In this work, we propose a novel approach for 3D surface reconstruction of the human jaw. Due to the difficulties of setting up a data acquisition system inside the mouth, we use an intra-oral camera to capture a sequence of calibrated images which is more comfortable to patients. Also it does not require a long time to scan a jaw. The resulting sequence of images covers the jaw and contains overlapped image regions. These sequential images are taken in pairs to perform image alignment by estimating projective transformations. This process incorporates points correspondences accurately found by the affine and scale invariant transform approach [1], known as ASIFT as shown in Fig. 1. After estimating the projective transformations, the image pairs are used together in order to build a panoramic image of the whole jaw as demonstrated in Fig. 2. The new view is used to build a 3D surface using the shape from shading (SFS) algorithm. The used SFS is depending on calibration parameters. We use a formulation of the SFS that uses intrinsic and extrinsic camera parameters such that we obtain a better surface. This technique is compared with former approaches and the difference is significant as illustrated in Fig. 3.

Figure 1: An example to stitch two images together: Point correspondences are demonstrated in (a) using the ASIFT algorithm. Correspondences after removing the outliers using RANSAC are shown in (b). Registration of the two overlapped images is depicted in (c).

Figure 2: A jaw is imaged as 9 overlapped images illustrated from left to right. The stitching results (panoramic image) is shown at the last column where each sub-image is boxed by a green line to show the overlap between the views.

1 Shape from Shading using a Calibrated Image

In our approach, the CCD camera is calibrated and the camera parameters are used in the SFS algorithm to obtain a metric representation of the teeth and gum surfaces. To calibrate the camera, the relation between the 3D point \( P = (X, Y, Z)^T \) and the corresponding image coordinates \( p = (x, y)^T \) is written as; \( s \mathbf{p} = \mathbf{M} \mathbf{P} \) where \( s \) is a scalar, \( \mathbf{p} \) and \( \mathbf{P} \) are the extended vectors \( \left[ p^T \right]^T \) and \( \left[ P^T \right]^T \), and \( \mathbf{M} \) is called the camera calibration matrix. In general, \( \mathbf{M} = \mathbf{K} \left[ Q, T \right] \) where \( \mathbf{K} \) is a matrix containing all the camera intrinsic parameters and \( Q, T \) are the rotation matrix and the translation vector respectively. The matrix \( \mathbf{M} \) has 12 elements but has only 11 degrees of freedom because it is defined up to a scale factor (e.g., [3]).

The perspective projection matrix \( \mathbf{M} \) can be decomposed as \([\mathbf{M} \mathbf{b}]\) where \( \mathbf{B} \) is a \( 3 \times 3 \) matrix and \( \mathbf{b} \) is a \( 3 \times 1 \) vector such that;

\[
\mathbf{s} \mathbf{p} = \mathbf{B} \mathbf{p} + \mathbf{b}, \quad \text{or} \quad \mathbf{P} = \mathbf{B}^{-1} (s \mathbf{p} - \mathbf{b}) = f(s(x,y)) \tag{1}
\]

This last equation represents a line in the 3D space corresponding to the visual ray passing through the optical center and the projected point \( \mathbf{p} \). By finding the scalar \( s \), \( f(s(x,y)) \) will define a unique 3D point \( \mathbf{P} \) on the object. The surface normal at \( \mathbf{P} \) is defined to be the cross product of the two gradient vectors \( \mathbf{r} = \frac{df(s(x,y))}{dx} \) and \( \mathbf{q} = \frac{df(s(x,y))}{dy} \). The surface reflectance \( R(s) \) becomes a function of the scalar \( s \) defined in Eq.(1), i.e.,

\[
R(s) = \frac{(\mathbf{r} \times \mathbf{q}) \cdot \mathbf{L}}{|| \mathbf{r} \times \mathbf{q} ||} \tag{2}
\]

The formulation of the SFS problem becomes finding the scalar \( s \) that solves the brightness equation \( g(s) = E(x,y) - R(s) = 0 \). This can be solved using a Taylor’s series expansion and applying the Jacoby iterative method [2]. After \( n \) iterations, for each point \((x,y)\) in the image, \( s_{x,y}^n \) is given as follows:

\[
s_{x,y}^n = s_{x,y}^{n-1} + \frac{-g(s_{x,y}^{n-1})}{\frac{dg(s_{x,y}^{n-1})}{ds_{x,y}}} \tag{3}
\]

\[
\frac{dN}{dS_x} = \frac{dN}{dS_x} - \frac{dV}{dS_x} \sqrt{(V^2)^{3}} \left( \frac{dV}{dS_x} \right) \tag{4}
\]

\[
\frac{dV}{dS_x} = \mathbf{B}^{-1} \frac{\mathbf{p}^T}{\mathbf{p}^T (0,s_{x,y}-1,0)^T} + \mathbf{B}^{-1} (0,s_{x,y}-1,0)^T \times \mathbf{B}^{-1} \frac{\mathbf{p}^T}{\mathbf{p}^T} \tag{5}
\]

where \( V = \mathbf{r} \times \mathbf{q} \)


