A Survey on 3D Digital Facial Reconstruction Algorithms

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Abstract*. Facial reconstruction is most often used for identification of living or deceased individuals. The development of technology and scientific progress in computer vision leads to the new research directions in digital facial reconstruction. Different algorithms can be developed to automate the facial reconstruction process which aids in objectivity and speed of facial reconstruction. This paper will give an overview of the field of digital facial reconstruction, its advantages and shortcomings. The main focus of this paper is the process of automated reconstruction and algorithms that make it function. The taxonomy will be explained and the most widely used approaches shown. Also, an overview of existing models and tools will be given, as well as a base model for digital facial reconstruction.*

Keywords. digital facial reconstruction, automated facial reconstruction, skull reconstruction, reconstruction algorithm, human face identification, facial mask generation

1 Introduction

When recognizing individuals, either deceased or living, one of the often used feature taken into account is their face. To this end, two main craniofacial identification procedures that use skulls and faces have emerged: facial reconstruction (or facial approximation) and photographic superimposition (Fig. 1). This paper focuses on facial reconstruction and explores different options for digital facial reconstruction. Digital facial reconstruction or approximation is a method of restoring the facial features of and individual for the purpose of identifying unknown skeletal remains or decomposed bodies to obtain information about the identity of the deceased (Imaizumi et al., 2019, Wilkinson, 2010). It is most often used in the field of forensic sciences and archaeology. The ultimate goal of the method is to enable recognition.

There is a great number of unidentified skeletal remains in Croatia whose identity still needs to be confirmed. So far, the only instance of facial reconstruction in Croatia has been done on one mummified body using modelling clay to reconstruct the face (Marić et al., 2020).

Digital facial reconstruction would be a great first step in identifying remains, because visualization triggers recognition, and once recognition is achieved, further tests, such as DNA analysis, can be done. To trigger recognition, the reconstructed face needs to be as accurate as possible. This approach has already been seen in reconstructions of archaeological burial sites where unknown skeletal remains were successfully reconstructed (Guyomarc'h, P. et al., 2018, Lee, W. J. et al., 2020). Today there are general models but more and more population-specific models are emerging as a more precise reconstruction tool.

There are three main schools of facial reconstruction: Russian (anatomical reconstruction method), American (anthropological reconstruction method) and Manchester (combined reconstruction method). The Russian or anatomical reconstruction technique was one of the first to be used for facial reconstruction. The technique is based on the reconstruction of muscles on the "muscle-by-muscle" principle in combination with soft tissue markers (STM) and ending with putting a thin layer of "skin" on the built face (Verzé, 2009). The American anthropological technique of reconstruction originated at the same time as the Russian, but is based on the principle of soft tissue reconstruction in layers, using existing craniometrics measures and soft tissue thickness tables (Verzé, 2009). The latest method is the Manchester or combined reconstruction method, and is a combination of the Russian and American methods. It uses the anatomical properties of the skull with soft tissue markers and enables more precise reconstruction in areas where there are no quality measures for soft tissues (Wilkinson, 2010, Guyomarc'h et al., 2014). This is also the most often used technique for digital facial reconstruction today.

Nowadays, with the advancement of technology, the methods of facial reconstruction are also evolving. Digital facial reconstruction opens up a number of new possibilities. Certain parts of the reconstruction can be automated, which speeds up the reconstruction and reduces the possibility of human error.

Digitalization also enables us to manipulate input variables (age, gender, race, BMI) or manually adjust certain elements of the reconstructed face and get a newly generated reconstruction immediately. Another advantage of digital facial reconstruction is that it increases objectivity and enables standardization. Manual reconstruction methods require a high degree of anatomical and artistic modelling expertise and are difficult and subjective. The interpretations of two different artists results in the creation of two different faces from the skull where the differences vary widely (Claes at al. 2010).

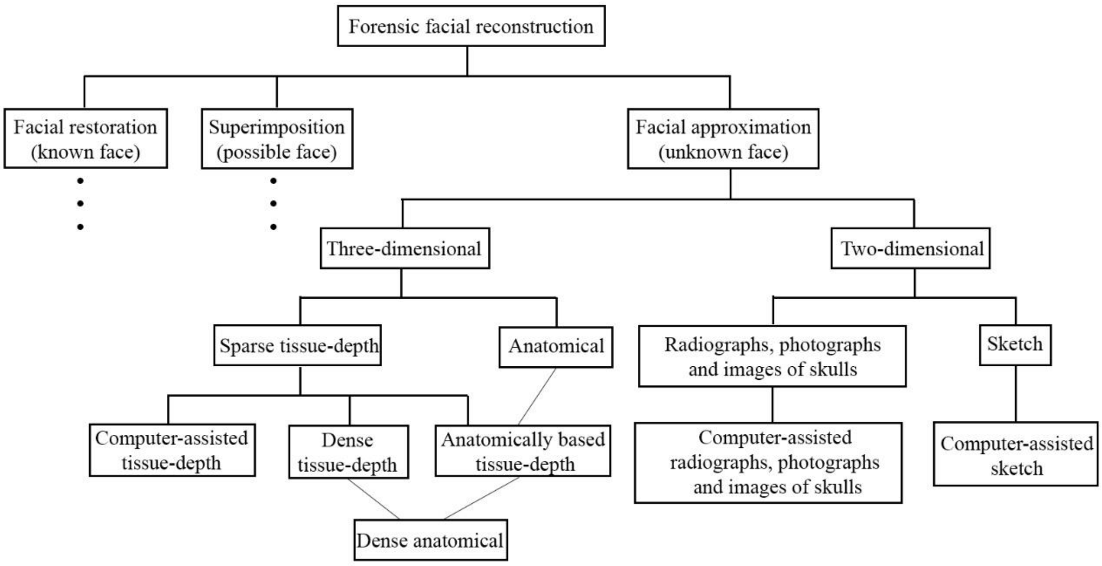

Figure 1. A taxonomy of forensic facial reconstruction (modified based on Turner et al. 2005)

The main advantage of digital facial reconstruction is its availability to the general public, and it can be practiced by researchers who do not have extensive knowledge in the fields of anatomy, soft tissue reconstruction and art.

There are still some challenges facing digital facial reconstruction. The main challenges can be divided into three categories: race, BMI and specific soft tissue structures. Race represents a problem, since skin is not preserved in skeletons, and while an experienced forensic anthropologist can determine a basic race category, getting the exact skin tone and texture is extremely difficult (Nieves D. A., 2020). The second challenge is BMI. The BMI plays a large role in recognition, but it is hard to determine it exactly only from skeletal remains. (De Greef, S., 2009). Lastly, a challenge is determining specific soft tissue structures such as noses (Lee, K. M et al., 2014), ears (Guyomarc'h, P et al., 2012) and the mouth (Stephan, C. N. 2003). Those structures are a combination of muscles and cartilage and are therefore not preserved. They are highly specific and there are numerous papers describing specific methods on how to get the best reconstruction for those specific parts.

The aim of this paper is to give an overview of digital facial reconstruction today. The paper will show the different approaches used in digital facial reconstruction, their results and methodology, as well as the base model of the reconstruction process.

2 Research methodology and literature review

In reviewing the literature, the scientific databases Web of Science and Scopus were used. The keywords used in the search were “3D facial reconstruction skull algorithm”. A further look at the categories section revealed that the most prevalent fields were computer science, anthropology/archaeology and medicine. There were certain criteria the articles needed to meet in order to be chosen for this paper: the reconstruction had to be digital, it had to be based on human skulls and had to suggest a new algorithm for the improvement of automated reconstruction. Our initial search showed 38 results in the WoS database and 28 in the Scopus database. After we filtered out works referring to superimposition and surgery we were left with 12 papers in WoS and in 14 Scopus.

Once the papers were chosen, seven parameters to consider in the papers were determined: population, sample size, age range, scanning method, type of data, number of landmarks and the method that was used. Those parameters were compared across 14 studies. The results are displayed in Table 1.

Table 1. Comparison of papers on digital facial reconstruction

Paper	Population	Sample size	Age	Scanning method	Data type	Landmarks	Method
Jones et al. (2001)	/	/	/	CT	/	/	Strip plastic facial reconstruction, Warped mapping between skulls
Vandermeulen et al. (2006)	/	13	/	CT	DICOM	/	Statistical deformation model
Hu et al. (2013)	/	110	/	CT	/	/	Hierarchical dense deformable model
Bai et al. (2016)	Chinese	331	11-75	CT	3D polygonal mesh	/	Statistical Shape Models
Madsen et al. (2018)	/	30/9	/	CT/MRI	/	20	Probabilistic Joint Face-Skull Model MCMC based Morphable Model parameter reconstruction method
De Buhan et al. (2018)	French	26	20-40	CT	DICOM	<53	Marching Cube, Iterative Closest Point Algorithm (ICP)
Guyomarc'h et al. (2018)	Danish	1	54	CT	DICOM	38	Geometric Morphometrics (GMM), Thin Plate Spline (TPS)
Gietzen et al. (2019)	German	43	/	CT	DICOM	57	Dense statistics of soft tissue thickness model
Shui et al. (2020)	Chinese	140	/	CT or laser	Triangle meshes	78	Statistical Shape Model
Knyaz et al. (2020)	India	24	/	Photogrammetry	/	16	Generative adversarial network model
Yang Wen et al. (2020)	Chinese	200	19-75	CT	DICOM	/	Region Fusion Strategy
Putu H. Suputa et al. (2020)	/	/	/	CT	DICOM	/	3D Laplacian Surface Deformation
Bin Jia et al. (2021)	Chinese	213	/	CT	/	/	Heat flow geodesic grid regression (HF-GGR) model

Research by Stephan et al. (Stephan et al., 2019) shows that there are four main methods of facial approximation: (a) two-dimensional representation of the face over a photograph of the skull, (b) three-dimensional manual construction of the face in clay or mastic over the skull or skull cast, (c) computerized sculpting of the face using haptic feedback devices and a 3D scan of the skull, and (d) computerized construction of the face using more complex computer automated 3D routines. Nowadays, rapid advances in computer science and computer vision specifically have opened new opportunities, but forensic anthropology has not yet taken significant part in these advances. There have been many studies from the anthropological standpoint that deal with facial reconstruction, positions of different facial parts and soft tissue prediction, but the research on different algorithms for automatic face reconstruction is still in the beginning phase.

Automatic approaches for craniofacial reconstruction can be classified in two main groups (Miranda et al. 2018): using facial soft tissue thickness by using anthropological landmarks (Shui et al., 2020, Bai at al. 2013) and using dense vertices of 3D skull and head surface shapes (de Buhan & Nardoni, 2018).

Shui et al. (Shui et al., 2020) proposed a new digital craniofacial reconstruction method based on Statistical Shape Model (SSM) using Generalized Procrustes Analysis (GPA), Principal Component Analysis (PCA) and Partial Least Squares Regression (PLSR). The proposed method consists of digitization of an unidentified skull, calculating geometric measurements, alignment of the skull, sexual dimorphism and computerized craniofacial reconstruction. GPA and PCA were applied to construct the skulls SSM, Support Vector Machines (SVM) with Radial Basis Function (RBF) were used to predict the gender. In the last step, craniofacial reconstruction was done by using PLSR.

Bai et al. (Bai at al. 2013) created a new method for craniofacial reconstruction based on Least Squares Canonical Dependency Analysis (LSCDA), which can extract high order nonlinear correlated information of two variables via linear projection. The authors first create statistical models for skull and skin. To this end, they use PCA. They then use LSCDA to extract the maximum dependency of faces and skulls in the shape parameter spaces. According to that dependency, the relationship between skull and skin is established by Least Squares Support Vector Regression (LSSVR) which is used to reconstruct the facial appearances for an unknown skull.

The paper (de Buhan & Nardoni, 2018) by De Buhan et al. proposes a numerical face reconstruction method based on the “physical” deformation of templates of coupled faces and skulls onto the unknown target skull. The approach combines the use of a skulls/faces database and an original shape matching method used to link the unknown skull to the database templates. Final face is seen as an elastic 3D mask that is deformed and adapted onto the unknown skull. The proposed methods main advantage is that it is simple to implement and does not require any a-priori landmark marking, which allows automatic processing of the database.

Guyomarc’h et al. (Guyomarc’h et al., 2018) presented a case study on the case of Tycho Brahe, Danish astronomer whose remains were analysed. Cranial remains were poorly preserved, with only a partial facial skeleton, and digital anthropology tools were used to estimate the missing parts of his skull. The research focuses on the missing data estimation which was done using Geometric Morphometrics (GMM) and Thin Plate Spline (TPS), where PCA was used for limiting distortion.

Jones (Jones, 2001) proposes an approach based on volumetric data and uses a fast distance field computation algorithm to create a closed skull model as the base of his reconstruction. To create a clear image of the face he uses mathematical morphological operations: erosion for removal of external parts, dilation for adding boundaries, opening for enlarging details and closing for creating the closed skull model. In the finale step, the author uses warps based on correlated points and a reference skull database to determine the corresponding tissue depth at those points.

In the paper presented by Madsen et al. (Madsen et al., 2018) the authors have combined a statistical face and skull shape model. They use the Markov Chain Monte Carlo (MCMC) approach which relies on a set of distances between the skull and the sampled faces (tissue depth markers). In the end, the reconstruction is based on a probabilistic model that combines two independent statistical shape models. The result is a full distribution of likely faces. This approach can also be used for creating the reconstructed face of a partial skull.

Knyaz et al. (Knyaz et al., 2020) are incorporating machine learning techniques into the field of facial reconstruction. The authors approach facial reconstruction as a multi-modal data translation problem and develop a generative adversarial network model (GAN) based on the translation of skull depth maps to face depth maps. One of the biggest contributions of this paper is the development of a fully automated photogrammetric system for textured skull 3D models.

Gietzen et al. (Gietzen et al., 2019) use volumetric CT scans and optical 3D surface scans. They extract

the skulls and heads (face) as triangular surface meshes and their relationship is established by pairing the mesh with a template model and PCA. The result is three models: the parametric skull and head models and a facial soft tissue thickness FSTT model. To generate the FSTT in a statistical evaluation process the authors measure the distances between corresponding skulls and heads

The paper (Hu et al., 2013) by Hu et al. proposes the creation of several local models alongside the globe model and as a result they obtain the hierarchical model. The significance of this model is that the face and skull are represented as dense meshes without landmarks. Using cubes algorithm, the skull and face surfaces are shown in the form of triangle meshes, after which follows a two-step mesh registration method using non-rigid mesh registration algorithm and a linear combination model. Alongside the general model, the local shape varieties are segmented mostly focusing on the eye, nose and mouth and in the final step the local shape models are combined with the global model.

Vandermeulen et al. (Vandermeulen et al., 2006) presents a statistical deformation model in which the hard tissue (skull) and soft tissue (head) are segmented, the images are turned into signed distance transform (sDT) maps, then all reference skulls and heads are non-linearly warped to the target skull. In the last step, the zero iso-level surface of the arithmetic average of the warped reference head sDT maps represents the reconstructed face.

Mansour et al. (2017), use a correlation based paradigm to perform craniofacial reconstructions. They use a novel ridge regression (RR) technique combined with the principal element study (PCA) method. They use a hybrid evolutionary computing scheme which is comprise of Particle Swarm Optimization (PSO) and Differential Evolution (DE) and is based on landmarks.

In the paper by Jia et al. the authors encode craniofacial geometry as a geodesic grid and apply it to craniofacial training data using the heat flow method. (Jia et al., 2021). They combine the partial least squares regression model with a face statistical model to construct the geodesic grid. Once the grid is constructed the heat flow method is used to establish geodesic distances between two vertices on the reconstructed surface and partial least squares regression (PLSR) are applied.

Suputa et alt. describe the Laplacian volumetric model which relies on point clouds that consist of about 400 000 separate points (Suputa et alt., 2020). The authors triangulate the surface based on neighborhood information of the collected points and construct a coordinate system. In the end the face is rendered using detail-preserving surface editing (elastic surface) methodes. The Laplacian surface model has shown to have better results in term of accuracy at reconstructiong facial impressions the the volumetric model.

The Region fusion model presented by Wen shows a reconstruction based on combining separately reconstructed regions of the skull (Yang Wen., 2020). This method combines the Gaussian Process Latent Variable Model and Latent Space Representation of the Skull and Face (GP-LVM) with the Least Square Support Vector Regression (LSSVR).

The most significant improvement seen is the near-disappearance of 3D reconstruction that uses clay and plastic. 3D digital facial reconstruction is the dominant technique, and every year more progress is being made.

3 Digital facial reconstruction – general approach

As we have seen from the examples in Table 1, there are a number of methods available for digital facial reconstruction today, but the general base model of the reconstruction process can be seen in every approach. Fig. 2 shows the general base model made by Claes and Vandermeulen (Claes et al. 2010) with modifications by the authors for the purpose of this paper.

The model illustrates the process of facial recognition, with an alternative version of step B. The alternate version of step B, hereby referred to as B1 “Digitalization of live subject’s skulls” is most commonly used when creating a new population-specific profile or testing the accuracy of an existing profile. In those cases, we are dealing with live human subjects and not just skulls, and extra steps need to be taken, such as the separation of the soft tissue from the CT scan of the skeleton.

All reconstructions, as shown in Fig. 2 start with the skull. In the anthropological examination (Fig. 2(A)), the experts determine the properties of the skull such as age, sex, ancestry, BMI, dental examination, etc. It is important to note that BMI can sometimes not be ascertained, but if it is possible, it is of great importance to the reconstruction process (Claes et al. 2010, De Greef et al., 2009).

After the skull examination has been finished, digitalization may begin (Fig. 1(B)). In the case of constructing a new population-specific face profile, the first step is digitalization of live subjects’ skulls (Fig. 2 (B1)), a non-destructive and non-invasive process.

The next step, and undoubtedly the most important in digital facial reconstruction, is generating the

craniofacial model (CFM) (Fig. 2(C)). A CFM codes the acquired knowledge about human face shapes and how they relate to the skull and anatomical landmarks underneath them (Claes et al. 2010). The CFM consists of three components: 1. Craniofacial template, 2. Craniofacial information and 3. Craniofacial deformation. The craniofacial template is the starting point of the CFM and contains the reference facial knowledge (Claes et al., 2010). Craniofacial information contains the knowledge about the surface of the skull, tissue thickness, muscles, etc. Craniofacial deformation refers to template that can be manipulated to better fit the underlying skull.

The skull representation (Fig. 2(D)) represents a copy of the actual skull and contains anatomical markers. The number of landmarks used varies between papers and can go from 9 (Duan et al., 2015) to 102 (Guyomarc'h et al., 2014) or more.

The next step is the combination of the CFM and the skull representation in the reconstruction process (Fig. 2(E)). This is achieved by determining the geometric relationship between the CFM and the represented skull (Claes et al., 2010).

The step after the reconstruction is texturing and rendering of the face (Fig. 2(F)). These are the most important details, as they are the ones that help with strengthening the recognition process. However, they can be hard to interpret properly, because they are characteristics that are often impossible to generate from the skull itself such as an exact skin tone, scars, BMI, etc. (Claes et al., 2010, Claes et al., 2010).

One additional step done when creating a population specific profile or testing the accuracy of a model is the comparison with soft tissue scans of living subjects. This is the final step and can be achieved if recognition is possible (Rajapakse et al., 2012, Thiemann et al., 2017).

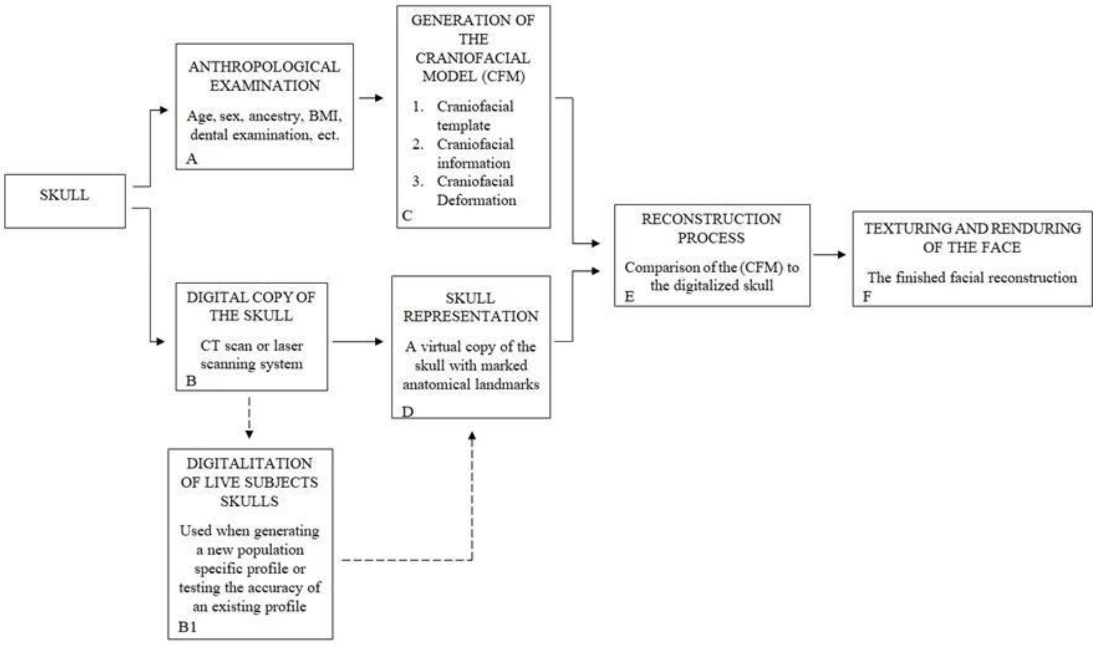

Figure 2. The modified general base model of the digital reconstruction process (modified from Claes et al. 2010)

4 Discussion

Digital facial reconstruction can be done with a number of methods but the most prevalent is CT scans (Shui et al., 2020 – Vandermeulen et al., 2006).

One of the first methods used was a combination of strip plastic facial reconstruction and warped mapping between skulls (Jones, et al., 2001.). While it showed some promise, the emersion of statistical deformation models (Vandermeulen et al., 2006.), hierarchical dense deformable model (Hu et al., 2013.), statistical shape models (Bai et al., 2016., Shui et al., 2020.) and evolutionary computing (Mansour, 2017.) proved to be more reliable. However, with the advancement of technologies and landmark mapping, the previously mentioned methods together with dense statistics of soft tissue thickness models (Gietzen et al., 2019.) started being replaced with methods that needed less landmarks and were more easily automated. Such methods are geometric morphometrics (Guyomarc'het et al., 2018.), Iterative Closest Point Algorithms (Gietzen et al., 2019.), generative adversarial network model (Knyaz et al., 2020.), 3D Laplacian Surface Deformation (Suputa et al., 2020), Region Fusion Strategy (Wen et al. 2020) and Heat flow geodesic grid regression (Jia et al. 2021).

This review revealed that there are two dominant uses for digital facial reconstruction: archaeological cases where the face of a historically relevant person is being reconstructed (Guyomarc'h et al., 2018, Lee, W. J. et al., 2020), and the development of new and improved models for automated digital facial reconstruction (Shui et al., 2020, Vandermeulen et al., 2006).

A conclusion presented in most works (Shui et al., 2020, Vandermeulen et al., 2006) is the need for a stronger reference face pool as the basis for both the construction of new methods and the use of digital facial reconstruction for identification purposes. Some approaches however, have gone in a different direction trying to eliminate the need for an existing reference collection (Jones, 2001). In most research work, the sample size is still relatively small (Miranda et al., 2018, de Buhan & Nardoni, 2018), and a bigger sample size would be needed to generate a more precise model. A possible improvement would also be to add uniformed criteria for facial reference pools. As we have shown in Table 1, certain information, like population, sample size, age ranges or number and types of landmarks is missing in almost all of the revived papers. A solution for getting the best information for further research is creating a number of categories that have to be filled out while conducting research on reference pools. The data in those categories can be specific to the research, but all the information should be available.

Population specifically-generated masks have proven to increase the accuracy of reconstruction (Imaizumi, K., 2019). Furthermore, once a specific mask has been created for a population specific algorithm can be generated to improve the accuracy of specific soft tissue structures such as the nose, ears and the mouth, which in turn increases the accuracy of the reconstruction even more.

Digital facial reconstruction is still a relatively new tool in the field of forensic science, but it holds tremendous potential. New and improved methods for generating faces and improving accuracy are being developed worldwide and population-specific profiles play a large role in that. For now, digital facial reconstruction is still only a last resort tool for forensic identification and is used only if no other method is available.

Further, the process of digital facial reconstruction is only partially automated. A lot of progress has been made with reconstructions using artificial intelligence, but there are still no widely used tools in forensic investigations (Mesejo, P. 2020.). Digital facial reconstruction as of now still requires an experienced researcher to be present, control the process and apply the finishing touches.

5 Conclusion

The aim of digital facial reconstruction is to reconstruct a lifelike face from a skull that can trigger recognition. It is a valuable tool used in many disciplines such as anthropology, archaeology and forensics.

All facial reconstructions are established on the same principles, generating a face based on the underlying skull structure by recreating the facial muscles. Most approaches have a uniformed general framework and still rely a lot on prior knowledge (age, sex, ancestry, BMI) and an existing database of face shapes to make an accurate reconstruction. To adjust for this, the model face allows for manual deformations to closer match the structure of the skull. In the final step, texturing and rendering of the face gives it its lifelike appearance and can be used for comparison with existing photographs. Although this process is not yet fully automated, it requires a lot less specific knowledge and can be done much faster than manual reconstruction. One of the main advantages is also the fact that generating the face is done relatively fast, and if alterations need to be made, the changes will be made instantly.

While the base framework for most methods is the same, there are a number of elements that can be changed and that lead to different levels of success in digital facial reconstruction. An important factor shown is the need for a strong and detailed database of faces for both the base of a new method and for the construction of a face for identification. Factors that cannot always be determined with an anthropological examination of the skull, such as BMI, scaring and birthmarks, play a vital role in identification and should be taken into account while creating a face model database.

Digital facial reconstruction has come far in the last few years and it is only going forward. While still not a mainstream tool for identification purposes, with the creation of new and more precise models it could soon take its place among accredited identification methods. Digital facial reconstruction is still as much an art form as it is a scientific method, but while before the emphasis was on the artists' interpretation, today it has shifted toward a reconstruction based on precise measurements and algorithms.

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