Geometric morphometrics aided by machine learning in craniofacial surgery

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Abstract

Geometric morphometrics aided by machine learning provide detailed and accurate statistical models of facial form. They promise to be extremely effective tools in surgical planning and assessment, however a clinical tool to use this information is still to be created.

Background

Attempts to quantify the face started as early as 4000 years ago with the ancient Egyptians and were further developed by applying the Golden ratio to the study of ideal facial form. (SEGHERS et al., 1964)Renaissance artists further built on these ideas and established the Neo-Classical Canons. For general assessment of the face, the aforementioned ideas are helpful and widely used as they provide the framework to set the limits of normality and acquire information about subsets of the population. (Harrar et al., 2018, Kim, 2007, Holland, 2008) Modern morphometrics can be divided into traditional (*i.e.* lengths, widths, angles, ratios and areas) and geometrical morphometric analysis (shape using Cartesian landmark coordinates that capture the morphology of the face). For orthognathic surgery, cephalometric analysis is widely used as a measurement tool and has become essential in surgical and orthodontic planning even though its application is limited to specific problems, such as prediction of soft tissue outcomes.

Geometric morphometrics and Statistical Shape Analysis

Geometric morphometric analysis studies shape using Cartesian landmark coordinates to capture the morphology of the face rather than linear, angular, or volumetric variables. Although these techniques have had a major impact in anthropology, they are relatively new to facial analysis. Facial 3D data can be acquired using CT, MRI, stereophotogrammetry, laser scanning and handheld structured light scanners.

Statistical Shape Analysis (SSA) is the field that involves statistical methods for analysing the shapes of objects. In this field, shape is defined as the geometrical information that remains when translation, rotation and scale effects are removed. SSA has been used successfully to solve a wide range of practical problems and applied in many disciplines like computer vision, machine learning and medical imaging. The process of building a statistical model is as follows: 1) creation of training set of a specific object, 2) alignment: aligning the objects to a common template by removing translation, rotation and scale 3) registration: bringing every object into dense correspondence and 4) statistical analysis of the registrated shapes. The use of SSA for 3D human face shapes was pioneered by Blanz and Vetter who introduced the 3D Morphable Model (3DMM).(Blanz and Vetter, 1999) In their seminal work, they built a 3DMM by applying Principal Component Analysis (PCA), a multivariate statistical procedure, in a set of 200 registered subjects of a similar ethnicity and age.

3DMMs are powerful statistical model as they are generative models, *i.e.* they can generate new instances of face shapes that are not in the initial data set. Since its first appearance, various 3DMMs have been proposed. The Basel face model used a dataset of 100 male and 100 female persons but a full population could not be described from this due to insufficient number of subjects. This issue was partially enhanced by the Liverpool-York Head Model of 1200 distinct identities, which is a craniofacial model, however, was finally addressed by the Large-Scale 3D Morphable Models (LSFM) including nearly 10,000 faces.

Large Scale Facial Model (LSFM)

To this date, LSFM is the largest 3DMM ever constructed. This model was automatically constructed from nearly 10,000 faces and trained on rich demographic information with wide variation in age and ethnicity. Due to the dataset's diversity, bespoke models for each group were built.(Booth et al., 2018) Figure 5 shows the mean face of the global and bespoke models for each group with the first five modes of variation. Similarly, this process can be performed for facial shape differences regarding ageing and for gender and ethnicity specific models. Moreover, texture models including the components can be created.

Craniofacial Surgery

Statistical shape models have been used in the treatment of patients with craniofacial syndromes. In a similar way as described above, statistical models of syndromic patients were generated. Then, differences between individuals with the same condition can be calculated as well as from a group from the general population. This information can be used for surgical planning and for the assessment of surgical outcome. In addition, Statistical models of pre and post-operative patients can be employed to quantify the effects of specific operations (Figure. 2).

Surgical planning for patients with craniofacial syndromes are extremely challenging due to the complexity of the deformities and their unique anatomy. The information gained from the models can be used to select and personalise procedures for specific patients. Statistical models of surgical procedures will allow more precise outcome prediction and likely results can be presented in a 3D format that are easily understood by non-clinicians. Although, geometric morphometric analysis in facial surgery is in its infancy and its ultimate role is undefined, the technique gives detailed information about shape and shape change. As no detailed statistical model of the facial skeleton exists, there are several unsolved challenges. For accurate surgical planning a combined skin and bone model would be necessary. Statistical shape models seem to have great potential to be used as a tool applicable to cosmetic surgery of the facial skeleton.

Recently, a fully automated large-scale clinical 3DMM has been introduced for diagnostics, risk stratification, and treatment simulation in plastic and reconstructive surgery. (Ref: Knoops et al. 2019 Unpublished work: A machine learning tool for automated diagnosis and computer-assisted surgical planning in craniomaxillofacial surgery) To this end, a 3DMM based on LSFM and enhanced by a set of 3D face scans of patients admitted for orthognathic surgery, was trained and demonstrated its potential for clinical decision making, including fully-automated diagnosis and surgery simulation. This proposed model is an important step towards making computer-assisted surgical planning cheaper, and more accessible for surgeons and patients. This model could potentially transform patient-specific clinical decision-making in orthognathic and craniofacial surgery by utilising regression techniques to simulate normalised patient faces for automated patient-specific surgical planning.

Conclusion

Anthropometrics provides a method for quantifying shape data about the human face. It can describe the limits of normality and give information about subsets of the population. As yet there is no ideal anthropometric technique universally applicable for surgical planning and each available technique has its advantages and disadvantages. Geometric morphometrics aided by machine learning techniques has resulted in very detailed and accurate statistical models of facial form. These models are in their infancy and they promise to be extremely effective tools in surgical planning and assessment. To date, there are no clinically available tools able to use the information they provide.

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Figure Legend

Figure 1. Mean face and 1st 5 principle components from LSFM

Figure 2. Mean pre and post op appearances of bipartition advancement patients with a colour map of the degree and vector of surface change induced by surgery

Figures

Figure 1

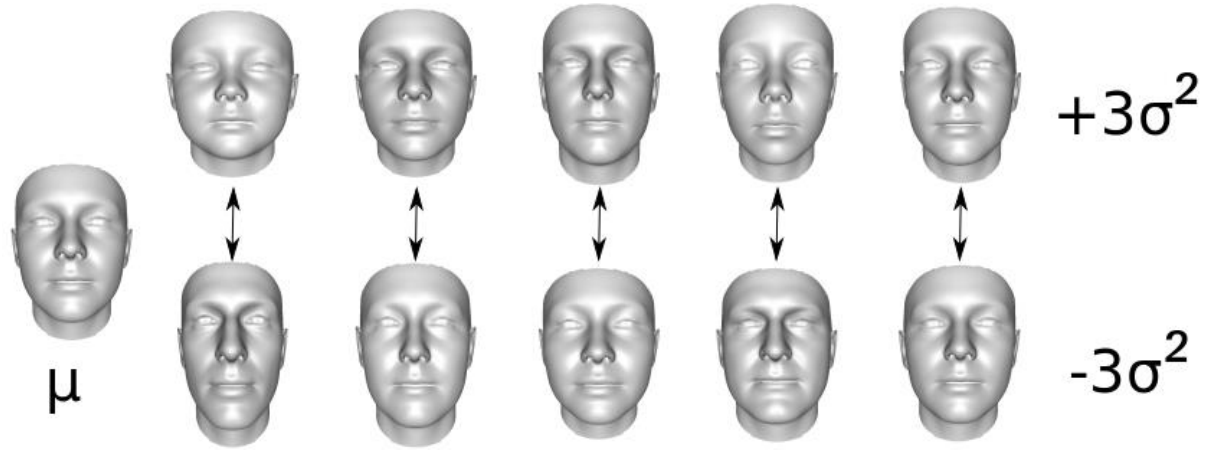

Figure 2