001 **CONSTRUCTION OF STATISTICAL SHAPE MODELS USING A PROBABILISTIC POINT-BASED SHAPE REPRESENTATION**

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Background: The majority of statistical shape analysis methods are based on point-based shape representations. These representations, however, have a notion of correspondences between a set of exemplar shapes, since (1) the order of the points can modify freely, and (2) the points are allowed to slide over the boundary surface of the shape while still representing the same shape. Ideally, the intrinsic distance metric of the shape space is invariant with respect to these modifications. Therefore, certain constraints on the position of the points are enforced, as to ensure corresponding points that identify the same point on all exemplar shapes to exist. A variety of approaches exist to solve this constraint [1]. A common approach is to employ point-cloud to point-cloud registration algorithms. More effective approaches formulate the constraint as an optimization problem whereby a certain quality criterion is optimized over the correspondences [2].

Aims: The aim of this abstract is to present an algorithm for the construction of Principal Component Analysis (PCA) shape models using point-based shape representations, while solving the correspondence problem at the same time. This algorithm extends the work of Hufnagel et al. [3].

Methods: Similarly to Hufnagel et al., a probabilistic point-based shape representation is used to construct Principal Component Analysis (PCA) shape models. This probabilistic representation assigns to each point a probability for that point to belong to the boundary surface of the respective shape, and helps to overcome the correspondence problem. This representation is estimated using Kernel Density Estimation (KDE) with a Gaussian kernel. Different from Hufnagel et al., an additional outlier distribution is added to the KDE representation in order to improve the robustness to outliers. For constructing the PCA model a distinction is made between three sets of parameters. The first set of parameters corresponds to the actual PCA model parameters, consisting of the mean shape, modes of variation, and corresponding standard deviations. The second set corresponds to the observation parameters, consisting of a rigid transformation and deformation coefficients with respect to the modes of variation. These observation parameters fit the PCA model to each of the exemplar shapes. The third set of parameters corresponds to the exemplar shape specific bandwidth parameters of the KDE representation. The PCA models are constructed by minimizing an energy function, obtained from a maximum-a-posteriori approach. This energy function consists of two terms; the first term originates from the exemplar shape likelihood, while the second term originates from the observation parameter likelihood. In contradiction to Hufnagel et al. the Expectation-Maximization (EM) algorithm is used for optimizing the energy function. In the E-step probabilistic correspondences are estimated. These probabilistic correspondences naturally arise from the probabilistic shape representation. However, in contradiction to Hufnagel et al., they are obtained using Sinkhorn iterations on the probabilistic correspondence matrix, leading to more accurate correspondences. In the M-step the PCA model parameters, observation parameters, and, different from Hufnagel et al., bandwidth parameters are estimated. Closed form expressions are obtained for all parameters except the modes of variation due to their orthonormality. This property is enforced via additional Lagrange multipliers, estimated in an iterative manner and different from Hufnagel et al., leading to better estimates for the modes of variation.

Results: The algorithm presented above is used to construct PCA models for different types of teeth. This task is complicated by the large anatomical variability observable over a population, as well as noise and outliers present in the exemplar shapes. The resulting models are compared to the models resulting from the original method of Hufnagel et al. using model specificity, generalization ability and compactness. This comparison shows improved values for compactness, specificity and generalization ability.

Conclusions: This approach overcomes the requirement for explicit correspondences while still using a compact point-based shape representation. Compared to the original method of Hufnagel et al., our approach provides more accurate (probabilistic) correspondences, better robustness to outliers, automated estimation of the exemplar shape specific bandwidth parameters, and a better estimation of the modes of variation. This results in an improved compactness, specificity and generalization ability.

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