CUSTOMIZED FACIAL CONSTANT POSITIVE AIR PRESSURE (CPAP) MASKS

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ABSTRACT

Sleep apnea is a syndrome that is characterized by sudden breathing halts while sleeping. One of the common treatments involves wearing a mask that delivers continuous air flow into the nostrils so as to maintain a steady air pressure. These masks are designed for an average facial model and are often difficult to adjust due to poor fit to the actual patient. The incompatibility is characterized by gaps between the mask and the face, which deteriorates the impermeability of the mask and leads to air leakage. We suggest a fully automatic approach for designing a personalized nasal mask interface using a facial depth scan. The interfaces generated by the proposed method accurately fit the geometry of the scanned face, and are easy to manufacture. The proposed method utilizes cheap commodity depth sensors and 3D printing technologies to efficiently design and manufacture customized masks for patients suffering from sleep apnea.

Index Terms— Sleep Apnea, CPAP Masks, Facial Modeling, 3D Printing, Automatic Design.

1. INTRODUCTION

Sleep apnea is a disorder characterized by chronic pauses in breathing. Breathing is usually interrupted by a physical block of airflow caused by the soft palate, that often also leads to snoring. It can cause serious problems including high blood pressure, mental deterioration, heart failure, sudden death, and daytime sleepiness. Surgical intervention, in which anatomical obstructions are removed, is considered in extreme cases. A more common treatment is creating an environment of continuous positive airway pressure (CPAP) to the sleeping patient. It requires the subject to wear a mask which is connected to a machine that supplies the positive airflow.

The currently available masks fit an average face in a given population or age group. The diversity of the geometries of human faces, especially, for children with problems in birth, poses a huge limitation to the current common practice in this domain. A mask which does not fit well, usually causes the air to leak, which reduces the efficiency of the device as continuous positive air pressure can not be guaranteed in this case.

In an attempt to solve this problem, we propose a fully automatic method for designing and manufacturing masks that best fit a given face of a specific patient. The procedure works as follows. At a pre-processing step, we manually mark the mask contact region on a smooth generic facial model. This step is performed once for all subjects. Next, we scan the face of the patient using a commodity range sensor for generating a geometric profile and capture a color image. Our system then automatically detects key facial feature points on the image, such as the tip of the nose, the corner of the eyes, etc. Based on these landmark points, we find a dense point-wise correspondence between a template model and the acquired one via a non-rigid alignment procedure. The registration enables finding a corresponding contact region that matches the geometry of the scanned face. Finally, we use the warped interface region as a set of positional constraints for automatically designing an individual mask. The resulting mask can then be produced by printing a mold of the mask, and injecting medical silicone into its cavity, or directly 3D printing a silicone interface.

The masks designed by our method optimally match the scanned face and do not require manual intervention during design and manufacturing of the masks. To evaluate the quality of the new design, we estimate the force variations along the contact region between the mask and the face. Unlike standard interfaces, the pressure using the proposed new design is uniformly distributed along the contact contour between the mask and the face. The result is convenient, compact, and efficient devices at a relatively insignificant additional cost.

2. RELATED EFFORTS

Several recent papers introduce attempts to simplify and partially automate the customization of personalized masks. Cheng et al. [1] proposed to reconstruct a three-dimensional facial model of the patient by immersing the face into Hygrogum material. After solidifying, the Hygrogum turns into a sub-millimeter accurate mold. Morrison et al. [2] and Cheng et al. [3] proposed to use a depth scanner for facial modeling. Amirav et al. [4] scanned hundreds of newborns, clustered them into three typical sets, and used a representative from each set to design three types of inhalation masks for babies. After digitizing the geometry of the face, almost
Fig. 1: The pipeline of the proposed method: First, a three dimensional model of the face using a depth sensor is acquired (A). Key characteristic points are then detected on the face such as the nose center, eye lashes, etc. (B). Based on these feature points, a generic template face is aligned with the scan (C). This registration enables automatic detection of the mask contact region upon the scanned face (D). We then automatically design a mask that matches the facial features (E).

all existing methods project the profile of a given mask onto the reconstructed facial surface for customizing the mask interface. Unlike existing methods, the proposed solution allows determining the contact region based on warping a pre-design model. The shape of the mask depends on the patient’s face, and it is designed to smoothly match the facial contours of the patient.

3. IMPLEMENTATION CONSIDERATIONS

Overview: A sketch of the proposed procedure is shown in Figure 1. Next, we describe each part of the system.

Face Model Acquisition: Range scanners measure the distance of each visible point in the scene from the sensor. There are various methods for capturing range images. Here, we used a structured light sensor which is comprised of a calibrated projector and a camera. The projector marks each point in the scene with a unique signature. It allows the camera, which is located at a known relative position, to identify each visible point. Then, a simple triangulation is performed for estimating the distance of each point from the camera.

We used a single depth scan acquired by a color structured light sensor, as the accuracy of this system is sufficient for our purpose as shown in Figure 1A. Alternatively, it would be possible to acquire multiple frames using off-the-shelf depth sensors, such as Intel’s RealSense, and to fuse them into a single three dimensional facial model via techniques such as those proposed in [5] or [6]. These methods reduce the noise in each single scan by fusing many scans together into a refined model.

Feature Points Detection: For initializing the alignment procedure, our system finds a small set of predefined characteristic points on the scanned face. These points can be detected on a color image using Active Shape Model algorithms such as [7]. In practice, we estimate the position of approximately sixty landmarks on the face, see Figure 1B. To ensure robustness to outliers, we remove feature points detected at pixels whose depth value was not evaluated.

Similarity Initial Alignment: Based on the detected landmark points, we estimate the similarity transformation applied to the template face, see Figure 1C, which minimizes the distances between corresponding feature points on the template and the target face. Notice that throughout the alignment process, the scanned facial model remains static and only the template face is transformed.

Denote the set of feature points detected on the scan as \( \{r_{scan}^1, ..., r_{scan}^k\} \), and the set of corresponding feature points on the template face, which we selected in advance, as \( \{r_{temp}^1, ..., r_{temp}^k\} \). For initializing the scaling factor \( \alpha \), we minimize the term

\[
\min_{\alpha} \sum_{i,j} ||\alpha \cdot d(r_{temp}^i, r_{temp}^j) - d(r_{scan}^i, r_{scan}^j)||^2.
\]

Here, \( d(\cdot, \cdot) \) represents the Euclidean distance between a couple of points.

Next, we calculate the rotation matrix \( R \), the translation vector \( t \) and update the scaling factor \( \alpha \) iteratively, by minimizing

\[
\min_{R \in SO(3), t \in \mathbb{R}^3, \alpha \in \mathbb{R}_+} \sum_{i=1}^k ||(\alpha R r_{temp}^i + t) - r_{scan}^i||^2
\]

The optimization is done by an alternating minimization of the three variables. The process converges after few iterations with an accurate similarity transformation that we use for initializing the non-rigid alignment algorithm described next.
Non-Rigid Alignment: At a preprocessing step, we mark the region of contact of the mask on the generic face, see Figure 1C. In order to find a corresponding region on the scanned subject, we elastically deform the template face until it is aligned with the scanned one, see Figure 1D. The elastic energy we minimize penalizes local stretching and bending. Thus, the resulting registration is an almost isometric map between the faces.

The procedure is performed in an iterative closest point fashion. Each iteration involves four steps. First, we find for each vertex of the template face an approximate nearest neighbor on the reconstructed one. Next, we eliminate pairs from the obtained correspondence list which are too far from one another or have normals with different orientations. Based on the remaining pairs in the list, we then estimate the displacement of each point of the template face, by minimizing an energy term we describe next. Finally, we check the norm of the motion between the last consecutive iterations and, if necessary, readjust the weights in the objective function for the next iteration.

In the nearest neighbor matching step, for each point of the template face \( v_i^{temp} \), a close point on the scanned surface \( c_i^{scan} \) is found. First, we construct a KD-tree for the point cloud of the scanned surface. The KD-tree is constructed by recursively splitting a volumetric cell along the \( x \), the \( y \), or the \( z \) axes, into two subcells where each contains half of the points. The recursion stops when it reaches a leaf cell which contains a single point. For finding the nearest neighbor of a query point, we travel along the KD-tree until we reach a leaf corresponding to the approximate nearest neighbor. In cases where the depth image of the subject is available, we find the nearest neighbor by projecting each template point onto the scan image grid and associate with the point that belongs to the nearest pixel. This reduces the complexity from \( O(n \log m) \) for the KD-tree to \( O(n) \), where, \( n \) denotes the number of queried points and \( m \) is the number of points on the scanned surface.

The obtained list of point correspondences \( \{(v_i^{temp}, c_i^{scan})\}_{i=1}^{p'} \) may include outliers. This can introduce undesired artifacts in the deformation procedure that follows, as the scanned surface may have holes and noise. Thus, we remove matching pairs which are more than five millimeter apart, and pairs whose normal directions differ at more than twenty five degrees.

Based on the remaining matching pairs \( \{(v_i^{temp}, c_i^{scan})\}_{i=1}^{p''} \), we elastically deform the template face. The deformation is modeled by a displacement field \( d = (d_1^{temp}, \ldots, d_m^{temp}) \). Namely, we optimize over the change in position of each point on the template face, such that \( v_i^{temp} \leftarrow v_i^{temp} + d_i^{temp} \).

The displacement is found by minimizing the following
\[
E(d) = \alpha_{p2point} \cdot E_{p2point}(d) + \alpha_{p2plane} \cdot E_{p2plane}(d) + \alpha_{memb} \cdot E_{memb}(d) + \alpha_{ref} \cdot E_{ref}(d),
\]

where \( \alpha(i) \) are positive scalar weights and the energy terms are given by

- Point-to-point energy - The sum of squared Euclidean distances between corresponding points in the list
\[
E_{p2point}(d) = \sum_{i=1}^{p'} \|v_i^{temp} + d_i^{temp} - c_i^{scan}\|^2.
\]

- Point-to-plane energy - the sum of squared Euclidean distances between a point on the template and the tangent plane of the corresponding point on the scanned surface
\[
E_{p2plane}(d) = \sum_{i=1}^{p'} \|n_i^{scan} \cdot (v_i^{temp} + d_i^{temp} - c_i^{scan})^T\|^2,
\]

where \( n_i^{scan} \) is the unit normal at the vertex \( c_i^{scan} \).

- Biharmonic energy - this regularization term enforces the smoothness of the displacement field as functions on the template face.
\[
E_{memb}(d) = \sum_{i=1}^{n_{temp}} \sum_{j \in N(v_i^{temp})} \|w_{i,j} (d_i^{temp} - d_j^{temp})\|^2,
\]

where \( w_{i,j} \) are the cotangent weights, see e.g. [8] for more details, and \( N(v_i^{temp}) \) are the set of neighboring vertices of \( v_i^{temp} \). For more details about this energy, we refer to [9] and [10].

- Constraint energy - this term measures the sum of squared Euclidean distances between the detected corresponding feature points.
\[
E_{ref}(d) = \sum_{i=1}^{k} \|v_i^{temp} + d_i^{temp} - v_i^{scan}\|^2.
\]

Each of the above energy terms is weighted differently in the objective function. To make the registration robust to local minima, we perform the alignment gradually in a coarse-to-fine fashion. At the first iteration we set \( \alpha_{p2point} = 0.1 \), \( \alpha_{p2plane} = 1 \), \( \alpha_{memb} = 100 \) and \( \alpha_{ref} = 10 \). At the end of each iteration, we measure the norm of the displacement field.
relative to the previous iteration. If the value is below $10^{-2}$, we decrease $\alpha_{memb}$ and $\alpha_{ref}$ by half. The algorithm converges after $10 - 20$ iterations with an accurate and smooth alignment.

Automatic Interface Design: To customize a mask interface which fits the geometry of the patient with smooth contact boundaries, we model the interface with non-uniform rational basis spline (NURBS). This tool is frequently used in computer graphics for modeling shapes as it provides an intuitive design framework. The surfaces modeled using NURBS can be modified by editing the position of control points based on which the surface is smoothly interpolated. For more details about this technique, we refer to [11].

For fitting the mask to the warped contact region, we first place the generic mask interface next to the warped model, and then modify the position of control points along the side facing the model, see Figure 1E). We use 256 control points which we translate to the position of the corresponding points on the warped contact region. The correspondence between the control points and the contact region is manually determined a priori.

4. RESULTS

The generic template face we used contains approximately 36,000 points. The initial mask interface was manually designed using CAD tools and has roughly 20,000 points. For the automatic interface design we used a Python script coded in Blender which uses its NURBS tool. The resulting mask interface is shown in Figure 1E.

For evaluating the mask interface fitting to the scanned face, we performed an experiment for estimating the force distribution along the contact rim. The face was modeled as a soft physical body with a friction of 50. We then simulated a collision between the mask interface and the face using Blender’s physical simulation. Next, we calculated the norm of the relative motion between each point on the face before and after the simulation. We repeated this experiment twice, once for the mask that was designed for an average facial model and once for a mask designed for the specific patient. The results are shown in Figure 2. The pressure along the contact region generated by the personified mask is shown to spread more evenly compared to the generic mask designed for an average facial model.

5. CONCLUSIONS

We introduced a method for an automatic CPAP mask modeling given a facial depth scan. A generic face with predefined mask contact contour is matched to the scanned model using an iterative elastic registration method. The warped region is then used for setting constraints for the mask interface design. The resulting mask fits the facial features of the patient making the mask impermeable, more efficient, and more convenient compared to existing designs.

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6. REFERENCES

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