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Article

On the geodesic distance in shapes K -means clustering

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Abstract: Using Information Geometry tools, we represent landmarks of a complex shape as probability densities in a statistical manifold. Then, in the setting of shapes clustering through a K -means algorithm, we evaluate the discriminative power of two different shapes distances. The first, derived from Fisher-Rao metric, is related with the minimization of information in the Fisher sense and the other is derived from the Wasserstein distance which measures the minimal transportation cost.

Keywords: Shape Analysis, Clustering, K -means algorithm, Fisher-Rao metric, Wasserstein distance

1. Introduction

Shapes clustering is of interest in various fields such as geometric morphometrics, computer vision and medical imaging. In the clustering of shapes is important to select an appropriate measurement of distance among observations. In particular we are interested to classify shapes which derive from complex systems as expression of self-organization phenomenon. We consider objects whose shapes are based on landmarks [1–3]. These objects can be obtained by medical imaging procedures, curves defined by manually or automatically assigned feature points or by a discrete sampling of the object contours.

Since the shape space is invariant under similarity transformations, that is translations, rotations and scaling, the Euclidean distance on such a space is not really meaningful. In Shape Analysis [4], in order to apply standard clustering algorithms to planar shapes, the Euclidean metric has to be replaced by the metric of the shape space. Examples were provided in [5,6], where the Procrustes distance was integrated in standard clustering algorithms such as the K -means. Similarly, [7] applied standard hierarchical or K -means clustering using dissimilarity measures based on the inter-landmark distances. In a model-based clustering framework, [8,9] developed a mixture model of offset-normal shape distributions.

We describe each landmark of a planar shape via a bivariate Gaussian density, where the means are the landmark geometric coordinates and capture uncertainties that arise in landmark placement while the variances derive from the natural variability across the population of shapes. According to Information Geometry, we assume the space of bivariate Gaussian densities as a statistical manifold [10,11] with the local coordinates given by the model parameters. Next, we define distances between landmarks related with different Riemannian metrics. These distances are induced by the geodesics of the two metrics (geodesic distances). Applications of geodesics to shape clustering techniques were provided, in a landmark-free context, by [12,13].

At first we consider the Fisher-Rao metric as a Riemannian metric on the statistical manifold of the Gaussian densities. The induced geodesic distance is related with the minimization of information in the

32 Fisher sense. Another suitable distance is the Wasserstein distance, which is induced by a Riemannian
 33 metric and is related with the minimal transportation cost.

34 The geodesic distances induced by Wasserstein and Fisher-Rao metrics can be used to define shape
 35 distances. In this work, the discriminative power of these shapes distances will be evaluated, in the
 36 setting of shapes k -means clustering, on simulated data sets.

37 2. Geometrical structures for a manifold of probability distributions

We call "manifold" a geometric object which is locally Euclidean then described by local coordinates. Manifolds can be used to study patterns from complex systems. Since pattern recognition essentially relies on quantitative assessment of the proximity of points, for the comparison of patterns we need a well-suited similarity measure (distance or divergence). From Differential Geometry we know that a Riemannian metric on a differential manifold X is induced by a metric matrix g , which defines an inner product on every tangent space of the manifold as follows: $\langle u, v \rangle = u^T g_{ij} v$ with associated norm $\|u\| = \sqrt{\langle u, u \rangle}$. Then the distance between two points P, Q of the manifold is given by the minimum of the lengths of all the piecewise smooth paths γ joining these two points. Precisely the length of a path is calculated by using the inner product:

$$\text{Length of } \gamma = \int \|\gamma'(t)\| dt$$

and so

$$d(P, Q) = \min_{\gamma} \{\text{Length of } \gamma\}.$$

38 A curve that encompasses this shortest path is called a Riemannian geodesic and the previous distance
 39 is named geodesic distance. We remark that in general the concept of geodesic is related to connections
 40 defined on a manifold. If a connection is not Riemannian then a geodesic is different from a shortest path.

41 Probability theory, in the presence of non-deterministic phenomena, provides a natural description
 42 of the raw data. Each measurement x is regarded as a sample from an underlying probability distribution
 43 of the measurement characterized by its probability density function $p(x/\theta)$. Measurements described by
 44 the distribution parameters θ , may contain more information than a measurement expressed as a value
 45 and an associated error bar. Therefore we apply pattern recognition methods directly in the space of
 46 probability distributions. Let P a family of probability density functions $p(x | \theta)$ parameterized by $\theta \in$
 47 \mathbf{R}^k . It is well known that we can endowed it of a structure of manifold, called statistical manifold, whose
 48 local coordinates are the parameters of the family. As an example we consider the family of p -variate
 49 Gaussian densities:

$$f(x | \theta = (\mu, \Sigma)) = (2\pi)^{-\frac{p}{2}} (\det \Sigma)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)\right\}$$

50 where $x = (x_1, x_2, \dots, x_p)^T$, $\mu = (\mu_1, \mu_2, \dots, \mu_p)^T$ is the mean vector and Σ the covariance matrix.
 51 Note that the parameter space has dimension $k = p + \frac{p(p+1)}{2}$. In particular we are interested in the case
 52 $p = 2$.

53 Two geometrical structures have been extensively studied for a manifold of probability distributions.
 54 One is based on the Fisher information metric (Fisher-Rao metric), which is invariant under reversible
 55 transformations of random variables, while the other is based on the Wasserstein distance of optimal
 56 transportation, which reflects the structure of the distance between random variables.

57 In the statistical manifold of bivariate Gaussian densities, we will consider these two different
 58 Riemannian metrics which in turn induce two types of geodesic distances.

59 *2.1. Fisher-Rao metric for Gaussian densities*

60 The geometry of the Gaussian manifold endowed with the Fisher-Rao metric was intensively studied
 61 in the literature. In order to avoid considering manifolds with boundaries, it is convenient to assume that
 62 all densities are non-degenerate, so that covariance matrices are invertible. In this case, one can define the
 63 manifold of n -dimensional Gaussian densities as the set $\mathbb{R}^n \times \mathbb{R}^{n(n+1)/2} = \mathbb{R}^{n+n(n+1)/2}$ with local charts
 64 given by the obvious identification $N_n(\mu, \Sigma) \mapsto (\mu_{i,i=1\dots n}, \sigma_{ij,i=1\dots n,j \leq n})$. Where the σ_{ij} are the elements
 65 of the matrix Σ . A tangent vector at a point (μ, Σ) of the manifold is just a vector from $\mathbb{R}^{n+(n+1)/2}$.
 66 While quite tractable, this choice of parametrization does not give any insight about the structure of
 67 the manifold. A more enlightening approach is obtained by considering groups of transformations, as
 68 detailed below.

Let $\text{symm}^+(n)$ be the group of symmetric positive definite matrices endowed with the product [14]:

$$(A, B) \mapsto A \circ B = A^{1/2} B A^{1/2} \quad (1)$$

69 and let us denote, using a common abuse of notation, the group of translations of \mathbb{R}^n also by \mathbb{R}^n .

Now, define the group $G(n)$ as the semi-direct product:

$$G(n) = \text{symm}^+(n) \ltimes_{\rho} \mathbb{R}^n \quad (2)$$

where the action ρ of $\text{symm}^+(n)$ on \mathbb{R}^n is given by left multiplication with the square root of the matrix, namely:

$$\rho(A)u = A^{1/2}u, A \in \text{symm}^+(n), u \in \mathbb{R}^n \quad (3)$$

70 In the sequel, we are dropping the ρ subscript in the semi-direct product and assume it implicitly.

71 An element in $G(n)$ can be represented as a couple (A, u) with $A \in \text{symm}^+(n), u \in \mathbb{R}^n$. The group
 72 product is obtained from the action ρ as $(A, u) \cdot (B, v) = (A^{1/2} B A^{1/2}, A^{1/2} v + u)$.

The inverse of an element (A, u) is given by $(A^{-1}, -A^{-1/2}u)$. The group $G(n)$ is a Lie group with Lie algebra $\mathfrak{g}(n) = \text{symm}^+(n) \oplus \mathbb{R}^n$ with $\text{symm}^+(n)$ the vector space of symmetric matrices. Finally, the left translation by an element (A, u) is the mapping:

$$(B, v) \mapsto L_{(A,u)}(B, v) = (A, u) \cdot (B, v) \quad (4)$$

Being a affine map, its derivative is its linear part. The Frobenius inner product on the space of square matrices of dimension n , defined as $\langle A, B \rangle = \text{tr}(A^t B) = \text{tr}(AB^t)$, jointly with the standard euclidean inner product on \mathbb{R}^n , induces a left invariant metric by:

$$\langle\langle (X, \eta), (Y, \xi) \rangle\rangle_{(A,u)} = K \text{tr} \left(A^{-1/2} X A^{-1} Y A^{-1/2} \right) + \eta_1^t A^{-1} \eta_1 \quad (5)$$

73 where $(X, \eta), (Y, \xi)$ are tangent vectors to $G(n)$ at (A, u) and $K > 0$ is a fixed scaling factor, that may be
 74 arbitrary chosen to balance the relative contributions of the matrix part and the translation part.

It turns out that the metric obtained that way is exactly the Fisher-Rao metric on the manifold of multivariate Gaussian densities. Using the notations of [15], the length element of the Fisher-Rao metric g_F is:

$$ds^2 = \frac{1}{2} \text{tr} \left(\Sigma^{-1} X \Sigma^{-1} X \right) + \eta^t \Sigma^{-1} \eta \quad (6)$$

75 with (X, η) a tangent vector at (Σ, μ) .

76 The expression of ds^2 is the one of a warped product metric [16], that allows some simplifications
 77 when computing the geodesics between two densities with same means. A closed form for the geodesic
 78 distance between two densities with diagonal covariance matrices may also be obtained as follows [17]:

$$d_F(\theta, \theta') = \sqrt{2 \sum_{i=1}^2 \left(\ln \frac{|(\frac{\mu_i}{\sqrt{2}}, \sigma_i) - (\frac{\mu'_i}{\sqrt{2}}, -\sigma'_i)| + |(\frac{\mu_i}{\sqrt{2}}, \sigma_i) - (\frac{\mu'_i}{\sqrt{2}}, \sigma'_i)|}{|(\frac{\mu_i}{\sqrt{2}}, \sigma_i) - (\frac{\mu'_i}{\sqrt{2}}, -\sigma'_i)| - |(\frac{\mu_i}{\sqrt{2}}, \sigma_i) - (\frac{\mu'_i}{\sqrt{2}}, \sigma'_i)|} \right)^2} \quad (7)$$

79 where $\theta = (\mu, \Sigma)$ with $\mu = (\mu_1, \mu_2)$ and $\Sigma = \text{diag}(\sigma_1^2, \sigma_2^2)$, $\theta' = (\mu', \Sigma')$ with $\mu' = (\mu'_1, \mu'_2)$ and
 80 $\Sigma' = \text{diag}((\sigma'_1)^2, (\sigma'_2)^2)$.

81 For general Gaussian densities with Σ any symmetric positive definite covariance matrix, a closed
 82 form for the geodesic distance is not known and one has to solve numerically a system of differential
 83 equations:

$$D_{tt}\mu - D_t\Sigma\Sigma^{-1}D_t\mu = 0 \quad (8)$$

$$D_{tt}\Sigma + D_t\mu D_t\mu^t - D_t\Sigma\Sigma^{-1}D_t\Sigma = 0 \quad (9)$$

84 where the expression D_t (resp. D_{tt}) stands for derivative (resp. second derivative) with respect to t . A
 85 geodesic between two densities can be found by a shooting approach, that starts with one density as
 86 an initial condition to the system 8 and iteratively adjusts the initial speed vector of the curve so as to
 87 reduce the distance to the target density until the desired accuracy is reached. A collocation algorithm
 88 can be also used, and is a common choice for solving ordinary differential equations with boundary
 89 conditions. It is generally more stable than the shooting method, but may require more computations. In
 90 both cases, a tricky part of the process is to ensure that the Σ matrix remains positive definite. A rewrite
 91 of 8 with the Cholesky decomposition $\Sigma = L^t L K$ allows this condition to be satisfied by design and is the
 92 preferred choice. Another option to get an approximate value is to use the formula 7 after diagonalizing
 93 the covariance matrices.

94 As regard to the Riemannian metric g_w which induces the Wasserstein distance [18], for Gaussian
 95 densities the explicit expression of the distance is the following:

$$d_W(\theta, \theta') = |\mu - \mu'| + \text{tr}(\Sigma) + \text{tr}(\Sigma') - 2\text{tr}(\sqrt{\Sigma^{\frac{1}{2}}\Sigma'\Sigma^{\frac{1}{2}}}) \quad (10)$$

96 where $|\cdot|$ is the euclidean norm and $\Sigma^{\frac{1}{2}}$ is defined for a symmetric positive definite matrix Σ so that
 97 $\Sigma^{\frac{1}{2}} \cdot \Sigma^{\frac{1}{2}} = \Sigma$. We remark that, if $\Sigma = \Sigma'$, the Wasserstein distance reduces to the Euclidean distance.

98 Otto proved that, with respect to the Riemannian metric which induces the Wasserstein distance,
 99 the manifold of Gaussian densities has non-negative sectional curvature. We deduce that the Wasserstein
 100 metric is different from the Fisher-Rao metric. Indeed, for example in the univariate case, the statistical
 101 manifold of Gaussian densities with the Fisher-Rao metric can be regarded as the upper half plane with
 102 the hyperbolic metric, which has negative curvature as it is well known.

103 Once a distance is defined, it can be used for clustering on a manifold. It is proved that the distance
 104 induced from Fisher-Rao metric and Wasserstein distance are in the more general class of Bregman
 105 divergences defined by a convex function Ψ [19]. For this class, a theorem states [20] that the centroid
 106 for a set of n points $\theta_i, i = 1, 2, \dots, n$ in the statistical manifold of the Gaussian densities is the Euclidean

107 mean $\frac{1}{n} \sum_{i=1}^n \theta_i$. We will use this result in the next section where a K -mean shapes clustering algorithm is
 108 defined using geodesic distances.

109 3. Clustering of Shapes

110 We will consider only planar objects, as for example a flat fish or a section of the skull. The "shape"
 111 of the object consists of all information invariant under similarity transformations, that is translations,
 112 rotations and scaling [4]. Data from a shape are often realized as a set of points. Many methods allow us
 113 to extract a finite number of points, which are representative of the shape and are called landmarks. One
 114 way to compare shapes of different objects is to first register them on some common coordinate system
 115 for removing the similarity transformations [2,21]. Alternatively, Procrustes methods [22] may be used
 116 in which objects are scaled, rotated and translated so that their landmarks lie as close as possible to each
 117 other with respect to the Euclidean distance.

Suppose we are given a planar shape configuration, S , consisting of a fixed number K of labelled landmarks

$$S = \{\mu_1, \mu_2, \dots, \mu_K\}$$

with generic element $\mu_k = \{\mu_{k1}, \mu_{k2}\}$ for $k = 1, \dots, K$. Following [23], the k -th landmark, for $k = 1, \dots, K$, may be represented by a bivariate Gaussian density as follows:

$$f(x | \theta_k = (\mu_k, \Sigma_k)) = (2\pi)^{-1} (\det \Sigma_k)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)\right\} \quad (11)$$

with x being a generic 2-dimensional vector and Σ_k given by

$$\Sigma_k = \text{diag}(\sigma_{k1}^2, \sigma_{k2}^2) \quad (12)$$

118 where $\sigma_k^2 = (\sigma_{k1}^2, \sigma_{k2}^2)$ is the vector of the variances of μ_k .

119 We remark that, in the previous representation, the means represent the geometric coordinates of
 120 the landmark and capture uncertainties that arise in landmark placement. The variances are hidden
 121 coordinates of the landmark and reflect its natural variability across a population of shapes. Equation
 122 (11) allows to assign to the k -th landmark the coordinates $\theta_k = (\mu_k, \sigma_k)$ on the 4-dimensional manifold
 123 which is the product of two upper half planes.

124 Let S and S' two planar shapes registered on a common coordinate system using Procrustes method.
 125 We parameterize them as follows: $S = (\theta_1, \dots, \theta_K)$ and $S' = (\theta'_1, \dots, \theta'_K)$.

126 The distances between landmarks allow to define a distance of the two shapes S and S' . Precisely
 127 a shape metric for measuring the difference between S and S' can be obtained by taking the sum of the
 128 geodesic distances between the corresponding landmarks, according to the following definition:

$$D(S, S') = \sum_{k=1}^K d(\theta_k, \theta'_k) \quad (13)$$

Please note that this expression is not the geodesic distance on the product manifold that one would have expected from the landmark model. This last distance is given by:

$$D(S, S') = \sqrt{\sum_{k=1}^K d(\theta_k, \theta'_k)^2} \quad (14)$$

129 and is a L^2 distance instead of 13 that is L^1 . It turns out that according to simulations done, the L^1
 130 approach is more robust and gives all the time better clusterings.

131 Then a classification of shapes, using in turn, as distance d , the distance d_F induced from Fisher-Rao
 132 metric and the Wasserstein distance d_W , can be done following the standard methodology. In particular
 133 the k-means clustering procedure allows to the variances to vary step by step in each cluster fitting better
 134 real shape data.

135 4. K-means clustering algorithm

136 The proposed shape distances are implemented in two different K-means algorithms: Type 1 and
 137 Type 2. While in the Type 1 algorithm the landmark coordinates variances are assumed isotropic across
 138 the clusters, in Type 2 the variances are allowed to vary among the clusters.

139 Our task is clustering a set of n shapes, S_1, S_2, \dots, S_n into G different clusters, denoted as
 140 C_1, C_2, \dots, C_G . We

141 4.1. Type 1 algorithm

142 1 Initial step:

143 Compute the variability of the k -th landmark coordinates $\sigma_k^2 = (\sigma_{k1}^2, \sigma_{k2}^2)$, for $k = 1, \dots, K$.

144 Randomly assign the n shapes, S_1, S_2, \dots, S_n into G clusters, C_1, C_2, \dots, C_G .

145 For $g = 1, \dots, G$ calculate the cluster center $c_g = (\theta_1^g, \dots, \theta_K^g)$ with k -th component $\theta_k^g = (\mu_{gk}, \sigma_k^2)$
 146 obtained as $\theta_k^g = \frac{1}{n_g} \sum_{i \in C_g} \theta_k^i$, where n_g is the number of elements in the cluster C_g and θ_k^i is the k -th
 147 coordinate of S_i given by $\theta_k^i = (\mu_{ik}, \sigma_k^2)$.

148

149 2 Classification:

For each shape S_i , compute the distances to the G cluster centers c_1, c_2, \dots, c_G .

The generic distance between the shape S_i and the cluster center c_g is given by:

$$D(S_i, c_g) = \sum_{k=1}^K d(\theta_k^i, \theta_k^g).$$

149

150

Assign S_i to cluster h that minimizes the distance:

$$D(S_i, c_h) = \min_g D(S_i, c_g).$$

151 3 Renewal step:

152 Compute the new cluster centers of the renewed clusters c_1, \dots, c_G .

153 The k -th component of the g -th cluster center c_g is defined as $\theta_k^g = \frac{1}{n_g} \sum_{i \in C_g} \theta_k^i$.

154 4 Repeat 2 and 3 until convergence.

155 4.2. Type 2 algorithm

156 1 Initial step:

157 Randomly assign the n shapes, S_1, S_2, \dots, S_n into G clusters, C_1, C_2, \dots, C_G .

158 In each cluster compute the variability of the k -th landmark coordinates $\sigma_{gk}^2 = (\sigma_{gk1}^2, \sigma_{gk2}^2)$, for
 159 $k = 1, \dots, K$ and $g = 1, \dots, G$.

160 Calculate the cluster center $c_g = (\theta_1^g, \dots, \theta_K^g)$ with k -th component $\theta_k^g = (\mu_{gk}, \sigma_{gk}^2)$ obtained as

161 $\theta_k^g = \frac{1}{n_g} \sum_{i \in C_g} \theta_k^i$ for $g = 1, \dots, G$, where n_g is the number of elements in the cluster C_g and
 162 $\theta_k^i = (\mu_{ik}, \sigma_{gk}^2)$ for $i \in C_g$.

163

2 Classification:

For each shape S_i , compute the distances to the G cluster centers c_1, c_2, \dots, c_G .

The generic distance between the shape S_i and the cluster center c_g is given by:

$$D(S_i, c_g) = \sum_{k=1}^K d(\theta_k^i, \theta_k^g).$$

164

165

Assign S_i to cluster h that minimizes the distance:

$$D(S_i, c_h) = \min_g D(S_i, c_g).$$

3 Renewal step:

166 Update the variability of the k -th landmark coordinates in each cluster by computing $\sigma_{gk}^2 =$
 167 $(\sigma_{gk_1}^2, \sigma_{gk_2}^2)$, for $k = 1, \dots, K$ and for $g = 1, \dots, G$.

168 Calculate the new cluster centers of the renewed clusters c_1, \dots, c_G .

169 The k -th component of the g -th cluster center c_g is defined as $\theta_k^g = \frac{1}{n_g} \sum_{i \in C_g} \theta_k^i$.

170 4 Repeat 2 and 3 until convergence.

5. Numerical study

172 The purpose of the simulation study is to evaluate the cluster recovery of the proposed shape
 K -means algorithm and to test its sensitiveness with respect to different shape distances defined on the
 manifold of the probability distributions. The shapes are simulated according to a Gaussian perturbation
 model where the i -th configuration is obtained as follows:

$$X_{ig} = (\mu_g + E_i)\Gamma_i + \mathbf{1}_K \gamma_i^T \quad (15)$$

173 where

- 174 • E_i are zero mean $K \times 2$ random error matrices simulated from the multivariate Normal distribution
- 175 with covariance structure Σ_E
- 176 • μ_g is the mean shape for cluster g
- 177 • Γ_i is an orthogonal rotation matrix with an angle θ uniformly produced in the range $[0, 2\pi]$
- 178 • γ_i^T is a 1×2 uniform translation vector in the range $[-2, 2]$

179 Three types of covariance structures are considered:

- 180 • Isotropic with $\Sigma_E = \sigma \mathbf{I}_K \otimes \sigma \mathbf{I}_2$
- 181 • Heteroscedastic with $\Sigma_E = \text{diag}[\sigma_1, \sigma_2, \dots, \sigma_K] \otimes \sigma \mathbf{I}_2$
- 182 • Anisotropic with $\Sigma_E = \sigma \mathbf{I}_K \otimes \text{diag}[\sigma_x, \sigma_y]$ with $\sigma_x \neq \sigma_y$

183 The data were generated from model (15) with sample size $n = 100$ and the number of clusters equal
 184 to $G = 2$. The mean shapes in each cluster were taken from the rat calvarial data set (Bookstein, 1991)
 185 corresponding to the skull midsagittal section of 21 rats collected at ages of 7 and 14 days.

186 Examples of the simulated data under the different covariance structures are provided in figures (1),
 187 (2), and (3). In the isotropic case (figure 1) all the landmarks coordinates exhibit the same independent

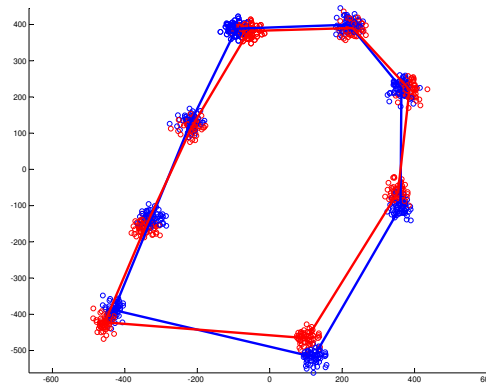


Figure 1. Independent spherical variation around each mean landmark

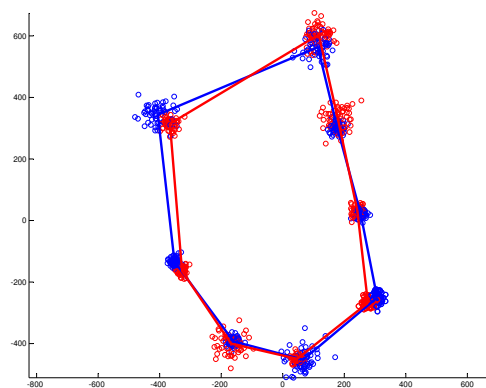


Figure 2. Heteroscedastic variation around each mean landmark

188 spherical variation around the mean. In the heteroscedastic case (figure 2), the spherical variation is
 189 allowed to vary between the landmarks and the clusters. Finally, in figure (1) is shown the anisotropic
 190 case where the variability of the landmarks coordinates is different in the horizontal and vertical
 191 directions.

192 The shape K -means algorithm is implemented by using:

- 193 • the geodesic distance under the round Gaussian model representation - dr
- 194 • the geodesic distance under the diagonal Gaussian model representation - $dd1$ (type 1 K -means
 195 algorithm) and $dd2$ (type 2 K -means algorithm)
- 196 • Wasserstein distance - dp

197 For each covariance structure we simulated 150 samples and for each sample we computed the adjusted
 198 Rand index ([24]) of each clustering method. The adjusted Rand index is a measure of cluster recovery
 199 since it measures the agreement between the true classification and the clustering results. It ranges from
 200 about 0 and 1 and it is 1 when the clusters are perfectly recovered.

201 In figures (4), (5) and (6) are displayed the boxplot of the adjusted Rand index over 150 simulated samples

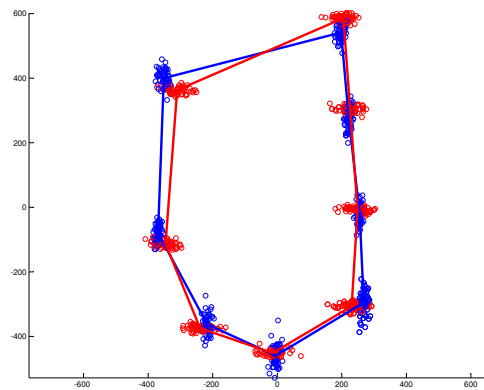


Figure 3. Anisotropy in the x and y directions around each mean landmark

202 for each clustering method. When the covariance structure is isotropic (figure 4), all the distances show a
 203 similar behaviour. In particular the Fisher-Rao distance with round Gaussian distribution (dr) and the
 204 Wasserstein distance (dw) yield the best clustering results. With the heteroscedastic setting (figure 5),
 205 both the Fisher-Rao with the round Gaussian distribution and the Wasserstein distance perform poorly
 206 in comparison to the Fisher-Rao distance based on the diagonal distribution. As expected, the models
 207 which take into account different landmark variances ($dd1$ -type 1 algorithm) and also differences in
 208 the variances between the clusters ($dd2$ -type 2 algorithm) show a very good behaviour. A very similar
 209 pattern is observed when anisotropy is also added in the covariance structure (figure 6).

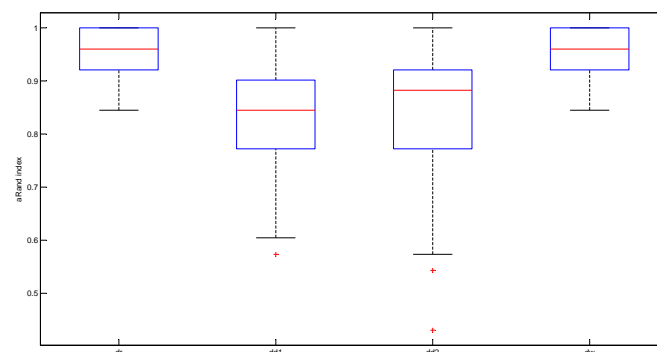


Figure 4. Isotropic case: aRand index median values are 0.96 (dr), 0.85 ($dd1$), 0.88 ($dd2$), 0.96 (dw)

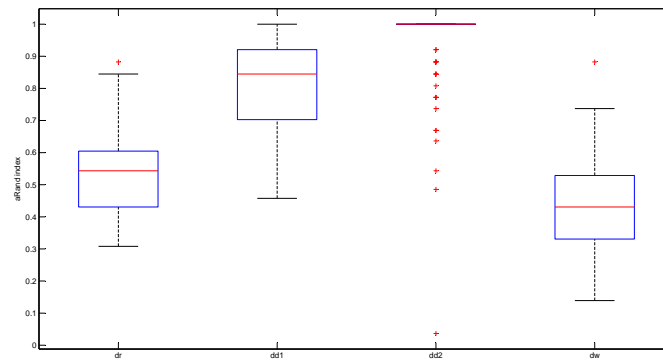


Figure 5. Heteroscedastic case: aRand index median values are 0.54 (dr), 0.84 (dd1), 1.00 (dd2), 0.43 (dw)

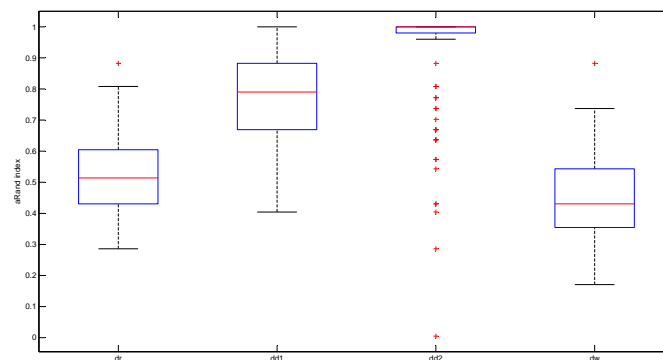


Figure 6. Anisotropic case: aRand index mean values are 0.51 (dr), 0.79 (dd1), 1 (dd2), 0.44 (dw)

210 6. Conclusions

211 In this paper, Information Geometry was used as a useful tool in the area of shape clustering. We
 212 first described a shape representing each landmark by a Gaussian model using the mean and the variance
 213 as coordinates, reflecting the geometrical shape of the configuration and the variability across a family of
 214 patterns, respectively. Within this framework we considered the Fisher-Rao and the Wasserstein metric
 215 for quantifying the difference between two shapes.

216 Two version of the Fisher-Rao metric were proposed, depending on how the variances in the data
 217 are employed. In one case (round Gaussian distribution model) the variance is considered as a free
 218 parameter, which is isotropic across all the landmarks. In the second case, the isotropic assumption is
 219 relaxed allowing the variances to vary among the landmarks (diagonal Gaussian distribution model).

220 The results of the numerical study have shown that the violation of the isotropic assumption on the
 221 landmarks variability may cause a severe loss in the clustering recovery. Indeed, this assumption is
 222 rarely satisfied in practice where it is regularly seen that landmarks have different variances. In such
 223 a case, the relative importance among landmarks must be taken into account in the similarity measure

224 adopted in the clustering algorithm. The proposed geodesic distance under the diagonal Gaussian model
 225 representation is able to face with this problems. A further assumption that may be violated is that
 226 in all the clusters the landmarks coordinates have a common covariance matrix. To cope with this
 227 we implemented a K -means shape algorithm that allows also for differences among the clusters in the
 228 landmark coordinates variability.
 229 Other extensions of the current work deserve further investigation as, for example, the use of geodesics
 230 in the case of the general multivariate Gaussian model and also to consider more general shape measures,
 231 such as α -divergences.

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