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Original article

Mesh correspondence improvement using Regional Affine Registration: Application to Statistical Shape Model of the scapula

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Abstract

Statistical Shape Models (SSMs) are efficient tools in several fields and especially medical applications. In order to be meaningful, SSM construction requires a dense correspondence matching between a significant number of objects, which remains a very challenging task. Nonrigid registration is an essential element in the SSM construction pipeline that allows establishing correspondences between shapes and capturing their local variations. We introduce the Regional Affine Registration (RAR) that is based on object segmentation where each region is affinely registered to its counterpart. The point-based RAR process can be used to initiate a farther nonrigid registration process. Experiments are performed using fiducial metrics to compare three registration approaches: RAR, segmentation-based, and classical approach. As an application, we integrate RAR in the construction of an SSM of the human scapula. The three approaches are used to match correspondences between 85 scapulae and a validation of the SSM is carried out by evaluating its compactness, generalization and specificity. Multilevel B-Spline nonrigid registration parameter optimization is also investigated in a feedback sense using an initial version of the model. The initial SSM is used to generate in-correspondence shapes, giving ground truth to optimization experiments. The RAR method proved to initiate better the nonrigid registration which gave more accurate correspondence among synthetic and real database shapes. This was also reflected in the SSM validation tests. We show that performing the nonrigid registration in an iterative manner did not necessarily improve the final result.

1. Introduction

Statistical Shape Models (SSMs) have become a widely used tool and have been studied extensively for the statistical analysis of 3D shapes. Such models draw meaningful statistical conclusions about a set of shapes, and therefore, can be used as prior information for image segmentation, analysis and processing tasks. Furthermore, SSMs are able to separate shape variations into groups, which form bases of a *shape space*. Not to mention, their "creativity" (i.e. generalization ability), SSMs can extend the subpopulation being modeled by generating completely new objects. A typical application is model-based segmentation. This is normally used when lack of information exists and thus a priori information about the missing parts is provided by the model [1,2].

The basic idea of SSM construction is to relate shape correspondences overall subpopulation's samples. First, all samples are translated, rotated, uniformly scaled and reflected into a common reference, that is eliminating all pose differences between them and only keeping *shape* ones. Secondly, they are landmarked and for each landmark a vector of correspondences on the samples is established. These correspondence vectors hold possible correlated shape variations of the subpopulation. Decorrelation, known as *shape decomposition*, can be applied using Principal Component Analysis (PCA) that provides new

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bases to neatly represent these variations. More precisely, PCA uses orthogonal transformations to linearly find uncorrelated variations called modes of variation. These modes are the shape space bases. This celebrated method also known as Karhunen–Loéve Transform (KLT) was introduced back in 1933 by Harold Hotelling [3] based on work by Karl Pearson [4]. A comprehensive text on PCA can be found in [5].

Pose differences between samples can be omitted by a rigid transformation and the distance between them can be globally minimized in a least square sense like Iterative Closest Point (ICP) algorithm [6]. In general, pose transformations are shape-dependent and have no satisfying generic scheme especially for complex forms like scapula. In other words, complex shape variations are difficult to locate without considering local transformations. Rueckert et al. [7] introduced a free form deformation (FFD) algorithm to elastically register local details between two images. The method was extended later by Schnabel et al. [8]. A different approach is presented by Davies et al. [9] who proposed to minimize a cost function based on the Minimum Description Length (MDL) of the resulting statistical shape model. The compactness of the model is to be minimized by iteratively displacing correspondent points toward their optimal positions. This manipulation could be applied based on point position parameterization by mapping the 3D object onto a sphere. Although this method outperforms the geometric ones in terms of compactness, it is computationally more expensive (at least $O(N_s^2)$ where N_s is the size of the subpopulation). Moreover, it is only applicable on non-complex sphere-like (genus 0) shapes. The scapula is genus 0, yet it is a complex shape too; unsatisfying results are obtained when applying conformal mapping on a scapula onto a sphere and registering angle preserving factors of the three edges in each cell before and after mapping. About 325 out of 10 000 points have their factor's standard deviation value between 1 and 250 (ideal conformal mapping must preserve angles ratios, i.e. neglected standard deviation for each point). Consequently, the first approach is adopted.

SSMs of the scapula in general have been rarely addressed. To build the SSM of the primate scapula, Yang [10] used the first approach described in this introduction. They defined a coordinate frame of the scapula attached to its glenoid using semi-automatic crest-lines-based method to perform initial alignment. Due to the complexity of the anatomy of the scapula, they had to initiate the elastic deformation with manual extraction of some characteristic points on source and target scapulae. The authors in [11] presented a model-based morphometric study of the scapulae of Felidae and focused on the correlations between forelimb postures and extracted scapular shape variations.

In our previous work [12] we proposed a fully automatic framework to efficiently tackle nonrigid registration challenges caused by the complexity of the human scapula and build its SSM. We automatically located three characteristic points on the scapula's surface, which are used for initializing a further rigid registration by means of a minimization algorithm. The deformation field was then calculated through a multi-resolution B-Spline algorithm [13], which we have enhanced by defining region-to-region correspondences. Regions were labeled on the surface of the scapula by developing a 3D Watershed-based segmentation method. To collect correspondences among scapulae, a *mean scapula* was constructed in an iterative way to eliminate bias to the initial reference like in [14]. Supposedly standing at equal distances from each sample, the mean shape was registered to each sample and the correspondences were identified.

A recent study on a statistical shape model of 27 healthy scapulae has been lately reported [15]. The authors used the Iterative Median Closest Point approach [16] to create a mean shape and the Coherent Point Drift algorithm [17] to perform the elastic deformation.

In this paper, we elaborate our approach showing quantitative analyses. We enhance the initial correspondence matching using *Regional Affine Registration* (RAR) that is practically composed of a rigid transformation and a nonuniform scaling between labeled regions. The transformed object is only used to find initial correspondences on the target. Those initial correspondences are used later by the B-Spline algorithm. In order to demonstrate how RAR would improve FFD, we create a synthetic subpopulation of $N_s = 96$ three-armed starfish-like shapes. In order to challenge the registration process, multiple variations are included near the arms of the synthetic starfish. Being synthetic, these shapes provide ground truth to compare three registration approaches: RAR, segmentation-based only, and classical approach. RAR is integrated in the construction of an SSM of the human scapula. The three approaches are used to match correspondences between $N_s = 85$ scapulae and a validation of the SSM is carried out by evaluating its compactness, generalization and specificity. Tuning of model construction parameters is performed based on a set of synthetic scapulae generated by an initial version of the SSM (i.e. using initial values of parameters). Visual analysis as well as validations on the model's compactness, generalization, and specificity are finally presented. Fig. 1 illustrates three elements of the developed pipeline. This paper is mainly concerned about the last two elements.

The remainder of this paper is organized as follows. In Sections 2, 3 we briefly introduce the synthetic database used to test the RAR, and the real database used for the construction of the statistical model. Section 4 recalls the problem of correspondence establishment and its connection to nonrigid registration and we introduce the RAR approach. We propose an outer loop for the nonrigid registration in Section 5. Sections 7 and 8 show how we manage validation tests. Finally, results are illustrated and discussed in Section 9.

2. Synthetic subpopulation

In order to test the proposed approach, we create a synthetic subpopulation of $N_s = 96$ three-armed starfish-like shapes. These shapes are created in the two-dimensional (2D) space where each shape contains $N_p = 306$ points uniformly spaced on each segment. Two vertices (D and E) are slid on the circle defined by the starfish vertices (D, E and F) and the other vertex (F) is shifted interiorly toward the circle center. Fig. 2a

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