Robust Image Segmentation through Outlier Handling Application to Automatic Plaque Burden Assessment

K. Lekadir[1], R. Merrifield[1], N. Keenan[2], D. Pennell[2], G-Z. Yang[1]

[1]Wolfson Foundation/Royal Society MIC Laboratory, Imperial College, London, United Kingdom, [2]CMR Unit, Royal Brompton and Harefield Trust, London, United Kingdom

Introduction:

Recent research has established the value of CMR in assessing plaque burden *in-vivo*. In order to obtain consistent analysis for longitudinal studies, inter- and intra-subject variability is a major consideration. In practice, the calculation of plaque burden involves extensive manual delineation and this is subject to significant operator bias in addition to being time consuming. Existing automatic segmentation techniques such as the Active Shape Models (ASM) [1], however, can be problematic when encountered by image noise and poor quality structural features. These artefacts introduce erroneous landmarks called outliers that can significantly degrade the performance of the ASM search. The aim of this work is to develop a technique for outlier handling prior to the ASM model fitting in order to obtain accurate and robust automatic segmentation.

Methods:

The outlier detection technique is based on the use of an invariant shape representation based on the ratio of interlandmark distances. This descriptor can be used as a local shape dissimilarity measure, thus it is ideal for outlier detection. Furthermore, the invariance allows an outlier analysis independently from non-shape parameters. Tolerance intervals T_{ijk} are estimated from the training samples for each descriptor r_{ijk} using the mean values and standard deviation s_{ijk}. Confidence measures f_r (ratio) and f_p (landmark point) are calculated as follows:

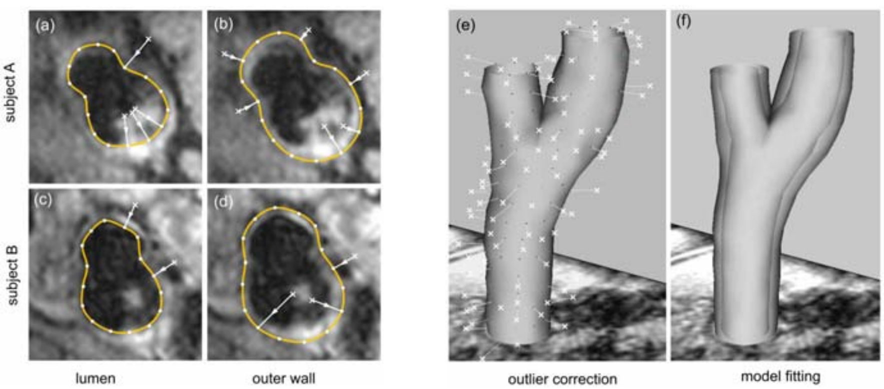
$$f_r\left(r_{ijk}\right)=\begin{cases}1 & \text{if } r_{ijk}\in T_{ijk}\\ 0 & \text{elsewhere}\end{cases} \qquad f_p(P_i)=\frac{1}{K_i}\sum_{j,k} f_r\left(r_{ijk}\right)\cdot f\left(r_{jki}\right)\cdot f\left(r_{kij}\right) \qquad \text{with } T_{ijk}=\left[\overline{r}_{ijk}-3s_{ijk},\overline{r}_{ijk}+3s_{ijk}\right] \text{ and } K_i=\text{number of ratios}$$

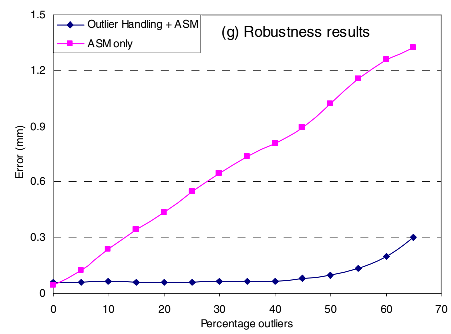
The landmark point confidence measure f_p takes values between 0 and 1 and describes the likelihood of a point to be lie on a correct boundary position. Based on this measure, landmarks are rejected as outliers iteratively. Before applying the model fitting procedure of the ASM search, the detected outliers must be corrected so their corresponding descriptors lie within the tolerance intervals. This is achieved by selecting the points that minimize the least-square function shown on the right:

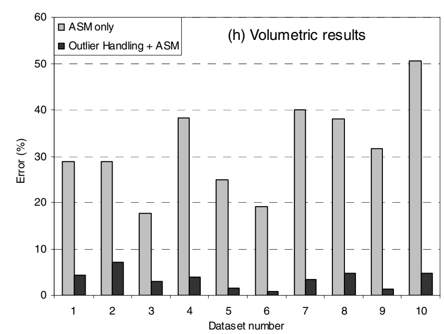
$$\sum_{j,k}^{inliers}\left(\frac{r_{ijk}-\overline{r}_{ijk}}{s_{ijk}}\right)^2$$

Images of the carotid bifurcation were acquired on a 1.5 tesla CMR scanner using a TrueFISP sequence with imaging parameters including: matrix size = 256 x 256, voxel slice = 0.47 x 0.47 x 2.0mm pixels, field-of-view = 120x24mm and Echo Time = 11ms. Ten asymptomatic patients were recruited for the study. Both the luminal and outer boundaries of the carotid bifurcation were delineated by an expert. The proposed method and the ASM were applied to the entire dataset for validation.

Results:







Figures (a)-(d) illustrate the result of the proposed method applied to short axis images located at the bifurcation point of two different subjects. The outliers (crosses) are efficiently handled. Figure (e) shows a 3D example of the outlier handling technique applied to the outer surface of the artery. The ASM model fitting is then successfully applied with result shown in figure (f). To assess the robustness of the technique to outliers, an increasing percentage of outliers was added to the manual delineations using non-Gaussian noise. The average segmentation errors plotted in Figure (g) show that the proposed method is able to handle a significant presence of outliers until over 50% which demonstrates its robustness.

Finally, the proposed technique was applied to the 10 subjects studied and Figure (h) shows the volumetric errors between automatic and manual segmentations. A low error (average 3.4% ± 1.8%) is maintained throughout the study using the proposed method whilst significant errors are introduced by the gold standard ASM.

Discussion:

Erroneous landmarks due to artefacts are a major problem in automatic segmentation. The result demonstrates that the proposed technique is capable of handling a significant presence of outliers. This increases the accuracy and robustness of the ASM image search and shows the potential clinical value for serial examination of plaque burden and for monitoring the efficacy of therapeutic measures. It is worth noting that the proposed method is applicable to other 2D and 3D image segmentation tasks that involve longitudinal studies with varying image artefacts.

References:

[1] T. F. Cootes, D. Cooper, C. J. Taylor, and J. Graham. Active Shape Models - Their Training and Application. CVIU, 61(1), 1995, 38-59.