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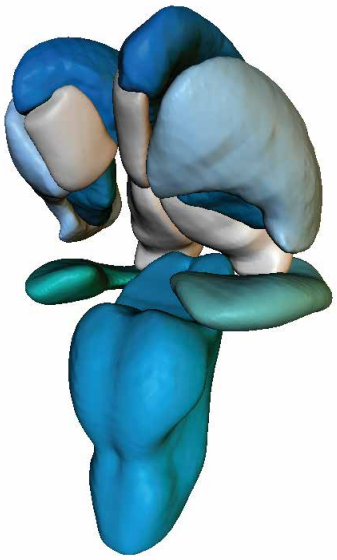


Technical Briefing:

A Model-based Machine Learning Approach to 3D Medical Image Analysis

At left: placing corresponding landmarks on anatomical surfaces such as deep brain structures is not possible manually

Background

Since their invention at the University of Manchester in the early 1990's, 2D Active Shape Models (ASMs)[1] and Active Appearance Models (AAMs)[2] have proved to be amongst the most successful approaches to medical image segmentation[3] with over 6,000 citations for the original ASM paper. The underlying idea is to use a set of examples that represent the statistical variability of an object's shape and appearance to train a deformable model.

This model can be altered in shape and appearance to best match a new, unseen example of the object, but only within the limits of what was previously learnt. This prevents the model from taking up implausible shapes when representing an object. imaging with its excellent soft tissue contrast.

Volumetric Modelling

The move from 2D to 3D shape required the development of fully automated model building from manually annotated example surfaces. For 2D models, it is relatively easy to place sets of landmarks on example shapes that have the same meaning or correspond[4]. But covering a surface with thousands of corresponding landmarks manually in 3D is impossible. Instead, it must be done automatically, and the most effective method for this has been shown to be by using the minimum information necessary which automatically produces sets of corresponding landmarks[5][6] for 3D AAM construction.

Image Understanding

In addition to the accurate and precise segmentation of anatomy in an image, using a 3D statistical model provides a number of key advantages:

Surface landmarks: The object is described by a dense set of true landmarks that correspond[4]. These can be used to define very accurate measurements between points or areas of interest as patches.

Population studies: Fitting model examples with dense, anatomically corresponded sets of landmarks means they can easily be aligned, allowing for careful comparison of populations[12]. For example, we can identify significant differences in shape and appearance within a population as disease progresses, or identify shape differences based on gender, ethnicity, size etc.

Use with multiple modalities: AAMs provide for a generic solution for virtually any anatomical structures or tissues[13], so a single model can be developed to deal with the anatomical appearance in multiple modalities such as CT, MR or ultrasound.

The way that Imorphics technology captures and describes population variation and normality provides for true image understanding and a natural way of organizing the Big Data of human shape and appearance in medical images.

A Learning Approach

Since its inception, Imorphics has developed several revolutionary patent-protected methods to radically improve the performance of 3D AAMs in a layered approach[7]. The first of these artificial intelligence methods is a scheme which optimally fits a series of local patch models to an AAM search result. This relaxes the constraints on the AAM in local areas, allowing a more accurate fit to the local shape.

The second is to classify each of the voxels, in and around the AAM search, using a number of machine learning methods to label voxels as diseased/non-diseased or inside/outside. This allows the search to identify fine detail which is often caused by disease, and not completely described by the model.

Producing Models

Using this technology, Imorphics can now build a prototype solution to demonstrate proof-of-concept in a matter of weeks from around 30 example images. To produce a deliverable version, typically requires another 100 examples with a representative demographic mix, and diseased cases. During the model-production process, we use unbiased "leave-one-out" tests of landmark-to-surface errors on unseen data[1] to ensure that the model performs to specification.

Imorphics fully-automated identification and segmentation solutions are usually specified with sub-voxel or sub-millimeter accuracy. Reproducability is excellent with typical CoVs of around 1%. In addition, Imorphics model-based solutions can readily deal with cropped images or missing anatomy.

Performance: How Do We Compare?

Each year, the prestigious MICCAI "Grand Challenges"[8] allows academia and industry to test their methods in a direct comparison with the state-of-the-art on previously unseen medical images. The testing is done live and concurrently in order to give a fair representation of clinical performance. Imorphics have won all four that they have entered:

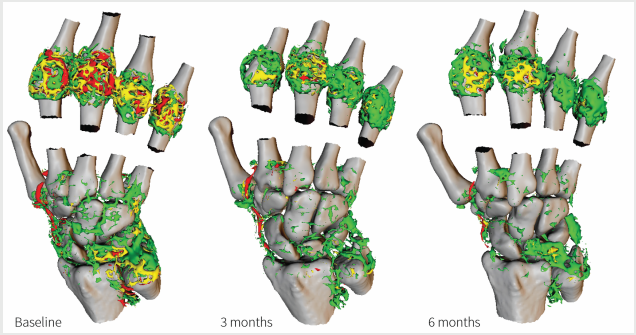
2010: "SKI10"[9]: knee bone and cartilage segmentation with an average distance error on 39,239 landmarks in MR images of 0.40 ± 0.71mm;

2012: "PROMISE12"[10]: segmentation with an error of 1.95 ± 0.36mm and DICE similarity coefficient (DSC) of 0.89 ± 0.03 in low resolution MRI images of the prostate;

2014: "VISCERAL"[11]: an average segmentation error of 0.36mm with a DSC of 0.90 in CT images of the liver, lungs, psoas muscles, kidneys and aorta.

2015: "Head&Neck"[14]: radiotherapy organs at risk segmentation in CT images. A mean DSC of 0.78 for optic nerves compared to the nearest competitor with 0.62.

Importantly, Imorphics had done no previous work on prostate, visceral or head/neck images before developing winning solutions in under two months.



Above: very accurate segmentation and true landmarks allows comparison of treatment effects over time, in this case a decrease in synovitis

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