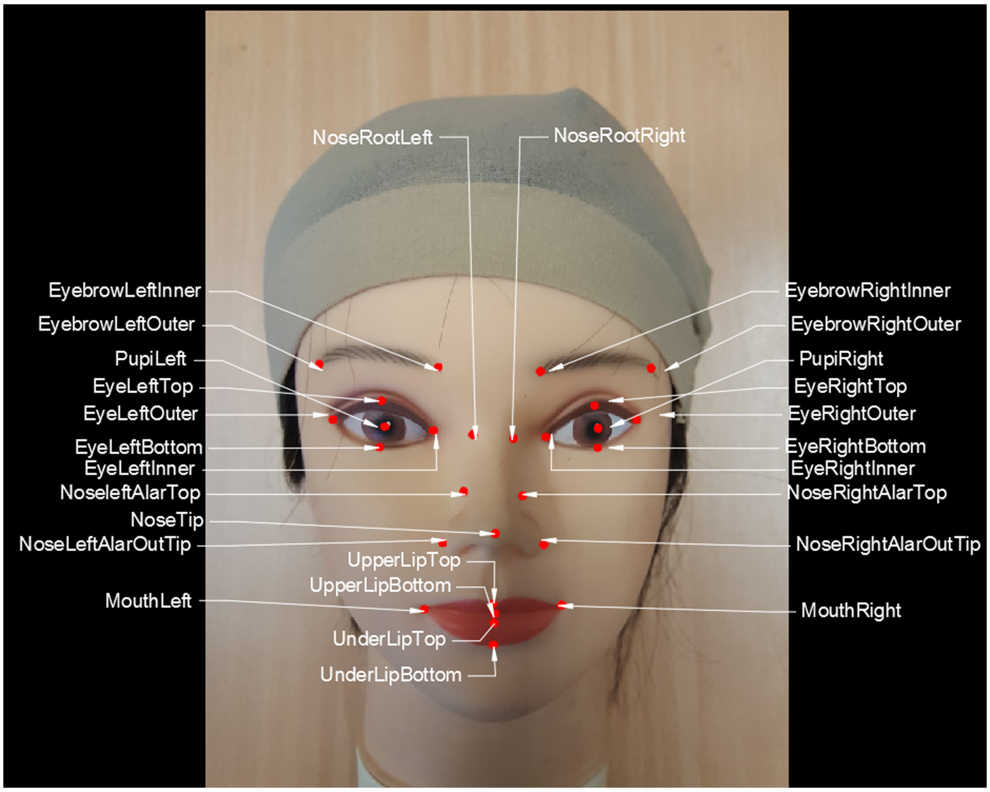

FIGURE 4 Landmarks of the face

5 | RESULTS

The error measurements ranged from a minimum of 0.0 mm to a maximum of 3.0 mm, with 0.40 ± 0.25 when viewed from the front, and the results on each side were slightly higher than those reported on each side (See Table 1).

Table 2 shows the results of the paired T-test comparing the accuracy of the frontal recognition and the recognition of each side. The difference was found to be statistically significant except for the case where the accuracy was better than that of each side and inclined downward when recognized from the front.

View	Avg ± SD (mm)
Frontal	0.40 ± 0.25
Left	0.50 ± 0.30
Right	0.46 ± 0.27
Upside	0.50 ± 0.26
Downside	0.42 ± 0.24

TABLE 1 Error by recognition position

	Avg ± SD (mm)	T value	P value
Left	−0.11 ± 0.10	−4.960**	0
Right	−0.06 ± 0.12	−2.463**	0.023
Upside	−0.10 ± 0.14	−3.411**	0.003
Downside	−0.03 ± 0.70	−1.633	0.118
			*p<0.04, **p<0.005

TABLE 2 Comparison of error values between the front and each side

Study	Direction	Avg ± SD (mm)	Max (mm)
Wagner and Wieneke[5]	Buccal	0.80 ± 0.30	2.10
	Lingual	1.00 ± 0.50	2.60
Wittwer et al[6]	Buccal	1.00 ± 0.50	2.00
	Lingual	0.70 ± 0.30	1.2
Elian et al[7]	Global	0.89 ± 0.53	1.96
Casap et al[8]	Global	0.35 ± 0.14	0.73
Wang et al[4]	Global	0.71 ± 0.27	1.03
Claes et al[9]	Global	3.381 ± 2.57	13

TABLE 3 Error of navigation system

6 | DISCUSSION

To improve the efficiency and accuracy of surgery in the oral and maxillofacial region, various methods for constructing a navigation system have been studied.[3] Many papers have reported the accuracy of the tool and the navigation system for implant placement. The error values are shown in Table 3. Wang et al reported a marker-free AR Navigation system that was used in maxillofacial surgery. The average accuracy was 0.71 ± 0.27 mm.[4] Compared with these results, the accuracy we obtained is believed to be a satisfactory level for clinical practice

In this study, facial recognition and facial soft-tissue marking points are 2-dimensionally recognized and expressed. Thus, it cannot be regarded as a strict navigation. However, the approximate position information of the injection is sufficient for Botox and filler. This can be especially useful for physicians and dentists who have little experience in this type of surgery or for those who want to study the procedures. It can also be easily implemented as a mobile app without any additional equipment. Botox is precisely injected into the target muscle area to avoid damage to the surrounding major anatomical structures. Thus, the anatomical variation of each individual patient should be considered at the point of entry using the app for clinical practice. For this, it is necessary to register medical data (eg, MRI) using recognized marker points. The fact that the patient's image is matched with a standard facial muscle image instead of the actual patient's facial muscle information can be considered a limitation of this study. This could be improved if the facial muscle part is extracted using the actual patient's MRI image. However, the actual facial muscles are very thin and may be difficult to extract from MRI images.[10] Kim et al reported a template-based facial-muscle prediction model, introduced to avoid laborious segmentation from medical images and presented a useful soft-tissue simulation strategy for cranio-maxillofacial surgery using a facial muscle template model.[11] The position of major facial expression muscles required for Botox procedures is related to the position of major structures (eg, eyes, nose, mouth).[12] Therefore, a standard facial-muscle image matched to the recognized face of an actual patient would help locate the main muscles. Because of the constraints mentioned above, the AR app should be limited in practice and should only be used as a guide. However, this guide can be of great help to clinicians who have little practical experience. It can be also used as an educational tool for dental colleges and medical-school students. It can also serve as a reference for patients who want to undergo Botox therapy. The main advantage of this method is that smartphones or tablets are already equipped with the equipment needed to utilize these AR-based procedures. It is therefore worthwhile to use it for clinical and educational purposes owing to its low costs.

7 | CONCLUSION

We implemented an AR application for Botox injections using the Unity3D engine and evaluated the recognition accuracy of soft-tissue markers. The error measurements ranged from a minimum 0.0 mm to a maximum 3.0 mm, with 0.40 ± 0.25. The accuracy we obtained is believed to be of a satisfactory level for clinical practice. In the facial region, the method of increasing surgical efficiency by using the AR technique had enough accuracy to be used for surgery and presents great potential for further development. Currently, we recommend avoiding clinical use until a patient's actual facial-feature data can be mapped to the AR overlay.

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AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST

Authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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