Chapter 5
Computational Image-Guided Technologies in Cranio-Maxillofacial Soft Tissue Planning and Simulation

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Abstract Due to the complexity and unpredictability of cranio-maxillofacial (CMF) surgery, computer simulations have been proposed to assist the surgeon in the decision-making process of surgical planning. Current planning solutions require the use of different and unconnected tools to account for the necessary balance and interplay between functional and aesthetic aspects of CMF surgery, which ultimately makes an effective combination and analysis of the information difficult. In this article we present current approaches and new trends suggested to alleviate these issues and to promote the development of clinically relevant and seamless, yet effective, computational solutions for CMF surgical planning.

Keywords Neurosurgical procedures • Computer assisted systems • Preoperative planning • Intraoperative navigation • Charge coupled device • Dynamic reference frame

Introduction

Cranio-Maxilofacial Surgery

Cranio-maxillofacial (CMF) surgery is a surgical specialty that deals with the treatment of inborn or acquired facial disfigurements. These conditions can be such as cleft lip- and palate, craniofacial malformations, aftermath of facial trauma or of ablative tumor surgery. Surgical interventions in the CMF area and even their planning make high demands on the spatial sense of the surgeons.

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L.E. Ritacco et al. (eds.), *Computer-Assisted Musculoskeletal Surgery: Thinking and Executing in 3D*, DOI 10.1007/978-3-319-12943-3_5

This is on one the hand due to the close proximity of highly vulnerable anatomical structures and on the other hand due to the complex morphology of the region. Modern image-guided techniques are the basis for diagnostics, therapy and documentation. These technologies enable us to produce patient-specific models of the clinical situation. They give us the possibility to perform accurate planning and transfer the planning to the operation theatre. These technologies have made their way into the clinical routine of highly advanced treatment centers [1–5]. One of the most evident indications for the use of virtual planning tools in CMF Surgery is the planning of surgical intervention for patients suffering of malocclusion. Malocclusion can either be caused by a malposition of teeth in the level of the alveolar crest or by an incorrect positioning of the upper and lower jaw relative to each other. For the former, an orthodontic treatment will deliver satisfactory results. For the latter, only a surgical procedure will provide a causal therapy. These interventions are called orthognathic surgeries and their aim is to change the position of the maxillary and mandibular bone, relative to each other and to the skull base. As these interventions are highly elective, an accurate and extensive preoperative planning has to be conducted.

To update the planning procedure several systems for virtual three-dimensional visualization and procedure planning based on volume datasets have been recently introduced in some clinical centers, routinely substituting the conventional two-dimensional cephalogram based planning-approach, and especially improving the prediction of soft tissue deformations [6]. In order to ensure an optimal pre-operative skeletal planning of the patient with his postoperative facial appearance, a highly reliable and accurate prediction system is required. In order to realize the pre-operative surgical plan in the operation theatre, the planning and prediction software should be linked to a navigation system for the intra-operative control of the relocation of the upper and lower jaw.

Image-Guided in CMF Soft-Tissue Surgical Planning

Over the last 20 years computer-assisted surgical simulation and intervention planning has made its way into clinical routine in CMF surgery. Due to the close proximity of highly vulnerable structures in the viscero-cranium region, virtual planning has been used to create highly accurate three-dimensional (3D) models of the patient's anatomy and clinical scenario (virtual osteotomies, cephalometric analysis, etc.). Furthermore, in CMF surgery the complexity of the surgical scenario is enhanced by the difficulties to predict soft-tissue variations from bone relocations due to the low correlation between hard-, and soft-tissue variations [7–10]. This makes the surgical plan very challenging and highly dependent on the surgeon's experience. This has led to the development of computer simulations, which provide a unique tool to predict the surgical outcome. With these tools, surgeons are able to pre-operatively assess the implications of various surgical scenarios (bone relocations). However, several deficiencies presumably stemming from the lack of interdisciplinary work between scientists and medical practitioners still exist. The following summarizes the main technical challenges in CMF soft tissue simulation.

The basic components for CMF soft-tissue simulation are:

- *Geometrical modeling of hard and soft tissues from Computed Tomography (CT) medical images.*
- *Physical models employed to realistically link the internal stress and deformation of tissues.*
- *Realistic modeling of external forces and constraints to establish a connection between internal deformation and applied forces.*
- *Fast and reliable solver for the resulting differential equations.*

The generation of patient-specific models involves the task of semi- or fully-automatic segmentation of hard and soft tissues. Research in automatic segmentation of the facial soft tissues is, however, still in its infancy. The segmentation of facial soft tissues from diagnostic Computed Tomography (CT) or Magnetic Resonance Images (MRI) is thus still an active research area [11–14]. There are several aspects that make the segmentation a complex task. First, the facial region is one of the most complex anatomical regions of the human body. Second, most of the facial muscles are paper-thin and often even smaller than the voxel resolution of the imaging device, which leads to partial volume effects. Lastly, the complexity of the segmentation task is further increased by imaging noise and poor contrast (in particular in cone beam computed tomography – CBCT); by the presence of high-density artifacts (*e.g.* from dental fillings or implants), and muscles that are overlapping or in contact one with another.

As stated above, segmenting the facial soft tissues is in the mathematical sense an ill-posed problem and still a very active field of research. In [15] Rezaeitabar et al. proposed a specifically tailored region growing approach to segment two facial muscles *i.e.* the masseter and the temporalis. Ng et al. published a series of papers [16–18] where they described segmentation approaches for different facial muscles. Their methods are based on a Gradient Vector Flow (GVF) snake based approach. Kale et al. proposed in [19] a Bayesian and Level-set framework to segment facial soft-tissue from CT and MRI data sets. Through modeling of the partial volume effect they also tried to segment the very thin facial muscles. Drawback of the method is that they require a co-registered CT and MRI data set of the patient. Whereas CT is commonly available, MRI is generally not used and would only add to the costs of the intervention.

Once the segmentation is completed, a computer simulation can be executed to predict the deformation behavior of facial tissues following an orthognathic procedure. Computer-assisted facial soft-tissue simulation was originally introduced by Terzopoulos et al. [20] and Lee et al. [21] where a simple mass-spring modeling (MSM), consisting of a multi-layered facial tissue was applied for soft tissue simulation in CMF. Keeve et al. [22] presented a MSM-based approach with prismatic elements, and compared the result with FEM simulations (Finite-Element Model) in terms of accuracy and computational cost. Zachow et al. [23] suggested a fast tetrahedral volumetric FEM, which can be used in clinical practice.

Due to the high computational and modeling demands of advanced FEM methods, none of the proposed approaches have reached clinical routine and have only been used with clinical data through a dedicated setup where an specialist conducts the modeling and simulations, which are then presented and discussed back with the surgeon [24–28]. **For clinical use, it is important to provide the surgeon with the ability to seamlessly test different surgical approaches without incurring into long computational times or overly complex modeling processes**. From discussions with opinion leaders and own experience, we believe that the surgeon needs to be in control of the surgical plan (as opposed to rely on back-and-forth interactions with an engineer) and should have appropriate tools (i.e. speed, usability and accuracy compatible with the clinical workflow) to plan the surgical procedure.

Cotin et al. [29] proposed a hybrid method using MTM (Mass-Tensor Modeling) for enhanced local deformations in simulation of liver surgery. Mass Tensor Modeling was later extended by Picinbono et al. [30] to consider non-linear, anisotropic elasticity. Chabanas et al. [31] proposed a mesh-morphing algorithm to minimize the laborious efforts in preparing finite-element meshes. Based on the seminal work of Cotin et al. [29], Mollemans et al. [32] first applied MTM to CMF soft-tissue simulation, and evaluated the method qualitatively and quantitatively on ten clinical cases. From the simulation point of view, MTM has been widely accepted for CMF soft-tissue simulation due to its efficiency, accuracy and low computational time. Similarly, GPU-based simulation models have been proposed to deliver fast mechanical simulations [33–37]. Nonetheless, the integration of these methodologies to clinical routine is hindered by the lack of a complete solution that considers the clinical workflow and moreover provides an acceptable accuracy in the error sensitive regions of the face [38–42]. Furthermore, available commercial packages for CMF soft tissue simulation lack appropriate segmentation routines and rely on extensive manual corrections.

Developing clinically relevant solutions that counter accuracy limitations by bringing additional non-imageable anatomical and clinical information into the simulation workflow has shown to leverage the development of new technologies in CMF soft tissue simulation [43–49]. These implementations have resulted in an average simulation error of 1 mm, which is sufficient for surgical planning. In this way, the simulation is capable of providing the surgeon with a post-operative scenario, from which adaptations or changes to the surgical plan can be performed in order to prepare the patient for the changes in his/her appearance. In these approaches, however, the surgeon follows a trial-and-error scheme to determine the final surgical plan that yields a satisfactory soft tissue outcome.

Functional Aspects in CMF Planning

In cranio-maxillofacial surgery the determination of a proper surgical plan that yields a desired aesthetic facial profile while considering functional aspects of the post-operative scenario is very important for a successful treatment outcome. As described above, current solutions do not provide surgeons with tools to effectively consider the complex interplay between aesthetic and functional aspects, which in light of the complexity of the surgical scenario makes the planning of CMF surgeries very difficult, and ultimately highly dependent on the surgeon's experience. The functional aspects independently investigated in the literature are described below.

Functional aspects to be considered for the surgical plan include reestablishment of the dental occlusion through occlusion analysis [50]. This analysis requires the identification and geometrical assessment of the upper and lower dental arches. The common clinical approach is to use dental casts to define pre-operatively the desired occlusion, which is then transferred intra-operatively using a manufactured splinter. These approaches present some limitations, such as reduced spatial information with respect to the rest of the anatomy, as only a partial observation of the surgical scenario is represented. Furthermore they do not allow for a comprehensive analysis of the effects of the planned occlusion on surrounding hard and soft tissues [51].

Computerized models haven been proposed to perform a virtual assessment of the occlusion. The accuracy of these models has been analyzed with respect to the different imaging parameters and processing steps [52–54], and improvements to deal with metal artifacts and low image resolution have been proposed by combining information from CT imaging and laser scanned dental casts [55–57].

Virtual assessment of occlusion has been proposed by applying semi-, and automatic approaches using registration techniques incorporating collision constraints [58–60]. These approaches enable a precise alignment of the dental arches in a virtual scenario. However, they decouple the occlusion analysis from the other functional and aesthetic aspects of the surgical plan.

Another aspect of the surgical plan to be considered is the evaluation of the airways after orthognathic surgery. Several studies have analyzed the impact of different surgical plans (e.g. mandibular setback, advancement, bimaxillary, etc.) on the geometrical and volumetric changes of the upper and lower airways [61–69]. Similarly, these approaches do not consider the joint analysis of functional and aesthetics aspects of the surgical plan.

To obtain a clinically relevant solution including airway analysis, it is important to develop automatic or nearly automatic segmentation approaches that can be seamlessly integrated into a unique platform.

Airway segmentation is an active area of research since many years. Of particular interest are the segmentation techniques using CT images, see for example [70]. The main application has been the analysis of airways for geometric measurements or navigated interventions. With the availability of CBCT the need for semi- or even fully automatic airway segmentation has become essential for surgical plans incorporating this functional aspect. As CBCT mainly finds its application in the cranio-maxillofacial surgical field, a heuristic approach was proposed in [71] for the analysis of the upper airway. In [72] a more elaborated snake-based method has been described to automatically segment the upper airway.

Due to the low radiation dose of CBCT, its use has recently attracted attention for CMF soft-tissue prediction. In [38] an evaluation of a commercial system for CMF soft-tissue prediction was conducted using CBCT data of patients undergoing orthognathic surgery. The study highlighted the marked simulation errors around the error-sensitive regions of the lips, as well as the importance of evaluating the accuracy of the soft-tissue predictions on the different regions of the face, as opposed to an overall global evaluation over the entire face [73]. Nonetheless, the common agreement is that CBCT presents great opportunities for CMF soft-tissue prediction and surgical planning, and thus it should be further investigated [39].

Fast Patient-Specific Modeling

Generating patient-specific models has been a bottleneck in the CMF surgical planning pipeline. Current commercially available software tools typically rely on basic image thresholding techniques followed by cumbersome manual corrections. Moreover, the situation is worse when such approaches are used on CBCT images, as their low contrast hinders the task of image segmentation. It is therefore crucial to develop appropriate approaches for fast and accurate bone and soft tissue segmentation. One such approach employed for CMF planning has been the use of statistical shape modeling techniques, which learn from data the anatomical variability of the studies population [74]. When combining these approaches with domain-knowledge, where the user assists the automated approach by placing anatomically or surgically important landmarks, it is possible to realize a fast patient-specific modeling [75]. Furthermore, the topology-preserving feature of this approach enables incorporation of other type of valuable information used for modeling and simulation.

Dealing with Metal Artefacts: Spatially-Varying Gaussian Process Modeling

To deal with image artefacts in CBCT imaging, new modeling schemes are being proposed. One of them is the so-called spatially-varying Gaussian Process Modeling [76]. In this framework, a-priori information on the localization of the metal artefacts can be encoded on the reference model and used during model morphing (see Fig. 5.1). In this way, noisy information stemming from the metal artefacts can be neglected and exchanged with the statistical information built in the statistical shape model driving the model morphing process. The framework, also available through the open source library Statismo [75], enables definition of different morphing models, allowing in turn definition of different transformation properties and features (Fig. 5.2).

Seamless Surgical Planning: The Direct and Inverse Surgical Planning

Despite of the complexity of the surgical scenario, the available technologies must ultimately serve as a vehicle for the surgeon to plan the surgical plan in a seamless manner. It is thus crucial to develop technologies that leverage the work of the

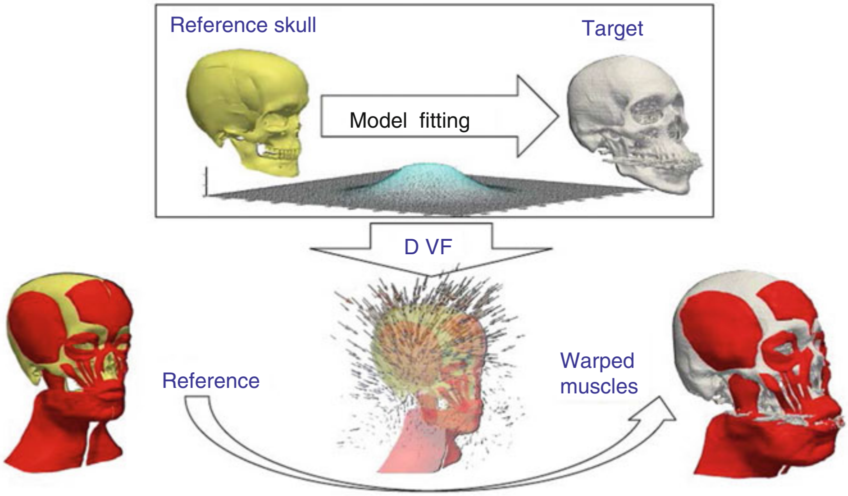

Fig. 5.1 Fast patient-specific modeling using statistical shape modeling techniques. A Reference skull is morphed to match the patient's anatomy, as imaged via CT or CBCT, following population-level statistics and anatomical landmarks. A displacement vector field (*DVF*) is then obtained allowing propagation of other type of information. As exemplified in the lower part of the figure, facial muscle information can then be effectively estimated

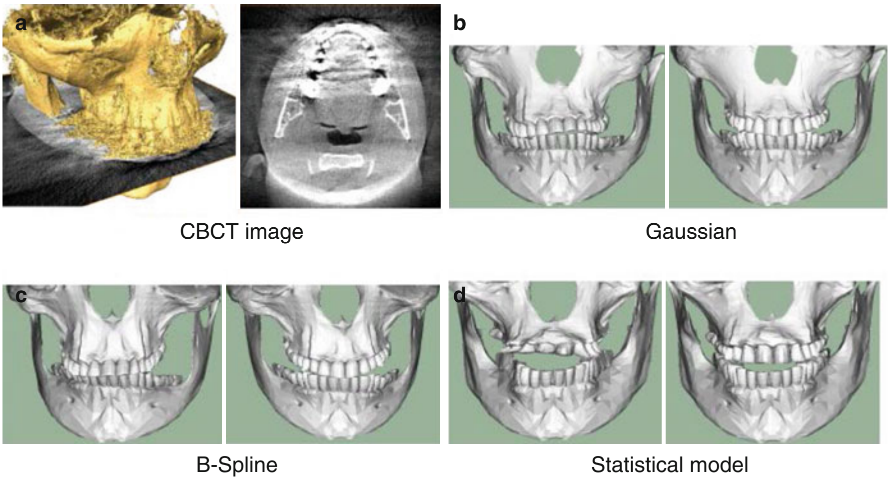

Fig. 5.2 Registration of skulls from CBCT data: (**a**) shows a slice through the image and a reconstruction of the surface obtained using threshold segmentation. (**b**–**d**) show registration results obtained using different deformation models. The left images show a normal registration, while in the right images a spatially-varying registration has been used, showing the ability of the method to deal with metal artefacts

surgeon, allowing him to test different options and interact with the bone and soft tissue components of the surgical plan.

Recently, a shift paradigm was presented whereby the necessary planning is computed from the desired post-operative outcome [75]. This paradigm shift, coined *"Inverse Planning"*, enables the surgeon to look at the surgical plan from a different perspective, allowing him to directly define the desired outcome, without the need of the commonly used trial-and-error scheme available in current solutions.

Inverse Soft Tissue Modeling

The proposed approach employs a fast biomechanical model to derive from the desired facial outlook the necessary surgical plan. Based on the desired facial outlook the deformation of internal soft tissues is calculated, followed by constrained surface registration between bone segments and internal soft tissues. The proposed registration component considers collision and occlusion constraints, and its formulation allows us to derive in a straightforward manner different levels of interplay between quality of occlusion and compliance to the desired outlook (i.e. constraints relaxation). Furthermore, and in regards to a biomechanical simulation that would model the entire ensemble of bone and soft tissues, the proposed approach avoids known issues of layer detachment and convergence related to the high elasticity transition present at the interface of bone and soft tissue materials. We remark that this approach differs from the classical inverse modeling proposed in computational mechanics and used in implant shape design in [28], as our method deals with the ill-posedness of the problem by considering occlusion and geometrical constraints through a registration component that effectively penalizes the set of numerical solutions.

By combining the direct (i.e. soft tissue simulation from bone displacements) and the inverse soft tissue modeling (i.e. specification of bone displacement to yield a desired outcome) it is possible to yield an effective system that, in a transparent way, enables the surgeon to work on the surgical plan.

Due to airways and tongue volume constraints in complex CMF cases, large rotational and translational planning are rarely operated in one single step and surgeons typically divide it into a series of surgeries, which in turns translates into small deformations in engineering mechanics. Nonetheless, to cover these rare cases for large deformation problems, we will consider modifying the classical FEM inverse approach [77] in which the inverse modelling is transferred to a direct problem by super-imposing boundary conditions and transferring the unknown set of displacements to the other side of the continuity equation [78].

Preliminary results, shown on Fig. 5.3, on a set of clinical cases showed in five out of six CT cases a high level of agreement to the actual surgical plan. In one case the proposed approach was confirmed to improve the actual executed plan. As an additional evaluation, simulated soft-tissue outcomes were compared using the predicted and real clinical plan, resulting in a close agreement between the facial simulation results using the predicted and actual planed approach (Fig. 5.4.).

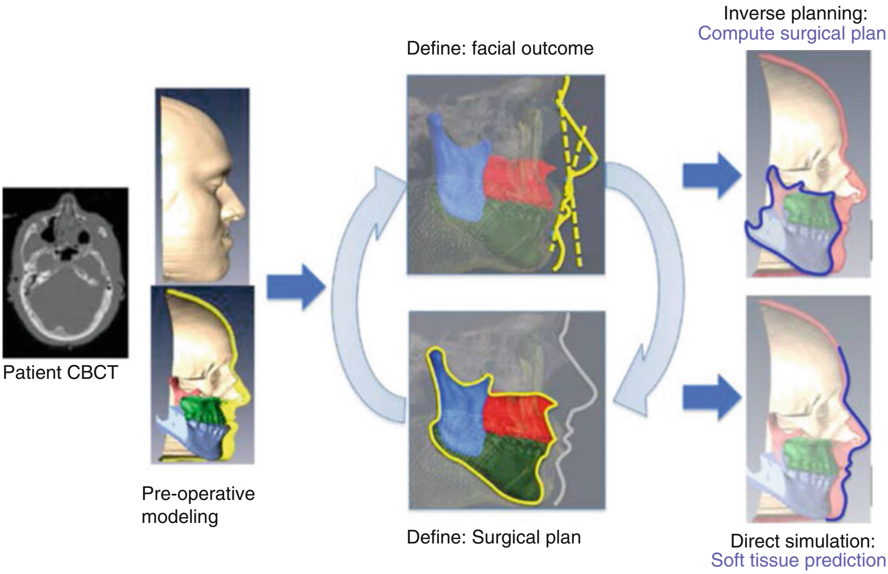

Fig. 5.3 Direct-inverse planning approach. From the pre-operative CBCT scan, a detailed patient-specific model will be created. The surgeon then has the option to interact with the bone segments and perform a direct simulation for soft tissue prediction (*lower part of the figure*), or define the desired facial outcome and obtain the required surgical plan, subject to functional considerations (*upper part of figure*), and assisted by cephalometric guides (illustrated with *dashed lines*). A fast simulation enables the surgeon to seamlessly interact in one mode or the other

Discussion and Conclusions

The human face is a fundamental part of our identity. It centralizes the senses of vision, hearing, taste and smelling, and provides us with channels to participate and integrate in society. The complexity of the clinical scenario is complex, as it requires high understanding of the balance amongst aesthetic, functional, psychological and sociological implications of the surgical outcome. Furthermore, the degree of unpredictability on the surgical outcome makes the decision-making process, on a patient-basis, highly complex. This has called for the development of computational means to assist the surgeon on the task of planning the surgical approach. We believe, however, that more research efforts are essential and needed in order to bring these tools to a level where they can effectively and jointly consider aesthetic and functional aspects for the planning of CMF surgeries.

Based on the observations from the state of the art it can be concluded that functional aspects are of importance and need to be considered in CMF planning. However, there is need to foster the interdisciplinary research with the development of novel approaches that concurrently make use of functional and aesthetic information, and are developed in light of the clinical requirements and workflow. In this regard, it is necessary to enhance these enabling-technologies by developing advanced segmentation

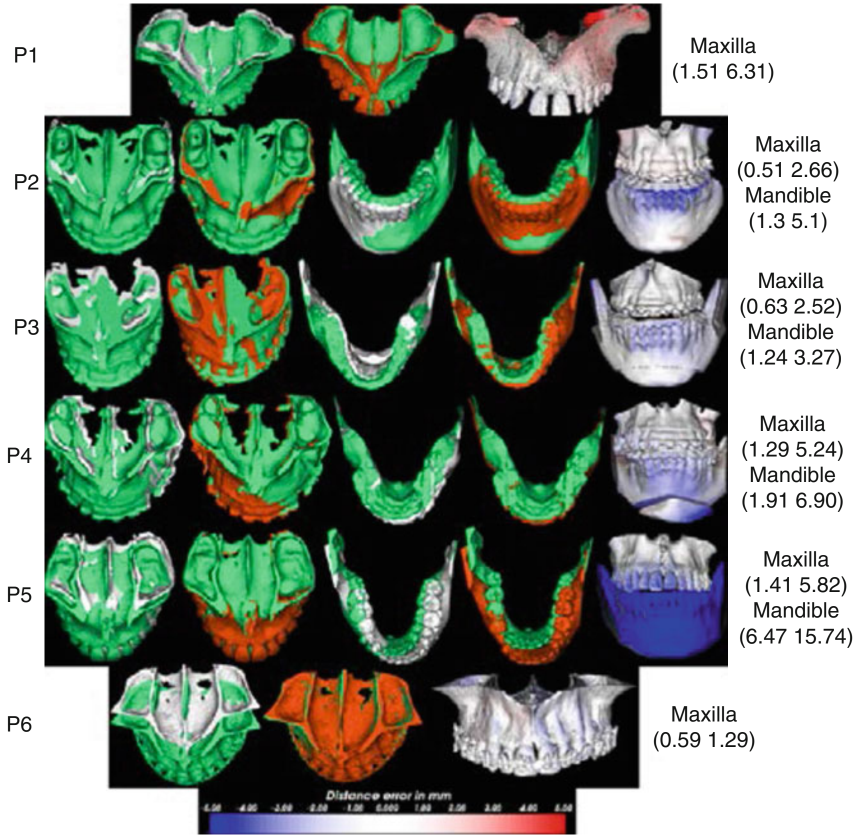

Fig. 5.4 Predicted (*orange color*), actual post-operative (*green color*), and pre-operative segments (*white color*) for the respective patients. The distance errors from the post-operative segments are shown as color-coded images on the predicted model on the rightmost column with the (median maximum) error values in mm indicated for the respective segments. The *blue color* means the proposed approach falls posteriorly than the real post-operative segment (Adapted from Luthi et al. [74])

algorithms for CBCT imaging as well as algorithms allowing the surgeon to seamlessly interact with the surgical plan or the desired soft tissue outcome, all while jointly considering the functional and aesthetics aspects mentioned above.

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