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SHAPE: A visual computing pipeline for interactive landmarking of 3D photograms and patient reporting for assessing craniosynostosis

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Abstract

3D photogrammetry is a cost-effective, non-invasive imaging modality that does not require the use of ionizing radiation or sedation. Therefore, it is specifically valuable in pediatrics and is used to support the diagnosis and longitudinal study of craniofacial developmental pathologies such as craniosynostosis — the premature fusion of one or more cranial sutures resulting in local cranial growth restrictions and cranial malformations. Analysis of 3D photogrammetry requires the identification of craniofacial landmarks to segment the head surface and compute metrics to quantify anomalies. Unfortunately, commercial 3D photogrammetry software requires intensive manual landmark placements, which is time-consuming and prone to errors. We designed and implemented SHAPE, a System for Head-shape Analysis and Pediatric Evaluation. It integrates our previously developed automated landmarking method in a visual computing pipeline to evaluate a patient's 3D photogram while allowing for manual confirmation and correction. It also automatically computes advanced metrics to quantify craniofacial anomalies and automatically creates a report that can be uploaded to the patient's electronic health record. We conducted a

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Carsten Görg: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization. **Connor Elkhill:** Writing – original draft, Visualization, Software, Methodology. **Jasmine Chaij:** Writing – original draft, Validation, Methodology. **Kristin Royalty:** Validation. **Phuong D. Nguyen:** Resources, Conceptualization. **Brooke French:** Resources, Conceptualization. **Ines A. Cruz-Guerrero:** Software, Methodology. **Antonio R. Porras:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

user study with a professional clinical photographer to compare SHAPE to the existing clinical workflow. We found that SHAPE allows for the evaluation of a craniofacial 3D photogram more than three times faster than the current clinical workflow (3.85 ± 0.99 vs. 13.07 ± 5.29 minutes, $p < 0.001$). Our qualitative study findings indicate that the SHAPE workflow is well aligned with the existing clinical workflow and that SHAPE has useful features and is easy to learn.

Keywords

3D photogrammetry; Craniosynostosis; Interactive patient reporting

1. Introduction

Three-dimensional (3D) photogrammetry is an imaging technology that uses multiple cameras in a stereo configuration to produce a three-dimensional model of a subject. In the medical field, specifically in pediatrics, it is often used to assess craniofacial anomalies and evaluate longitudinal changes. Unlike traditional medical imaging modalities such as computed tomography (CT) or magnetic resonance (MR), 3D photogrammetry is non-invasive, does not require the use of ionizing radiation or sedation in young children, and it is fast to acquire, which are critical advantages in pediatric patients. For these reasons, 3D photogrammetry has become popular in pediatric craniofacial clinics, and several research works have shown its potential to plan treatments and evaluate surgical outcomes [1–4].

However, the clinical use of 3D photogrammetry presents important challenges. The lack of a stabilizing mechanism for the patient's head leads to inconsistent head pose and position between image acquisitions, and with variable quality among operators. Moreover, unlike uniform voxel-based images, 3D photograms are represented as 2D-manifold meshes containing vertices and triangles with varying densities, resulting in non-uniform spatial resolutions. Most existing methods for 3D photogram analysis have relied on the conversion of 3D photograms to voxel-based image representations to enable the use of traditional image processing techniques, which suffer from inaccuracies associated to cascaded processing and error accumulation in addition to being computationally intensive. Hence, the use of 3D photogrammetry has been mostly limited to research and most automated analysis methods have failed at clinical translation.

The evaluation of head development using 3D photograms typically relies on the segmentation of specific anatomical landmarks [5] that are used to compute simple morphometric measurements [6–8] and/or to segment the head surface from the lower cranial structures [1]. In current practice, the placement of these landmarks is a highly manual process that lacks reproducibility, is time consuming, and is prone to errors [9]. For that reason, recent automated methods have been presented to directly operate on 3D photograms for both landmark detection and evaluation of pediatric head development landmarks [10]. However, despite their potential, existing methods often require substantial data pre-processing, have not been embedded in user friendly interfaces that can enable their use by clinical practitioners or manual adjustments for potential inaccuracies, and do not generate comprehensive patient evaluation reports that can integrate on existing clinical workflows. Each of these factors make translation into clinical practice infeasible, rendering state-of-the-art methods to evaluate pediatric craniofacial patients unavailable for care.

In this work, we address these problems and present a framework to translate existing methods for landmark detection and analysis of head development into clinical practice. We designed and implemented a unified System for Head-shape Analysis and Pediatric Evaluation (SHAPE). The system reads in a patient's 3D photogram, automatically places a set of craniofacial landmarks, allows for their manual confirmation and correction, and automatically computes both a series of standard clinical craniofacial measurements and machine learning-based metrics of head development prior to building an analysis report for upload to the patient's electronic medical record. We also conducted a user study with our professional clinical photographer to compare SHAPE to the current workflow for 3D photogrammetry analysis.

2. Clinical background and related work

2.1. Clinical background on craniosynostosis

Craniosynostosis is the premature fusion of one or more cranial sutures resulting in local cranial growth restrictions and cranial shape anomalies that require surgical intervention [11]. Patients with this condition are clinically evaluated both before and after surgical treatment to determine their phenotypical severity, plan their surgical treatment and evaluate its effectiveness [12]. Although computed tomography (CT) images are acquired before surgery to obtain a confirmation of diagnosis, repeated and post-surgical CT images are avoided to minimize patient exposure to harmful radiation and/or sedation [13–16]. Hence, objective information about post-surgical development and treatment effectiveness have traditionally been unavailable. This has created a large variability of surgical approaches and outcomes among surgeons and institutions [17–20]. Although many craniofacial clinics have started using 3D photogrammetry as an alternative evaluation method to traditional radiographic imaging [5,21], the lack of established metrics and repeatable frameworks to quantify highly variable head anomalies have prevented the use and standardization of this imaging modality in widely adopted clinical protocols [5].

2.2. Analysis of clinical 3D photogrammetry data

Automated methods for landmark detection have been widely explored in traditional medical images [22–24] but these methods cannot be used in 3D photogrammetry due to the inherent difference in data structure. Specifically, 3D photograms are represented as unstructured triangulated point clouds with texture information as compared to traditional voxel-based image data representations.

Several methods using manually identified anatomical landmarks or requiring manual processing have recently been published for processing clinical 3D photogrammetry data. Porras et al. [1] first proposed a pipeline combining statistical shape modeling and machine learning techniques to automatically identify craniosynostosis, the specific phenotypes of single-suture fusions and evaluate surgical outcomes, which showed similar accuracy to CT image analysis. Bruce et al. [25] presented a principal component-based machine learning algorithm to characterize patients with metopic craniosynostosis using 3D photogrammetry and demonstrated its effectiveness in 14 patients with metopic craniosynostosis. Abdel Alim et al. [26] used various 3D photocephalometrics compared to estimated mean cranial shapes to evaluate differences between patients after three different forms of corrective surgery for sagittal craniosynostosis. While each of these works presents effective methods to evaluate patients using 3D photogrammetry, none of them were used in a clinical setting or quantified any potential improvements in clinical performance or efficiency.

There exist tools for surgical planning and forensics that integrate automated anatomical landmark detection. Cliniface [27] and Skeleton-ID [28] both implement and refine the MeshMonk [29] algorithm for facial landmark detection. However, a recent systematic review [30] on the accuracy and reliability of automated 3D facial landmarking in medical and biological studies, which included Cliniface, concluded that “compared to manual landmarking, automated landmark localization of individual facial landmarks reported in the literature is not accurate enough to allow their use for clinical purposes”. Translating current landmarking detection methods in a clinical setting therefore still requires supervision by a human expert. We developed a visual computing pipeline that takes 3D photogram data, supports human-centered interactive semi-automated landmark placement, and then automatically computes metrics and creates patient reports suitable for assessing craniosynostosis. Cliniface focuses on the analysis of facial morphologies, and its provided reporting feature is not suitable for assessing craniosynostosis, as it does not include longitudinal aspects and a comparison to a normative model. To our knowledge, Cliniface has not been formally evaluated in a clinical setting. Skeleton-ID does not have a reporting feature as it does not target clinical applications.

Recently, Elkhill et al. [10], based on previous work on traditional voxel-based image representations [1], proposed a new craniofacial landmark detection method that could be directly used on unstructured 3D photogrammetry data representations [10], within a fully automated processing pipeline to evaluate pediatric head development independently of patient age and sex [10]. Specifically, this fully automated processing pipeline utilized a geometric deep learning method that identifies a series of craniofacial anatomical landmarks in 3D photograms, which were used to isolate the head surface around the neurocranium. Fig. 1 shows the locations of the 27 craniofacial anatomical landmarks identified by this method. Then, a publicly available age- and sex-specific normative statistical model of cranial and head development [31] was used to quantify two age- and sex-independent machine learning-based metrics to evaluate patients with craniosynostosis: (1) the head shape anomaly index (HSA), which quantifies the severity of head malformations; and (2) the craniosynostosis risk score (CRS), which estimates the probability that quantified malformations are caused by craniosynostosis. The focus of the current work is on the creation of a software tool to translate these existing methods into a clinical setting and evaluate their clinical efficiency.

3. Methods

Our research study was approved by the local ethics review committee at the University of Colorado Anschutz Medical Campus (IRB #23–218). To respect the privacy of our pediatric patients, we used a consented adult volunteer in the presented screenshot of the general view of our system. Moreover, we removed any patient identifying information and hid facial features using black boxes in subsequent patient analysis examples.

3.1. Existing workflow and clinical environment

Our team has a professional clinical photographer who acquires and manually analyzes 3D photograms at the Children's Hospital Colorado Craniofacial Clinic using the commercial 3dMDhead System (3dMD, Atlanta, GA) and its software tool. This manual analysis requires individual landmark placement and calculates a series of simple craniofacial measurements based on their location. We used this standard-of-care system as reference for our user study. As part of the domain characterization, team members with backgrounds in pediatric plastic and reconstructive surgery, biomedical image computing, and human-centered computing visited the photographer during multiple craniofacial clinics to study and observe the current clinical workflow for 3D photogrammetry analysis. Based on their background, researchers in our team focused on different aspects of the workflow. Fig. 2 shows the 3D photogrammetry suite at Children's Hospital Colorado.

Existing Workflow: Fig. 3 (left) shows an overview of the current clinical workflow in our institution, which our team has developed during the last decade assisted by the 3D photogrammetry vendor. Importantly, given the currently manual and time consuming approach for 3D photogram analysis using the vendor's software, the personnel effort required for it, and the low clinical accuracy of the metrics utilized to identify cranial pathology, most institutions do not have a dedicated professional for this process, there is no widely accepted and standardized clinical 3D photogrammetry evaluation protocol and 3D photogrammetry is mostly used for research purposes. In our craniofacial clinic, our professional photographer sees every patient with craniosynostosis, who are positioned on the chair to capture their 3D photogram. For young patients, a parent or caregiver usually kneels in front of the patient (so it does not interfere with the acquired image) to hold them in place and encourage them to look at the front camera. After opening the 3D photogram in the 3dMD software tool on a dedicated desktop computer, the photographer first crops the patient's body and surrounding artifacts until only the head and face remain in the photogram. Then, she adjusts the orientation of the 3D photogram so it is aligned with the coordinate axes. Subsequently, she manually places 27 independent landmarks on the 3D photogram by selecting their name from a preset list and placing them on the photogram surface. After landmark placement and revision for accuracy, the photographer takes screenshots of a table that the software generates with simple automatically calculated craniofacial morphology metrics based on the location of previous landmarks. She also captures individual screenshots of the patient's head in the forward-facing direction, left and right oblique views, left and right lateral views, and top view. If other studies are available for the analyzed patient from previous visits, the photographer also locates and opens all the snapshots acquired from the last two photogrammetry studies. All the snapshots from the current and previous two studies are compiled together in one single document and saved in a HIPAA-compliant network drive.

After saving all compiled information, the photographer switches to a different computer with access to Epic (the hospital's electronic medical record system) and to the network drive where patient information is stored. In this computer, the photographer uses previous snapshots to compile three separately PDF files: (1) a file with a grid view of the snapshots acquired for the patient with different orientations together with a table summarizing landmark-based metrics (one page per 3D photogram); (2) a close-up of the tables presenting previous metrics (one page per 3D photogram); and (3) all the snapshots acquired from the latest 3D photogram acquisition. Finally, the photographer uploads the three generated PDF files into the patient's chart in Epic so they are available to the surgeons for patient evaluation.

Clinical Environment: During the current 3D photogram analysis workflow, the photographer faces multiple interruptions from patients or clinical staff. This results in continuous pauses and delays during and between all the steps required to complete patient analysis. These interruptions on the current manual processes that are normal in a clinical setting cause additional inefficiencies, and studies are sometimes not finished by the time patients are seen by the surgeons.

Given the lack of standardized clinical approaches to the acquisition and evaluation of 3D photogrammetry data, the clinical photographer developed this workflow in an organic fashion to accommodate her specific work environment and scheduling constraints. Although she moves through the multiple steps fast and efficiently, the existing workflow is complex and challenging to replicate. Therefore, patients who require a 3D photogrammetry appointment need to be scheduled around the availability of the one professional photographer available in the clinic, which substantially affects patient scheduling and limits clinical productivity.

3.2. Requirement analysis and revised workflow

Based on observations from our team members and discussion with the clinical photographer, we derived the following requirements for a translational system to support the analysis of pediatric craniofacial 3D photogrammetry.

R1: Automated placement of landmarks with efficient manual interactions to confirm or correct placements when necessary.—The manual process of placing all landmarks is slow and tedious. Although full automation would be ideal, the process and its outcomes must still be supervised by a human, since a correct landmark placement is essential for the downstream computation of craniofacial measurements.

R2: Intuitive interface for navigating 3D photograms.—This requirement is essential to enable the efficient manual confirmation and correction tasks in R1.

R3: Automated generation of an analysis report.—The current manual analysis report generation process requires many menial and time-consuming copy & paste operations. Automating the report generation will streamline the entire process by eliminating the most time-consuming step.

R4: Well organized workflow with clearly defined steps.—This requirement will help to resume the workflow after being interrupted and hence, will help increase operator performance.

Fig. 3(right) shows the corresponding adjusted workflow for SHAPE. Four steps the photographer currently performs manually are replaced by automated steps for placing the landmarks, computing metrics, and compiling the results into a report. The SHAPE workflow adds one manual step to confirm and correct the automatically placed landmarks.

3.3. Design and implementation of SHAPE

We utilized Munzner's Nested Model framework [32] for designing and evaluating SHAPE. During the iterative design process, we first replicated the features of the commercial 3dMD software necessary for the landmarking process; we followed a minimalist approach to keep the interface design clean, with the goal of making SHAPE easy to learn and transition to after working with the 3dMD software. In multiple iterations, we then revised the design and added new features, driven by the results of our requirement analysis. Since the clinical translation of 3D photogrammetry analysis is the main contribution of SHAPE, and our embedded methods for automatic landmarking and computation of craniofacial metrics have already been published, we evaluated SHAPE through a formal user study in a clinical setting.

Fig. 4 shows an overview of the SHAPE user interface. The main screen is used to display the 3D photogram, with overlaid landmarks. The side panel on the left includes two sections: Views (for selecting the data layers to be displayed) and Landmarks (the list of currently displayed landmarks and their locations). At the top of the user interface, we provide two arrays of buttons: Quick Navigation (for jumping to pre-defined camera views) and Workflow (for moving through the individual steps of the workflow).

Views: For our study setup, we only included two data layers, the head surface and the landmarks. They are selected by default. However, SHAPE allows visualization of various data layers from the underlying computational methods (e.g., color-coded representation of local metrics of head shape anomalies on the head surface as shown in [1]), or multiple data layers of the same type (e.g., landmarks computed by an external method or tool can be imported).

Landmarks: This panel lists 27 facial landmarks along with their current location. We replicated the order of the landmarks from the 3dMD software tool to enhance usability, since the photographer has memorized that specific order. Unlike the single-color landmark representation of the 3dMD tool, we used a color mapping to support quick identification and location of the craniofacial landmarks in SHAPE. Since representing each of the 27 landmarks in different colors would be too visually complex and would reduce any potential benefits from color-coding, we selected six colors (dark blue, red, cyan, yellow, green, and pink) and reused them across different facial regions. The selected colors are vivid, making them stand out when overlaid on skin-colored head shapes. In our approach, symmetric landmarks (e.g., left and right gonion) are represented in the same hue to facilitate easy verification of symmetries. Additionally, landmarks can be selected from the list, which causes them to be highlighted in the main view and tagged with a label displaying their name on the head surface.

Quick Navigation: Navigation shortcuts to standard camera views are useful to reduce the required amount of manual zoom, pan, and rotation interactions. Based on observations from previous photographer's workflow, we provide shortcuts to the following viewpoints: Left, Anterior, Right, Top, Under, Posterior, Tilt Down (bird's eye), and Tilt Up (worm's view). The photographer typically uses the Anterior view to place or verify the location of most landmarks, except for the opisthocranion (Left and Right views), gnathion (Tilt Up view), right tragion (Right view), and left tragion (Left view).

Workflow: The distinct steps of the workflow are represented by individual buttons, ordered from left to right: (1) loading the patient's 3D photogram; (2) automatically placing the landmarks followed by manual correction if necessary; (3) computing craniofacial measurements by analyzing the head surface; and (4) generating the patient report as a single PDF file. The explicit representation of the workflow steps helps the photographer resume work after an interruption occurs.

Bookmarks: Progress through the workflow can be saved and reopened at any stage of the workflow using the "Save bookmark" and "Load bookmark" buttons at the top right of the screen. This allows the user to save their progress through the workflow, including generated landmarks or results, and reopen their progress and resume work without having to repeat previous steps.

Interactions with the main view:

Panning, zooming, rotating: We provide the three standard methods of interaction to manipulate the position and orientation of the head image and any other data represented within the main view. Specifically, we implemented three standards interaction methods with the 3D graphical representations for consistency and to support learnability of the system: holding down the mouse wheel and dragging the mouse pans the image; scrolling the mouse wheel or holding down the right mouse button and dragging the mouse adjusts the zoom; and holding down the left mouse button and dragging the mouse rotates the image.

Correction of landmarks positions: The 3dMD software does not support the movement of already placed landmarks. To change the position of a landmark, the operator needs to first remove the landmark and then place a new one after re-selecting it from the preset landmark list. In SHAPE, the position of any landmark can be changed through direct manipulation. When the mouse cursor is moved over a landmark, its iconic representation changes to a hand to indicate a dragging mode. The landmark can then be moved by holding down the left mouse button and dragging the mouse to the new location. Changing landmark positions by direct manipulation increases the operator's efficiency, who does not need to refer back and forth between the positioned landmark on the head surface and its representation in the landmark list on the left panel.

Showing grid lines: Grid lines are helpful for assessing the placement of symmetric landmarks, especially combined with previous standardized view. Grid lines can be turned on and off using the *g* key, the same way as in the 3dMD software.

Creation of analysis reports: After discussions with our multi-disciplinary team, we streamlined the report presentation, and we revised and enhanced the content of the reports. Our clinical team indicated different preferences regarding the presentation of the information, preferring either a tabular view of the metrics or a visual representation. We also enhanced the reports by including automatically computed advanced metrics to quantify craniofacial anomalies (HSA and CRS) [10] and color-coded overlays of local malformations [1] on the patient's 3D photograms, since they have proven higher accuracy in evaluating craniosynostosis than the simple metrics provided by the current software (which SHAPE also provides).

Fig. 5 shows different components from the revised version of a report. It consists of two sections: craniofacial measurements and local malformations. The section on measurements presents a table with the complete list of measurements (rows) for each visit (columns). In addition, it shows the change over time for a few selected important measures as line graphs. The section on local malformations shows a matrix of different views of the patient's 3D photograms overlaid with a metric of head malformations [1]. Specifically, this color mapping indicates the local deviation from a reference normative statistical anatomical model, with positive values indicated overdevelopment and negative values indicating lack of volumetric growth. Each column in the matrix represents a specific visit and the three rows show the anterior, left oblique, and left views of the patient's head. The rest of symmetric and standard views were omitted in our figure for space reasons. The actual report is a PDF file, in which parts A, B, and C are represented on separate pages. Importantly, the creation of the analysis report is now completely automated.

Implementation and software availability: We implemented SHAPE using Python version 3.9, with wxPthon version 4.2.0 for the development of the software interface and VTK 9.1 for 3D visualization, rendering and data interactions. Our deep learning models were created using PyTorch and PyTorch Geometric. SHAPE was installed on a workstation computer with an Intel(R) Core(TM) i9–10900X CPU and 32 GB of RAM. During the user study, SHAPE was accessed on this workstation via Windows Remote Desktop Protocol (RDP). The deep learning models and methods for computing the craniofacial metrics that are embedded within SHAPE are publicly available at: https://github.com/cuMIP/3dphoto.

4. User study

4.1. Study design

To evaluate SHAPE in a clinical setting, we conducted a within-subject study with two conditions. We used the current clinical workflow with the 3dMD software based on manual landmark placement as our baseline condition, and the SHAPE workflow with our novel system as the comparative framework, see Fig. 3.

Study participant: we recruited the clinical photographer in our team as the study participant. As discussed earlier, there is only one person at the entire hospital who can perform the craniofacial 3D photogrammetry analysis with the existing workflow, which unfortunately limited our participant pool to the size of n = 1. Our clinical photographer is female, in the 40 to 50 years age group, and has worked in this position for over three years.

Study data: we attended three craniofacial clinics and used the 3D photogrammetry data generated from the first 15 males and 15 females with craniosynostosis see in our clinic after the beginning of our study, which represents a random sample from the patient population with craniosynostosis seen in our craniofacial clinic. No patients were excluded. The average patient age was 2.77 ± 3.24 years.

Study settings: we performed the baseline study with the current clinical workflow in real-time during the three craniofacial clinics in which we collected the data. We wanted to measure the operation time data under realistic conditions and avoid increasing the photographer's workload by requesting to repeat the analysis under controlled study conditions. Then, the photographer repeated the analysis for the same 30 patients using SHAPE at a different time.

Unified workflow steps: to align the steps of the current workflow and the steps of the SHAPE workflow for easier comparison, we created a unified workflow with three distinct steps: *Setup*, *Analysis*, and *Reporting*. *Setup* includes loading the 3D photogram, cropping and aligning it with the coordinate axes in the current workflow. In the SHAPE workflow, only 3D photogram loading is included in this step, since it implements functionality to achieve standard views that does not require spatial alignment. *Analysis* includes the manual placement of the landmarks and the automated calculation of craniofacial metrics for the current workflow. With the SHAPE workflow, this step includes automated landmark placement with manual confirmation and correction, and automated computation of craniofacial metrics. *Reporting* includes taking the screenshots and manually compiling them into PDF reports for the current workflow. With the SHAPE workflow, this step is fully automated and generated one PDF report.

Training to use SHAPE: we provided an introductory training for SHAPE to our photographer prior to this study. We first demonstrated the system with one patient, and then observed the photographer while she analyzed three additional patients. We provided help, clarification, and feedback when needed. These four patients used in the training were not part of the study dataset and were randomly selected under the same criteria that our study dataset.

Evaluation of performance improvement: After recording the time measurements for the individual steps in both study workflows, we calculated their means and standard deviations, and we evaluate statistical differences between the processing times with the current and our proposed workflows using the paired Wilcoxon signed-rank test.

Qualitative evaluation: After completion of the study, we conducted a semi-structured interview with the photographer to gain additional insights on the qualitative aspects of

SHAPE and how it compares to the current workflow. We received permission to audio record the interview. We transcribed the recording, summarized the main findings, and included selected quotes in the results section.

4.2. Results

Performance improvement results: Fig. 6 shows the completion times of the three workflow steps for both study conditions. SHAPE was significantly faster than the current workflow for the *Setup* and *Reporting* steps, since both steps are fully automated in SHAPE. The *Analysis* step takes approximately the same time in both workflows (3.43 ± 0.99 minutes with SHAPE vs. 3.32 ± 1.51 minutes with current workflow, $p = 0.76$). For SHAPE, the computational time on our workstation for both automated tasks in the *Analysis* step (landmark placement and computation of metrics) is about one minute. That leaves 2.43 ± 0.99 minutes for the manual task of confirming and correcting the landmark placements.

Overall, SHAPE allows for the evaluation of a craniofacial 3D photogram more than three times faster than the current clinical workflow (3.85 ± 0.99 vs. 13.07 ± 5.29 minutes, $p <$ 0.001).

Qualitative evaluation results: the photographer noted several positive impressions of SHAPE during the interview. “The automated landmarking is nice, it is very fast and the possibility of slightly adjusting landmarks by just dragging the points is useful. Indicating corresponding left and right landmarks by showing them in the same color is also useful”. These observations indicate that SHAPE supports **R1** and **R2**.

Opportunities for improvement were also noted. “Little things were challenging. The color of the [landmarking] dots was sometimes hard to see, some dots were not very visible, specifically yellow on skin color”. “The Quick Navigation buttons are generally useful, the worm’s view was most useful. But the initial alignment of the head was not always perfect. In those cases, the pre-defined views were also not aligned and had to be corrected. I ended up not using the [Quick Navigation] buttons as much and aligned the head positions manually instead”.

Regarding the automated landmarking process, the photographer stated that it is “definitely faster and easier to visualize. Seeing all the landmarks at once streamlines the placement process”. However, she also stated “I needed to correct the location of many of the landmarks, they are close but not perfect. Even with this limitation, the [new] workflow is still faster because no cropping is needed”. This observation suggests that while **R1** is supported, there is also room for improvement.

She further stated that the new workflow is pretty similar to the existing workflow and that “this tool [SHAPE] is very useful, definitely faster, and easy to adapt to. I could envision using it in the future. Some interactions are different, but more intuitive, for example, the buttons for rotating and panning the head work differently”. The workflow buttons at the top of the user interface organize the workflow and provide a useful structure. “They may make it easier for me to come back and continue after an interruption. However, to further streamline the process, it would be nice to automate everything after correcting the landmark placement". This observation indicates that **R4** is supported but also that **R4** may have been defined too strictly and may be dropped with further automation of the workflow.

Regarding the automated analysis report generation, she stated that "it is much faster but also more restrictive. I cannot manipulate things. The current report format works well for cranio [facial] patients, but templates or customization options would be useful to create reports for patients with other medical conditions". This observation indicates that **R3** is well supported for the specific case of craniofacial patients with craniosynostosis, which is our current focus, and that future customization could also support patients with other medical conditions.

Her concluding thought was that SHAPE could make it "easier for someone else to learn how to do this [analysis]. They would still need to know where to place the landmarks, but the automated report generation would make the process much simpler and easier to learn".

Additional observations from a clinical expert: To provide an additional perspective on the utility of SHAPE and how it compares to the original workflow, we present qualitative observations from a pediatric plastic and reconstructive surgery research fellow specializing in craniofacial surgery. The fellow is one of our team members and shadowed the professional photographer while using the 3dMD software in the current workflow and also observed the photographer using SHAPE during our study.

The fellow noticed that SHAPE made the process of landmarking patient photograms much easier since the photographer could bypass the orientation and cropping stage, which was one of the more tedious steps during photogram processing with the 3dMD software. The automated orientation of the patient also led to more consistent cephalometrics results, which is essential for accurate longitudinal documentation. In terms of the SHAPE interface, dragging landmarks to their correct locations, rather than deleting and re-placing them as required in the current vendor software tool, simplifies the workflow and provides more control through immediate visual feedback. Replicating some of the current vendor software tool features (e.g., snapping the patient's view to specific orientations: Left, Right, and Anterior) allowed the photographer to keep the parts of her current workflow that work efficiently.

The fellow also concluded that the automatically created analysis report is more informative and concise than current manual reports. For example, SHAPE creates an aggregated PDF that combines all patient visits in one table instead of creating three different documents, which makes longitudinal clinical patient evaluation easier. The fellow also commented that the graphs that track the patient's most important cranial metrics over time are highly useful to provide a quick overview and complement the detailed table.

Some challenges were also observed by the fellow. In only a few instances, an automatically placed landmark could appear in a wrong location inside of the photogram's mesh, which requires more clicks to locate and move it to its correct location. These rare errors are caused by low photogram quality (e.g., a patient was crying during the image acquisition and did not remain relatively still). A future improvement of the underlying model for placing the landmarks could address this issue.

The workflow step in SHAPE for computing age- and sex-specific metrics of head anomalies requires the patient's date of birth and gender. Currently, these need to be pulled from the patient's record and entered manually since SHAPE is not fully integrated with the hospital's electronic health records yet and therefore cannot read patient information automatically. Once clinically validated and fully integrated, this automation will further improve the efficiency of the SHAPE workflow.

The fellow also noted several specific clinical implications. The reduced time from image acquisition to uploading the report to the patient record can have significant impacts on the clinical workflow. It increases the likelihood that photograms are processed in time for each patient's appointment with their surgeon. The fellow observed multiple instances in the current workflow, where the photographer had to pause the processing of a photogram when another patient arrived for their appointment, which resulted in some photogram analyses not being ready for evaluation at the time of the patient's visit with the surgeon. Since SHAPE is more automated, it can be run more easily in the background while the photographer is dealing with a new patient or a different task.

The fellow noted that the redesigned format of the report may be easier to access by surgeons and may better support clinical decision making. The additional metrics provide objective age- and sex-specific information about the patient's head anomalies, in addition to a specific evaluation of any phenotype of craniosynostosis. This objective information is useful not only for patient evaluation but for treatment decisions and to quantitatively evaluate surgical outcomes. Importantly, both the quantitative and visual information provided by SHAPE will be highly valuable to support communication with parents who often need to make important decisions about invasive surgical treatments with important implications. Parents often have difficulty understanding the severity of the anomalies in their child's head, which is one of the reasons why there are delays in surgery. Seeing a clear visual representation of the localized anomalies may help parents understand why surgery is recommended.

5. Discussion

We presented a new computational framework and interface for the clinical translation of our methods for the automated analysis of pediatric craniofacial 3D photogrammetry data that we called SHAPE. Our system integrates existing methods for semi-automated craniofacial landmark placement, state-of-the-art metrics that provide improved accuracy during evaluation of pediatric head development compared to traditional morphometric measurements, and intuitive and interpretable visualizations of local head anomalies that are essential during clinical evaluation. We evaluated the system against the current clinical workflow and our quantitative results indicate that our framework enables an approximately three times faster workflow than the one currently used in clinical practice. Individually, two of the three workflow steps are also significantly faster in SHAPE, since they are completely automated. Interestingly, the *Analysis* step requires similar processing time in both workflows.

To better understand why the *Analysis* step was not faster in the SHAPE workflow, we analyzed the time measurements of this step at a more granular level. The *Analysis* step in SHAPE includes three subtasks: the automated landmark placement, the manual confirmation and if necessary correction of the landmark placements, and the automated computation of craniofacial metrics. Computing the landmarks and metrics takes about one minute on our workstation, which leaves a little less than 3 min for the manual task of confirming and correcting the placement of 27 landmarks. As explained by the photographer, this longer than expected time results from the need to "correct the location of many of the landmarks, they are close but not perfect". The time needed for correcting landmark position could likely be reduced by integrating a more accurate method for the automated landmark computation in the future.

Importantly, and despite taking similar landmark placement times, SHAPE provides significantly lower total processing time as compared to the current vendor software workflow (3.85 vs. 13.07 min in average). In addition, the time required to process a photogram with SHAPE has substantially lower variability as shown by the standard deviation of 0.99 min for SHAPE versus 5.29 min for the current clinical workflow. The increased consistency in processing times could help achieve more accurate patient scheduling, reduce photographer effort needs, and improve clinical efficiency to either reduce clinical hours or increase the number of patients that can be evaluated. Moreover, SHAPE improves upon the simple craniofacial metrics computed with the current clinical workflow using additional state-of-the-art machine learning-based metrics that have proven to be more useful to evaluate craniosynostosis in previous studies, and that enable interpretable graphic representations of the patient anomalies at every head location (see Fig. 5). These factors could translate to lower healthcare costs, improved patient satisfaction, and more accurate budget planning in a clinical setting.

In addition to the time required to complete the analysis, reproducibility of results is another important consideration. Even though the automated landmarking results may not always be perfect and require manual corrections, these correction are simpler than a fully manual placement, require less steps by the operator and may help achieving lower placement variations than a fully manual process that does not count with any realistic initialization. This consistent placement of landmarks becomes especially important when multiple photographers perform different parts of in longitudinal analysis of the same patient. As discussed in previous work [10], the list of 27 craniofacial landmarks used for craniofacial analysis includes landmarks classified differently according to the Bookstein classification system [33]. While Bookstein type I landmarks can consistently be placed at the same location by different observers, Bookstein types II and III landmarks are of subjective placement because of the lack of exact visual cues on the head surface. Hence, our automated landmark placement, even if it is regarded as an initial approximation, may help reduce inter-observer variability between different photographers who are expected to place the landmarks at slightly different positions. Future work includes the evaluation of inter-observer variability with the current clinical framework and SHAPE to quantify improvements.

Lessons learned:

The execution of this study provided several lessons learned on the process of translating interactive computational tools into a clinical setting. First, it was very helpful to have an established clinical workflow in place and to invest the time to study and understand it in detail. We were able to complete a comparative study of this nature because our institution has a standardized protocol for the analysis of 3D photogrammetry in the clinic. Without such an established protocol, we would not have had a baseline framework to compare the timing of the workflow steps. Additionally, it allowed us to design SHAPE to mirror the incremental steps within the existing workflow, which we believe greatly helped the understanding and adoption of the new tool by the expert photographer. Creating, implementing, and explaining a completely new workflow for our tool would have been much more challenging than adopting the existing workflow. Second, we saw benefits in executing our study in a real-world clinical setting that the expert user is familiar with. It revealed unexpected challenges with the existing workflow, such as numerous interruptions, that would not have been considered if this study had been performed in a controlled lab environment. Third, the existing rapport between the clinical and research teams was crucial for the execution of our study. The expert photographer who was recruited for this study was extremely willing to make their time available in the typically hectic clinical environment and was predisposed to help with our data collection. This support and commitment cannot be taken for granted and had a big impact on the successful execution of our study. This rapport is especially important for the translation of an interactive computational tool that requires regular interactions with an expert user. Our team also included a clinical research fellow who was instrumental in supporting the data collection and organization of the experiments. Being intimately familiar with both the clinical environment and the research side allowed the fellow to act as a bridge and efficiently connect the two groups in our team.

Implementation:

We implemented SHAPE using a modular design to support the integration of multiple data layers. SHAPE can therefore also be used as a testing environment and evaluation platform for other automated methods for landmarking or computation of craniofacial metrics. While we used SHAPE in this study specifically in the context of craniosynostosis, the system can easily be extended to process other kinds of 3D photogrammetry data with the integration of appropriate automated analysis methods.

Future work:

We will revise SHAPE by addressing some of the feedback from our user study. We will update our color template for the landmark representations to make them more visible when overlaid on skin color. We will also develop an interface to allow for the customization of the automatically generated reports: selecting time points (visits) that should be included in the table, selecting the measurements that should be included as line graphs, and selecting the views shown in the matrix of local malformations. Moreover, we will collect data about the satisfaction of the surgical team with the new generated reports using SHAPE.

Study limitations:

Our study has several limitations. We studied the existing workflow and the SHAPE workflow in different settings. We measured the timing of the analysis with the existing workflow during craniofacial clinics that are prone to interruptions (although any interruptions were excluded from our time measurements). To avoid interfering with our busy craniofacial clinic, we had to measure the timing of the analysis with the SHAPE workflow outside patient visit hours, which decreased the likelihood of interruptions that were only limited to those caused by staff. If we had conducted the analysis with the SHAPE workflow during a craniofacial clinic, the photographer may have been interrupted more often by the ongoing clinical operations while manually correcting the landmarking locations and the time measurements for the *Analysis* step may have been slightly longer due to the additional time required to resume this work step after an interruption. Importantly, the time measurements for the *Setup* and *Reporting* steps would not change since they are fully automated. The SHAPE workflow is less prone to interruptions because it has only one manual step compared to five in the current workflow.

A second limitation is related to our limited subject pool. Unfortunately, our hospital currently has only one professional photographer who can perform the analysis with the current workflow. Since the photographer is highly skilled at analyzing 3D photogrammetry data, it is reasonable to assume that study participants with less experience would require more time, especially with the current workflow, to complete the 3D photogrammetry data analysis.

6. Conclusion

3D craniofacial photogrammetry is an uprising imaging technology with important applications and unique advantages in pediatric medicine. Broad adoption is currently hindered by the lack of computational support for analyzing 3D photograms in a clinical setting. Commercially available software requires the manual placement of landmarks, which is tedious, time-consuming and error-prone, and does not provide advanced visualization and reporting functionality that is essential for clinical use. Although novel 3D photogrammetry analysis methods have been proposed during the last few years, they have not yet been translated into clinical solutions.

We presented SHAPE, an end-to-end visual computing pipeline to analyze 3D photograms. The input to the pipeline is a pediatric craniofacial 3D photogram and the output is an analysis report to assess craniosynostosis that can be readily uploaded into the patient's electronic medical record. We embedded our previously developed approaches for automatic landmarking and computation of advanced metrics to quantify craniofacial anomalies in an interactive visual system. The automatic placement of landmarks can be manually reviewed and corrected if necessary, and the analysis report is created fully automatically. We evaluated and compared SHAPE in a user study to the existing clinical workflow and found that SHAPE is more than three times faster.

Once it progressed from the pilot stage, we will consider releasing SHAPE as open-source software to allow other researchers to embed their own approaches for landmarking or advanced metric computation, and to evaluate them in a clinical setting. We hope that this will facilitate the translation of existing computational methods and make 3D photogrammetry more broadly available as an alternative imaging technology.

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Data availability

The authors do not have permission to share data.

References

[1]. Porras AR, Tu L, Tsering D, Mantilla E, Oh A, Enquobahrie A, Keating R, Rogers GF, Linguraru MG. Quantification of head shape from three-dimensional photography for presurgical and postsurgical evaluation of craniosynostosis. Plast Reconstruct Surg 2019;144(6):1051e–60e. 10.1097/PRS.0000000000006260, URL: http://journals.lww.com/00006534-201912000-00032.

[2]. Ho OA, Saber N, Stephens D, Clausen A, Drake J, Forrest C, Phillips J. Comparing the use of 3D photogrammetry and computed tomography in assessing the severity of single-suture nonsyndromic craniosynostosis. Plast Surg 2017;25(2):78–83. 10.1177/2292550317694845, URL: http://journals.sagepub.com/doi/10.1177/2292550317694845.

[3]. Nord F, Ferjencik R, Seifert B, Lanzer M, Gander T, Matthews F, Rücker M, Lübbers H-T. The 3dmd photogrammetric photo system in cranio-maxillofacial surgery: Validation of interexaminer variations and perceptions. J Cranio-Maxillofac Surg 2015;43(9):1798–803. 10.1016/j.jcms.2015.08.017, URL: https://linkinghub.elsevier.com/retrieve/pii/S1010518215002954.

[4]. Lo L-J, Yang C-T, Ho C-T, Liao C-H, Lin H-H. Automatic assessment of 3-dimensional facial soft tissue symmetry before and after orthognathic surgery using a machine learning model: A preliminary experience. Ann Plast Surg 2021;86(3S):S224–8. 10.1097/SAP.0000000000002687, URL: https://journals.lww.com/10.1097/SAP.0000000000002687. [PubMed: 33443885]

[5]. Kurniawan MS, Tio PA, Abdel Alim T, Roshchupkin G, Dirven CM, Pleumeekers MM, Mathijssen IM, van Veelen M-LC. 3D analysis of the cranial and facial shape in craniosynostosis patients: A systematic review. J Craniofac Surg 2024. URL: https://journals.lww.com/jcraniofacialsurgery/fulltext/9900/3d_analysis_of_the_cranial_and_facial_shape_in.1410.aspx.

[6]. Abdel-Alim T, Iping R, Wolvius EB, Mathijssen IM, Dirven CM, Niessen WJ, van Veelen M-LC, Roshchupkin GV. Three-dimensional stereophotogrammetry in the evaluation of craniosynostosis: Current and potential use cases. J Craniofac Surg 2021;32(3). URL: https://journals.lww.com/jcraniofacialsurgery/Fulltext/2021/05000/Three_Dimensional_Stereophotogrammetry_in_the.35.aspx.

[7]. Wood BC, Mendoza CS, Oh AK, Myers E, Safdar N, Linguraru MG, Rogers GF. What's in a name? Accurately diagnosing metopic craniosynostosis using a computational approach. Plast Reconstruct Surg 2016;137(1):205–13. 10.1097/PRS.0000000000001938.

[8]. Hauc SC, Long AS, Rivera JC, Ihnat J, Littlefield TR, Shah HP, Pondugula N, Junn AH, Almeida MN, Alper D, Persing J, Alperovich M. Predictive factors of outcomes in helmet therapy for deformational plagiocephaly and brachycephaly. J Craniofac Surg 2023;34(1). URL: https://journals.lww.com/jcraniofacialsurgery/Fulltext/2023/01000/Predictive_Factors_of_Outcomes_in_Helmet_Therapy.45.aspx.

[9]. Abdel-Alim T, Tio P, Kurniawan M, Mathijssen I, Dirven C, Niessen W, Roshchupkin G, van Veelen ML. Reliability and agreement of automated head measurements from 3-dimensional photogrammetry in Young children. J Craniofac Surg 2023;34(6):1629–34. [PubMed: 37307495]

[10]. Elkhill C, Liu J, Linguraru MG, LeBeau S, Khechoyan D, French B, Porras AR. Geometric learning and statistical modeling for surgical outcomes evaluation

in craniosynostosis using 3D photogrammetry. Comput Methods Programs Biomed 2023;240:107689. 10.1016/j.cmpb.2023.107689, URL: https://www.sciencedirect.com/science/article/pii/S0169260723003541.

[11]. Marios L, Alexiou G, Sfakianos G, Prodromou N. Craniosynostosis. In: Pediatric neurosurgery for clinicians. 2022, p. 135–45. 10.1007/978-3-030-80522-7_9.

[12]. Mathijssen IMJ. Updated guideline on treatment and management of craniosynostosis. J Craniofac Surg 2021;32(1):371–450. [PubMed: 33156164]

[13]. Kim HJ, Roh HG, Lee IW. Craniosynostosis : Updates in radiologic diagnosis. J Korean Neurosurg Soc 2016;59(3):219–26. [PubMed: 27226852]

[14]. Badve CA, K MM, Iyer RS, Ishak GE, Khanna PC. Craniosynostosis: imaging review and primer on computed tomography. Pediatr Radiol 2013;43(6):728–42. [PubMed: 23636536]

[15]. Ulma RM, Ranganathan KL, Vercler CJ, Garton HJL, Maher CO, Muraszko KM, Buchman SR. Weighing in on the controversy: Preoperative imaging in unicoronal craniosynostosis leads to strategic changes in surgical care. Plast Reconstruct Surg 2021;147(5):1133–9.

[16]. Kim D, Lee EK, Jeong JS, Gil NS, Hahm TS, Shin YH. Incidence and risk factors of unplanned intubation during pediatric sedation for MRI. J Magn Reson Imaging 2019;49(4):1053–61. [PubMed: 30350443]

[17]. Maugans TA, McComb JG, Levy ML. Surgical management of sagittal synostosis: a comparative analysis of strip craniectomy and calvarial vault remodeling. Pediatr Neurosurg 1997;27(3):137–48. [PubMed: 9548524]

[18]. Fearon JA, Ruotolo RA, Kolar JC. Single sutural craniosynostoses: surgical outcomes and long-term growth. Plast Reconstr Surg 2009;123(2):635–42. [PubMed: 19182624]

[19]. Whitaker LA, Bartlett SP, Schut L, Bruce D. Timing and methods of treatment for patients with craniosynostosis. In: Marchac D, editor. Craniofacial surgery. Berlin, Heidelberg: Springer Berlin Heidelberg; 1987, p. 118–22.

[20]. Szpalski C, Weichman K, Sagebin F, Warren SM. Need for standard outcome reporting systems in craniosynostosis. Neurosurg Focus 2011;31(2):E1.

[21]. Duncan C, Pears NE, Dai H, Smith WAP, O'Higgins P. Applications of 3D photography in craniofacial surgery. J Pediatr Neurosci 2022;17(Suppl 1):S21–8. [PubMed: 36388007]

[22]. Torosdagli N, Liberton DK, Verma P, Sincan M, Lee JS, Bagci U. Deep geodesic learning for segmentation and anatomical landmarking. IEEE Trans Med Imaging 2019;38(4):919–31. 10.1109/TMI.2018.2875814, URL: https://ieeexplore.ieee.org/document/8490669/. [PubMed: 30334750]

[23]. Torres HR, Morais P, Fritze A, Oliveira B, Veloso F, Rudiger M, Fonseca JC, Vilaca JL. Anthropometric landmark detection in 3D head surfaces using a deep learning approach. IEEE J Biomed Health Inform 2021;25(7):2643–54. 10.1109/JBHI.2020.3035888. [PubMed: 33147152]

[24]. Blum FMS, Möhlhenrich SC, Raith S, Pankert T, Peters F, Wolf M, Hölzle F, Modabber A. Evaluation of an artificial intelligence–based algorithm for automated localization of craniofacial landmarks. Clin Oral Invest 2023;27(5):2255–65. 10.1007/s00784-023-04978-4.

[25]. Bruce MK, Tao W, Beiriger J, Christensen C, Pfaff MJ, Whitaker R, Goldstein JA. 3D photography to quantify the severity of metopic craniosynostosis. Cleft Palate Craniofac J 2022;10556656221087071. 10.1177/10556656221087071, Publisher: SAGE Publications.

[26]. Abdel-Alim T, Kurniawan M, Mathijssen I, Dremmen M, Dirven C, Niessen W, Roshchupkin G, Van Veelen M-L. Sagittal craniosynostosis: Comparing surgical techniques using 3D photogrammetry. Plast Reconstruct Surg 2023;Publish Ahead of Print. 10.1097/PRS.0000000000010441, URL: https://journals.lww.com/10.1097/PRS.0000000000010441.

[27]. Palmer RL, Helmholz P, Baynam G. Cliniface: Phenotypic visualisation and analysis using non-rigid registration of 3D facial images. Int Archiv Photogram Remote Sens Spat Inf Sci 2020;XLIII-B2–2020:301–8. 10.5194/isprs-archives-XLIII-B2-2020-301-2020, URL: https://isprs-archives.copernicus.org/articles/XLIII-B2-2020/301/2020/.

[28]. Bermejo E, Taniguchi K, Ogawa Y, Martos R, Valsecchi A, Mesejo P, nez OI, Imaizumi K. Automatic landmark annotation in 3D surface scans of skulls: Methodological proposal and reliability study. Comput Methods Programs Biomed

2021;210:106380. 10.1016/j.cmpb.2021.106380, URL: https://www.sciencedirect.com/science/article/pii/S0169260721004545.

[29]. White JD, Ortega-Castrillón A, Matthews H, Zaidi AA, Ekrami O, Snyders J, Fan Y, Penington T, Van Dongen S, Shriver MD, Claes P. MeshMonk: Open-source large-scale intensive 3D phenotyping. Sci Rep 2019;9(1):6085. [PubMed: 30988365]

[30]. Al-Baker B, Alkalaly A, Ayoub A, Ju X, Mossey P. Accuracy and reliability of automated three-dimensional facial landmarking in medical and biological studies. a systematic review. Eur J Orthod 2023;45(4):382–95. [PubMed: 37042196]

[31]. Liu J, Elkhill C, LeBeau S, French B, Lepore N, Linguraru MG, Porras AR. Data-driven normative reference of pediatric cranial bone development. Plast Reconstruct Surg Glob Open 2022;10(8):e4457. 10.1097/GOX.0000000000004457, URL: https://journals.lww.com/10.1097/GOX.0000000000004457.

[32]. Munzner T. A nested model for visualization design and validation. IEEE Trans Vis Comput Graphics 2009;15(6):921–8.

[33]. Bookstein FL. Morphometric tools for landmark data: geometry and biology. 1st paperback ed., repr. Cambridge: Cambridge University Press; 2003.

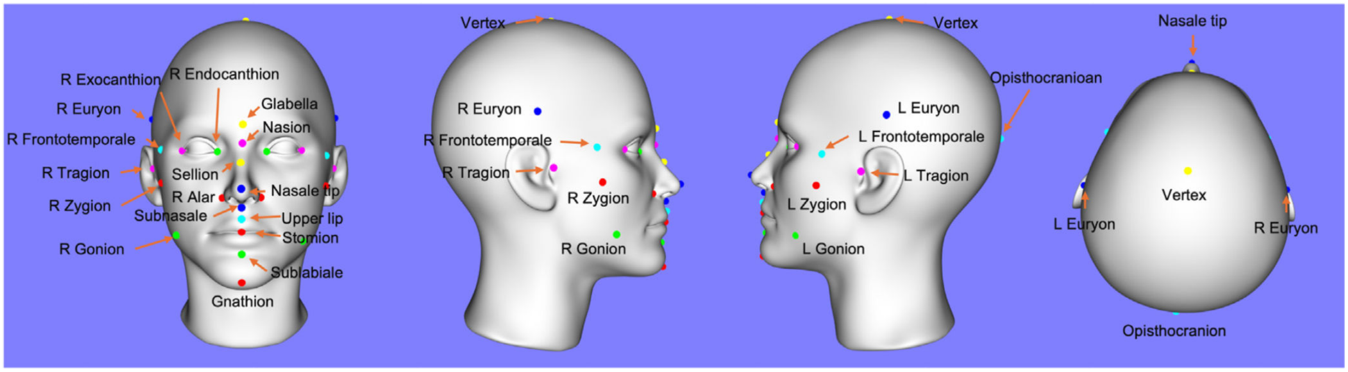

Fig. 1.

Location of the 27 craniofacial anatomical landmarks, including 11 landmarks along the midline of the face and 8 pairs of symmetric landmarks on the left and right sides of the head and face. Landmarks are colored according to their name, where left and right symmetric landmarks are both in the same color.

Fig. 2.
3D photogrammetry suite at Children's Hospital Colorado. Left and middle pictures show view from the photographer's side with lights on during recording from the front and side, respectively. The right picture shows the view from the patient's side.

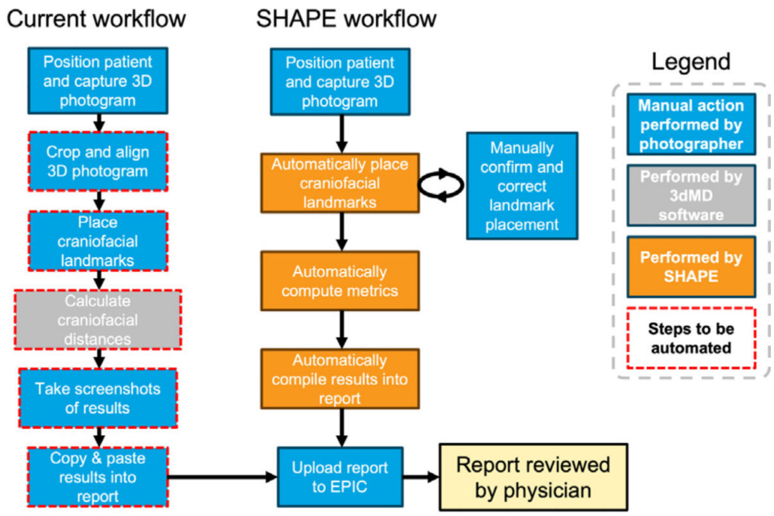

Fig. 3.

Comparison of workflows for 3D photogrammetry analysis and report generation. The current clinical workflow (left) contains more manual steps compared to the SHAPE workflow (right).

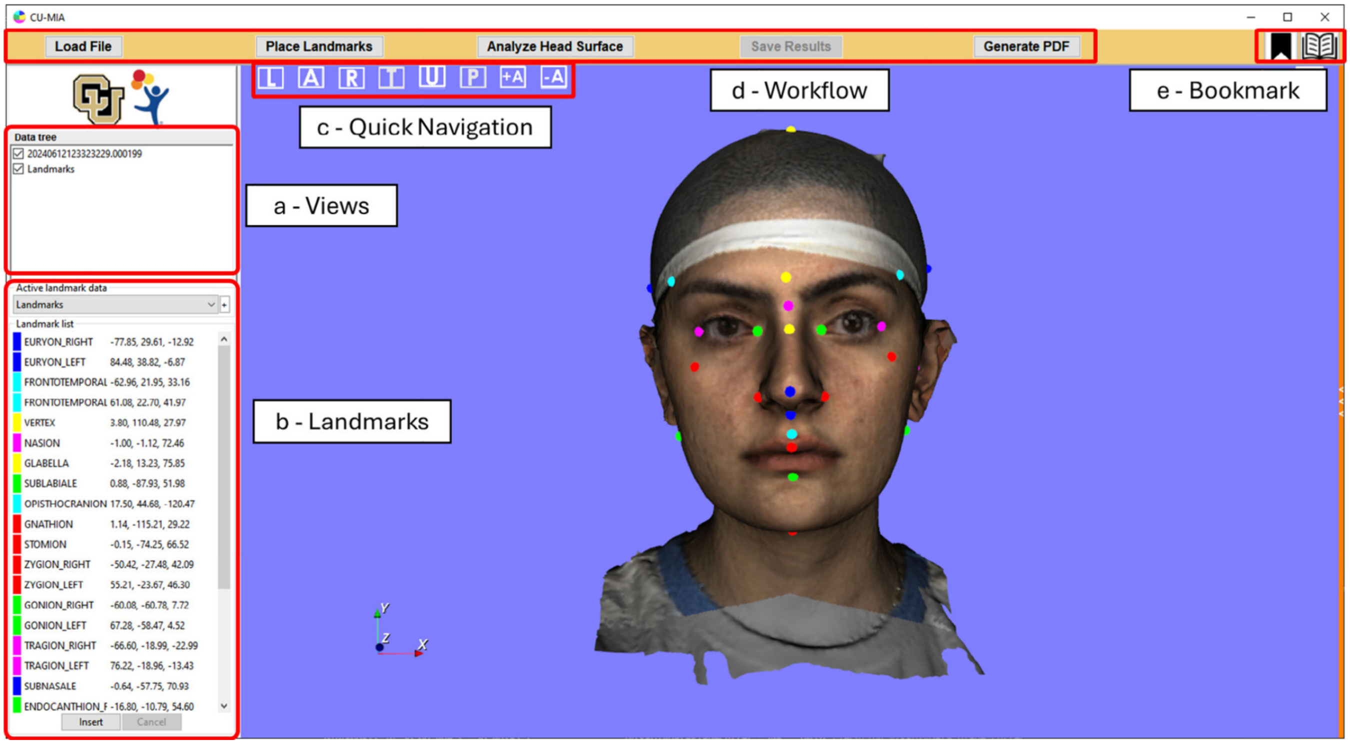

Fig. 4.

Screenshot of SHAPE. The main view displays a 3D photogram with automatically placed landmarks. (a) Views: list of available data layers to display. (b) Landmarks: list of placed landmarks, color coded, and their locations. (c) Quick Navigation: buttons to jump to predefined camera perspectives. (d) Workflow: steps of the workflow. (e) Bookmark: buttons to save and load progress at any stage of the workflow.

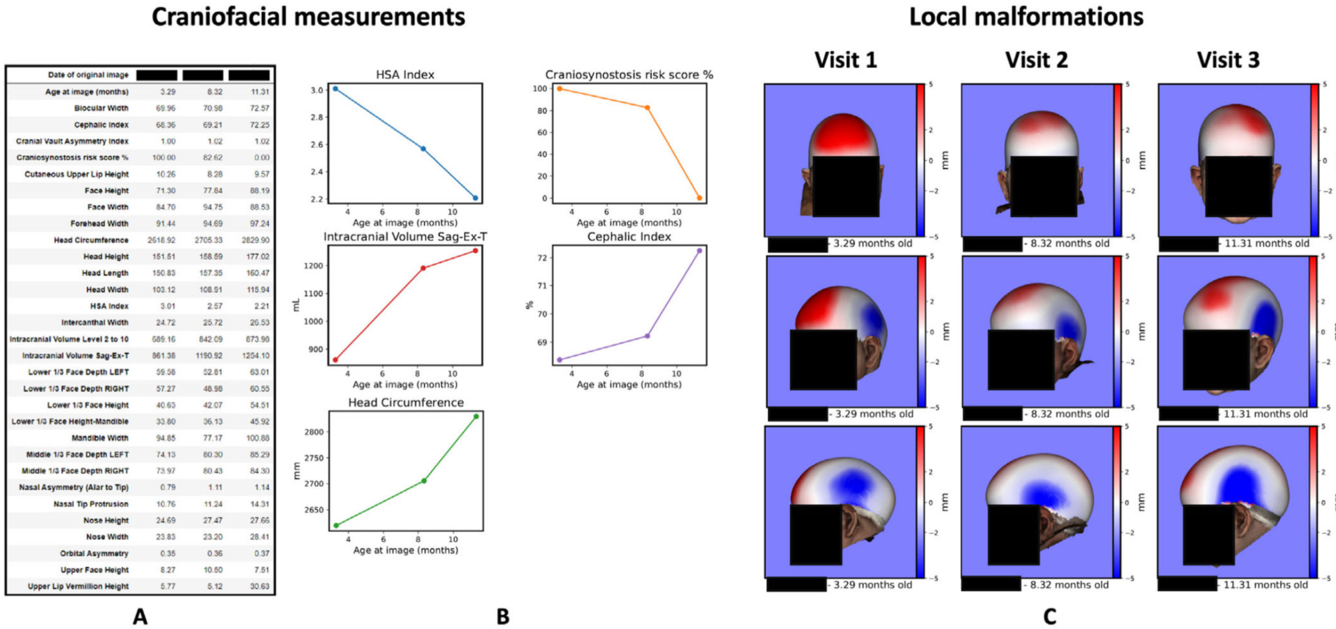

Fig. 5.

Example from automatically generated report of the longitudinal changes before and after surgical treatment of a male patient with craniosynostosis. (A) A table with craniofacial measurements derived from landmarks. Each column represents measurements for a specific visit, the dates are blacked out. (B) Graphical representation showing change over time for the five selected craniofacial measures of highest importance for our surgical team. (C) Color-coded local malformations on the patient's head for the last three patient visits. The first rows shows the anterior view, the second row the left oblique view, and the third row the left views. Facial features and dates are blacked out.

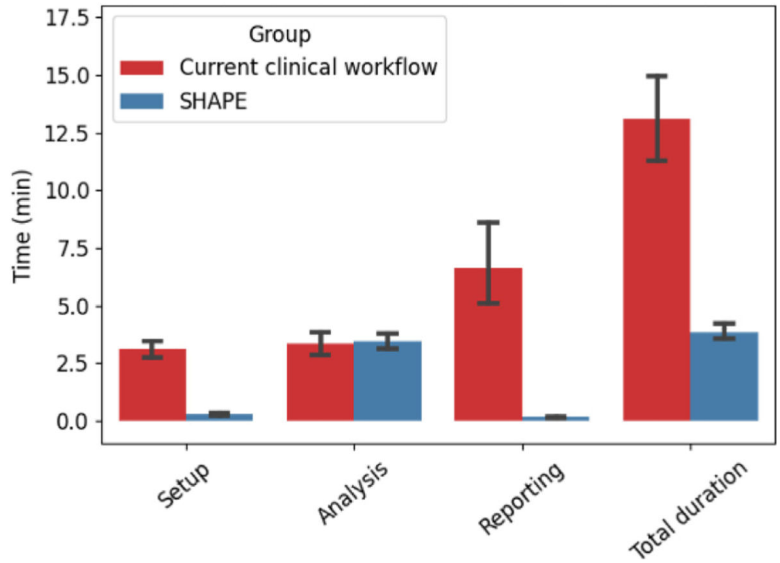

Fig. 6.
Completion times for the three steps of the workflow and for the total duration of the analysis for both study conditions.