Active Shape Models for Customised Prosthesis Design*

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Abstract. Images and computer graphics play an increasingly important role in the design and manufacture of medical prostheses and implants. Images provide guidance on optimal design in terms of location, preparation and the overall shape and configuration of subcomponents. Direct manipulation of a graphical representation provides a natural design environment. RaPiD is a CAD-like knowledge-based assistant for designing a dental prosthesis known as a removable partial denture (RPD). The expertise embedded in RaPiD encourages optimal subcomponent configuration, but currently supports only minor customisation. This paper describes how oral images and Active Shape Models (ASMs) are being used to address this limitation.

1 Background

Images and computer graphics are important in the design, manufacture and fit of many medical implants and prostheses. Typically they are involved in:

- optimising the location of the implant/prosthesis
- minimising bone/tissue removal for insertion and fit
- maximising accuracy of overall fit
- configuring and designing sub-components for optimal shape, fit and function
- determining and recording shape variation in relevant patient populations

For example, conventional radiographs and CT/MR images are all used in selecting the best location for a dental implant [9]. Radiographs are manually digitised in two dimensions to configure parameterised 3D models and provide

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input to CAD/CAM manufacture of hip and knee prostheses [3]. Nails, screws and plates for bone fixation following trauma [7] and spinal implants [4] all rely on imaging data. Extendible endoprostheses require accurate graphical design and expert configuration [10].

RaPiD is a knowledge-based assistant for designing a dental prosthesis known as a removable partial denture (RPD). Embedded design expertise encourages the correction, selection and configuration of subcomponents in a 2D CAD style and incorrect design is critiqued [8]. Manufacture takes place on a physical model according to the printed design specification.

RaPiD has undergone and is undergoing considerable validation and evaluation ([5],[6]). It has also recently been commercialised under UK government funding in co-operation with a specialist dental software company, Team Management Systems Ltd. Consequently, there is some confidence that RaPiD is well designed and will be of benefit to general dental practitioners. However, designs in RaPiD are still produced on a set of generic tooth icons and although some graphical tools support rotation and translation of teeth icons, this remains inadequate for customised design for individual patients. In the MINORI project (Model-based INterpretation of ORo-facial Images) we are addressing this problem.

2 The MINORI Project

2.1 Requirements

Hand-digitising of images can be slow and requires expert knowledge of the imaging method and the structures being identified. Computer vision techniques provide an alternative, automatic method. If such a system is to replace manual digitisation successfully, it must satisfy certain criteria. It must be able to work with available images, it must be sufficiently robust to work largely unsupervised and the measurements it provides should be sufficiently precise for the prosthesis designed.

2.2 Image Acquisition

Within a few years, most dental practices will have access to some form of digital image acquisition. Many commercially available systems already enable intra-oral pictures to be taken and stored on computer. Alternatively, digital cameras that are widely available and inexpensive can also be used to take pictures of casts of patients' jaws. To extract the dentition of a patient from such images, we restrict them to occlusal views only, where the arch of teeth is seen from above. Pictures of casts or intra-oral views can be used.

There is considerable variation in patient dentition: teeth can tilt, move, rotate and change shape. Additionally, in the case of RPD design, the images presented will have teeth missing. A successful approach will have to model all of these variations. As with any image analysis, the pictures should have sufficient contrast between the objects we want to segment and the background. Thus some care must be taken when acquiring the images to avoid artefacts such as varying shadows and background clutter being introduced.

2.3 Deriving the Active Shape Model (ASM)

RaPiD uses a two-dimensional polygon to represent each tooth boundary. 20-40 points per tooth boundary provide enough flexibility to model changes in shape, as well as position, rotation and scale variation. MINORI uses the same set of polygons to build an ASM, as described by Cootes et. al. [2]. The natural variation in shape is learned from a training set of manually digitised oral images. Together with the mean shape, this is then used to direct the search of a new image for similar structures. A few examples from the training set are shown below (Fig. 1). The model has 444 vertices in each complete set of tooth boundaries.

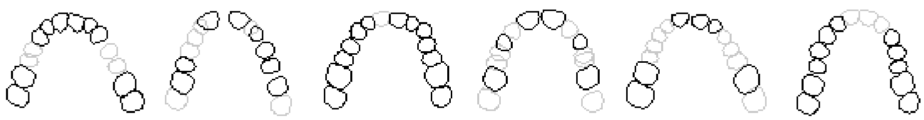

Fig. 1. Some examples from the training set

Each training shape example yields a shape vector. We compute the eigenvectors and eigenvalues of the covariance matrix of the shape vectors. The eigenvectors each represent a deformation of the mean shape, the eigenvector with the largest eigenvalue accounting for the major changes in shape seen over the training set. The first four modes of variation are shown below (Fig. 2).

The number of modes required to represent most of the variation seen in the training set is typically much smaller than the number of points in the shape vector; we have extracted a very compact representation of the deformations seen in natural teeth shapes. By varying the strength of each of the modes of variation we can synthesise new dentitions. As long as we restrict our deformations to within 3 standard deviations of the mean then the shapes are plausible.

2.4 Extracting Tooth Icons from New Images

Having computed a model of how dentition varies, we can use it to fit shapes to new images. The modes of variation reduce the search space from potentially a thousand dimensions to perhaps only twenty. Many schemes are possible to implement this search. Cootes et. al. describe a simple local optimisation strategy that proves very effective. Each vertex of the shape polygon is pulled towards any nearby strong edges in the image. From these pull vectors, the ideal translation, rotation, scaling and deformation are computed. The transformation is applied and the process is repeated until convergence. Given a suitably close initial

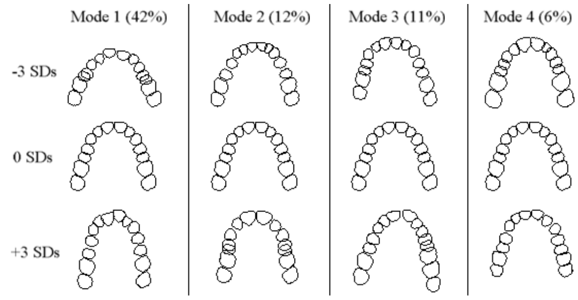

Fig. 2. The first four modes of variation. In each column the mean shape *(middle row)* is deformed by one of the eigenvectors. Mode 1 has captured the change in arch width from wide to narrow and explains 42% of the variation seen in the training set. The other modes explain the remaining variation, together the first four modes explain 71% of the total variation

placement, the shape converges on the teeth in the image, typically within fewer than fifty iterations.

A prototype version of MINORI has been implemented in Visual C++. The graphical user interface (GUI) is used both for hand-digitising the training set and for fitting to new images.

3 Conclusions and Future Work

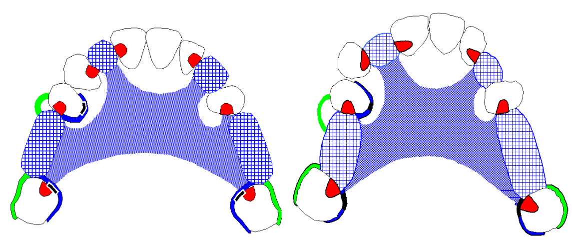

Fig. 3. A design produced in RaPiD using the generic tooth icons *(left)* and a design using the icons derived from MINORI *(right)* demonstrating the difference in design when the dentition is customised to the patient

It can be seen (Fig. 3) that a customised dentition can alter the design of an RPD so it is important to have a reasonable method for acquiring the dentition of the patient. The approach we have put forward here requires no specialist hardware other than the ability to digitise images and is therefore attractive to the general practitioner.

Many improvements to the current implementation are possible. The removal of the need for the user to initiate the search with an approximation is highly desirable. The search could become more robust, perhaps incorporating some of the ideas in [1]. The patching of missing teeth data from the mean causes the statistical analysis of the variation to be flawed, an approach which overcame this would be an improvement.

How many examples in the training set are required to capture all of the variation seen in teeth across the human population? Experiments with the thirty examples in our set show that the modes of variation are fairly stable as new examples are added, suggesting that some of the natural variation has already been captured. Further evaluation of the training set is ongoing.

The automatic digitisation of medical images has many potential applications: for planning surgery, to quantify the results of cosmetic surgery, for cephalometric measurements and as here, for designing customised prostheses. The use of ASMs is an approach capable of compactly encoding knowledge about the natural variation in shape for use in searching an image. We expect that the use of ASMs in customised prosthesis design applications like ours will become increasingly widespread.

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