Timeline of Developments in Algorithms for Finding Correspondences across Sets of Shapes and Images

Tim Cootes

July 19, 2005

This document lists some of the key papers in the developments of methods for finding correspondences across sets of shapes or images.
It concentrates on methods which assume no ordering of the images, and that the images are of different objects (thus we don't include work in the tracking or multi-view reconstruction literature).
We classify the methods into those that work on shapes (curves or surfaces) and those that work on image regions (in 2D or 3D). Typically the shape based methods control points constrained to lie on the shape, whilst the image methods control points moving anywhere, but constrained by the image intensities in some way.
We also highlight *pairwise* methods, in which correspondences across the set are found by performing a sequence of individual pairwise correspondences to optimise a pairwise function, and *groupwise* methods which explicitly aim to optimise a function defined on the whole set of shapes/images.
This distinction is actually somewhat blurred, because some of the explicitly pairwise methods actually end up optimising some (implicit and usually unstated) groupwise objective function. We assign the noble title of groupwise to those explicitly optimising a groupwise function (though it may be done in some pairwise manner).
This is a first draft, so may miss out some relevant work - if you think something significant is missing, please contact the author.

Year	Shape Correspondences	Region Correspondences
1994	Hill corresponds sets of shapes by pairing and merging, then refines each using the resulting shape model [1]	
1995	Baumberg iteratively refines crude correspondences across a set of closed curves modelled with B-splines	
1996	Greedy pairwise scheme [2]	
1997	Groupwise objective function (product of eigenvectors of covar) used for corresponding 2D shapes [3] Use of diffeomorphisms for shape alignment [3] Ramsay and Silverman: Functional Data Analysis book (apply diffeomorphisms to 1D functions to align them) [7]	'Morphable Models' use optical flow techniques to correspond 2D regions and build models[4, 5, 6]
1999	Brett *et.al.* use a pairwise method to correspond 3D surfaces [8]	Transformed Component Analysis allows translation of images before PCA, so as to optimise a suitable function [9] Salient features detected across a sequence used to automatically build appearance models [10]
2000	Shelton corresponds surfaces using an elastic deformation type technique, then refines the model iteratively. Applies to 2D images and 3D surfaces. [11]	
		Miller *et.al.* [12] introduce 'congealing' approach (maximising entropy on a per-pixel basis) and applies it to groupwise affine alignment.
2001	Minimum Description Length objective function for groupwise correspondences of shapes [13, 14][1] [15]. Belongie *et.al.* use 'shape context' and thin plate splines to correspond shapes [17] 3D shapes corresponded by using non-rigid registration of sets of binary label images (one for each part) [19, 20]	De la Torre [16] represents a face as a set of fixed shape regions which can move independently. Optimal locations are found by minimising a measure related to the total variance of the eigenmodels. Rueckert *et.al.* use non-rigid registration to correspond 3D images and build statistical shape models [18]
2002	MDL applied to 3D shapes [21]	In a technical report Cootes *et.al.* propose a framework for groupwise diffeomorphic correspondence to build appearance models [22]
2003	Review of some 2D MDL methods [23]. Thodberg and Olafdottir add curvature measures to MDL [24] Ericsson and Åström use cunning maths for a steepest descent version of MDL shape matching [26]	In a technical report, Baker and Matthews propose minimising a groupwise measure to build optimal appearance model [25] Jebara corresponds sets of images by treating pixels as 3D vectors. Optimises a groupwise function using quadratic programming [27]
2004		Cootes *et.al.* [28] describe an algorithm for groupwise diffeomorphic registration. Joshi *et.al.* [29] perform groupwise diffeomorphic registration onto an evolving estimate of the mean image.

[1] The details of the MDL theory in these papers is slightly flawed, the interested reader should refer to [21, 15].
Note: This is incomplete - I need to add more stuff to it!

References

[1] Andrew Hill and Christopher J. Taylor. Automatic landmark generation for point distribution models. In Edwin Hancock, editor, 5^{th} *British Machine Vison Conference*, volume 2, pages 429–438. BMVA Press, September 1994.

[2] Andrew Hill and Christopher J. Taylor. A method of non-rigid correspondence for automatic landmark identification. In 7^{th} *British Machine Vison Conference*, pages 323–332. BMVA Press, September 1996.

[3] A.C.W. Kotcheff and C. J. Taylor. Automatic construction of eigen-shape models by genetic algorithm. In 15^{th} *Conference on Information Processing in Medical Imaging*, pages 1–14, 1997.

[4] T. Vetter, M. Jones, and T. Poggio. A bootstrapping algorithm for learning linear models of object classes. In *Computer Vision and Pattern Recognition Conference 1997*, pages 40–46, 1997.

[5] Michael J. Jones and Tomaso Poggio. Multidimensional morphable models. In 6^{th} *International Conference on Computer Vision*, pages 683–688, 1998.

[6] Michael J. Jones and Tomaso Poggio. Multidimensional morphable models : A framework for representing and matching object classes. *International Journal of Computer Vision*, 2(29):107–131, 1998.

[7] J.O. Ramsay and B.W. Silverman. *Functional Data Analysis.* Springer-Verlag, New York, 1997.

[8] A. D. Brett and C. J. Taylor. A framework for automated landmark generation for automated 3D statistical model construction. In 16^{th} *Conference on Information Processing in Medical Imaging*, pages 376–381, Visegrád, Hungary, June 1999.

[9] B.Frey and N.Jojic. Transformed component analysis: Joint estimation of spacial transformations and image components. In 7^{th} *International Conference on Computer Vision*, pages 1190–1196, 1999.

[10] K. N. Walker, T. F. Cootes, , and C. J. Taylor. Automatically building appearance models from image sequences using salient features. In T. Pridmore and D. Elliman, editors, 10^{th} *British Machine Vison Conference*, volume 2, pages 463–562, Nottingham, UK, September 1999. BMVA Press.

[11] C.R. Shelton. Morphable surface models. *International Journal of Computer Vision*, 1(38):75–91, 2000.

[12] E.G.Miller, M.E.Matsakis, and P.A.Viola. Learning from one example through shared densities on transforms. In *IEEE Proc Computer Vision and Pattern Recognition*, volume 1, pages 464–471, 2000.

[13] R.H. Davies, T.F. Cootes, and C.J. Taylor. A minimum description length approach to statistical shape modelling. In 17^{th} *Conference on Information Processing in Medical Imaging*, pages 50–63, 2001.

[14] R.H. Davies, T.F. Cootes, C. Twining, and C.J. Taylor. An information theoretic approach to statistical shape modelling. In Tim Cootes and Chris Taylor, editors, 12^{th} *British Machine Vison Conference*, pages 3–11, 2001.

[15] R.H. Davies, C.Twining, T.F. Cootes, and C.J. Taylor. A minimum description length approach to statistical shape modelling. *IEEE Transactions on Medical Imaging*, 21:525–537, 2002.

[16] F. De la Torre. Automatic learning of appearance face models. In *Recognition, Analysis and Tracking of Faces and Gestures in Realtime Systems*, pages 32–39, 2001.

[17] S. Belongie, J. Malik, and C. Fuh. Matching shapes. In 8^{th} *International Conference on Computer Vision*, volume 1, pages 454–463. IEEE Computer Society Press, July 2001.

[18] D. Rueckert, A.F. Frangi, and J.A. Schnabel. Automatic construction of 3D statistical deformation models using non-rigid registration. In *MICCAI*, pages 77–84, 2001.

[19] A.F. Frangi, D. Rueckert, J.A. Schnabel, and W.J. Niessen. Automatic 3D ASM construction via atlas-based landmarking and volumetric elastic registration. In 17^{th} *Conference on Information Processing in Medical Imaging*, pages 78–91, 2001.

[20] A.F. Frangi, D. Rueckert, J.A. Schnabel, and W.J. Niessen. Automatic construction of multiple-object three-dimensional statistical shape models: Application to cardiac modeling. *IEEE-TMI*, 21:1151–66, 2002.

[21] R.H. Davies, C.Twining, T.F. Cootes, J.C. Waterton, and C.J. Taylor. 3D ststistical shape models using direct optimisation of description length. In 7^{th} *European Conference on Computer Vision*, volume 3, pages 3–20. Springer, 2002.

[22] T.F. Cootes, C.J. Taylor, C. Twining, and N.Thacker. A framework for building deformable atlases. Technical report, University of Manchester, `http://www.isbe.man.ac.uk/~bim/Papers/def_atlas.ps`, March 2002.

[23] H.H.Thodberg. Minimum description length shape and appearance models. In 18^{th} *Conference on Information Processing in Medical Imaging*, pages 51–62. Springer-Verlag, 2003.

[24] H.H Thodberg and H. Olafsdottir. Adding curvature to minimum description length shape models. In *14th British Machine Vision Conference*, volume 2, pages 251–260, 2003.

[25] Simon Baker, Iain Matthews, and Jeff Schneider. Image coding with active appearance models. Technical Report CMU-RI-TR-03-13, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, April 2003.

[26] A. Ericsson and K.Åström. Minimizing the description length using steepest descent. In *14th British Machine Vision Conference*, volume 2, pages 93–102, 2003.

[27] T. Jebara. Images as bags of pixels. In 9^{th} *International Conference on Computer Vision*, volume 1, pages 265–272, 2003.

[28] T.F. Cootes, S. Marsland, C.J. Twining, K. Smith, and C.J. Taylor. Groupwise diffeomorphic non-rigid registration for automatic model building. In 8^{th} *European Conference on Computer Vision*, volume 4, pages 316–327. Springer, 2004.

[29] S.Joshi, B.Davis, M.Jomier, and G.Gerig. Unbiased diffeomorphic atlas construction for computational anatomy. *NeuroImage*, 23:S151–S160, 2004.