Chapter 76
Groupwise Non-Rigid Image Alignment Using Few Parameters:
Registration of Facial and Medical Images

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ABSTRACT

Groupwise non-rigid image alignment is a difficult non-linear optimization problem involving many parameters and often large datasets. Previous methods have explored various metrics and optimization strategies. Good results have been previously achieved with simple metrics, requiring complex optimization, often with many unintuitive parameters that require careful tuning for each dataset. In this chapter, the problem is restructured to use a simpler, iterative optimization algorithm, with very few free parameters. The warps are refined using an iterative Levenberg-Marquardt minimization to the mean, based on updating the locations of a small number of points and incorporating a stiffness constraint. This optimization approach is efficient, has very few free parameters to tune, and the authors show how to tune the few remaining parameters. Results show that the method reliably aligns various datasets including two facial datasets and two medical datasets of prostate and brain MRI images and demonstrates efficiency in terms of performance and a reduction of the computational cost.

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INTRODUCTION

The process of image registration is to extract and combine significant information from a group of two or more images (Fischer & Modersitzki, 2008) by estimating the optimal transformations which allow them to be matched and their features aligned well (Sidorov K., 2010).

Non-rigid image registration is an important step in many image analysis problems. It involves geometrically distorting the images to align common features. Manual annotation of features is time consuming and prone to errors, and so can form a bottle neck in processes involving human-computer interactions such as image-based animation, image analysis and medical diagnosis and research. As a result, considerable research effort has been applied to developing fully automatic processes to align the images. One approach to image registration that is extensively used, is to select one image from the image set to act as a reference or template and then repeatedly align each image of the set to that reference by using a pairwise registration algorithm (Zitova & Flusser, 2003), (Cootes T., Twining, Petrovic, Schestowitz, & Taylor, 2005),(Cootes, Twining, & Taylor, 2004), (Rueckert, Frangi, & Schnabel, 2001) so as to find deformation fields between the reference and each image in the set.

If the images are very consistent, or the selected target image happens to be particularly well chosen, this approach might work well. However, using this approach gives us a biased representation to the reference image (Polfliet, et al., 2018), consequently there are likely to be some errors in the final alignment. If the selection of the reference image is not suitable and missing important features, the registration process will give sub-optimal results (Sidorov, Richmond, & Marshall, 2009), (Marsland, Twining, & Taylor, 2008). Also, the resulting information from the pairwise registration of two images, which does not include all the features of the images in the set, will lead to inaccurate results (Polfliet, et al., 2018).

Groupwise registration algorithms have been developed recently to avoid the problems of pairwise registration described above (Cootes T., Twining, Petrovic, Babalola, & Taylor, 2010), (Sidorov, Richmond, & Marshall, 2009), (Cootes T., Twining, Petrovic, Schestowitz, & Taylor, 2005), (Cootes, Marsland, Twining, & Smith, 2004), (Cristinacce & Cootes, 2008), (Davies, Twining, & Taylor, 2008), (Twining, et al., 2005). Groupwise methods use the information in all the images in the set in the registration process simultaneously. Therefore, this total information is used at each iteration instead of using only the information from two images (Sidorov, Richmond, & Marshall, 2009). So, the deformation fields, which are obtained during groupwise registration, are optimised simultaneously (Polfliet, et al., 2018), for performing the alignment efficiently (Sidorov, Richmond, & Marshall, 2009).

The algorithms of groupwise alignment have been experimentally demonstrated to be better than pairwise algorithms by computing the dense correspondences across a group of the estimated shapes (Sidorov, Richmond, & Marshall, 2009), (Cootes T., Twining, Petrovic, Schestowitz, & Taylor, 2005), which has not been exploited in the literature (Cootes T., Twining, Petrovic, Babalola, & Taylor, 2010), (Baker, Matthews, & Schneider, 2004), (Cootes T., Twining, Petrovic, Schestowitz, & Taylor, 2005).

Active Appearance Models (AAMs) (Cootes, Edwards, & Taylor, 2001), (Matthews & Baker, 2004) present efficient ways to optimize shape and appearance models (usually based on PCA derived models) to an image. The fitting of the AAM model is achieved by minimising an objective function to find the model shape update parameters δp, which comes from a Taylor series approximation. The AAM style optimisation is not suitable for a large number of parameters, as it requires inverting an N^2 matrix for minimising N parameters. Nevertheless, if a way can be found to reduce the number of parameters involved in the minimisation, AAM style optimisation represents an efficient alignment strategy, with very few parameters to tune.