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# A new sizing system based on 3D shape descriptor for morphology clustering

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ABSTRACT

The variety of human morphologies is an important issue for the textile-apparel industry. Indeed, sizing systems currently used by companies have to be continuously updated or adapted to the population target.

For this reason, the Textile-Apparel-Industry requires a very accurate sizing system to minimize their costs and satisfy their customers. However, the specific constraints of human morphotologies complicate the sizing system definition procedure and distributors prefer to use standard sizing system rather than an intelligent system suitable to their customers.

Until now, the morphotypes of a population are extracted from measurement charts. However, new technologies such as 3D body scanning open new opportunities to enhance the morphotype generation from a sample of population especially with the 3D data of bodies.

The aim of this research is to define an exhaustive methodology to obtain a clustering of human morphology shapes representative of a population and to extract the most significant morphotype of each class. A two-level clustering method (SOM + K-means) based on 3D scans to define 3D adaptive morphotypes mannequins is implemented and the performances are evaluated using real data from the French Sizing Survey conducted in 2003 by the French Institute of Textiles and Clothing.

The description of the 3D scans is performed with a computation of the geodesic distributions based on anthropometrics feature points of the human torso which enables a quantitative comparison of the morphologies. These geodesic distributions are then used as inputs for the clustering methods. Finally, a geometrical model associated with reverse engineering techniques has been realized to generate the 3D virtual parametric mannequins from the 3D body scanned of the morphotypes. Based on these morphotypes mannequins, we define an intelligent system for virtual try-on and a new sizing system can be defined in the future.



## 1. Introduction

In order to survive in an increasingly competitive market, clothing companies have different strategies which generally rely on the improvement of the product quality or the reduction of its price. Another opportunity for companies is to improve their sizing system to match with consumer requirements and also to propose to consumers new services for the try-on of their products.

All these considerations necessarily pass through the creation of a new intelligent system for virtual try-on which accurately takes into account the consumer morphology. Nowadays, consumer demand is oriented towards fitting clothing, therefore it is important to exactly define the morphology of its customers.

An obsolete sizing system where morphologies do not represent the targetted population leads to unsuitable clothing measurements. In order to solve this problem, the proposed solution consists in extracting the most relevant morphologies from a sizing survey. This system can then be implemented to define suitable sizing charts and/or virtual try-on solutions. Until now, sizing charts were only based on classification methods of body measurements. These methods fail to take into account the 3D morphology of the people. In order to solve this problem, the proposed solution consists in extracting the most relevant morphologies from a sizing survey. This system can then be implemented to define suitable sizing charts and/or virtual try-on solutions. The concept of 3D morphology which is crucial for the proper fit of the garment.

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It is generally established that the morphologies of a population are non-homogeneous. Thus, the purpose of this paper is to provide a new method able to divide a population into homogeneous groups in order to assign an adequate morphotype (centroid of morphological cluster) to each individual. Two individuals in a same group are expected to have similar morphology, so that a garment style, for a given size, can fit all of them.

Thereafter, a better understanding of the human shape by the textile and clothing industry could improve classification sizing strategies, reduce stocking costs and reduce the number of unsold items (Ben Azouz & Rioux, 2002).

The various analyses of most sizing surveys focus generally on the extraction of sizing systems from the morphological analysis of human body measurements. The classification is generally based on a statistical analysis of the anthropometric measurements taken manually or via body scanners. This explains the diversity and complexity of analysis methods with direct measurement on the body, 2D (measurement and analysis with a front and side in some cases) or 3D (3D technology scanners).

The following techniques, ranked according to their complexity, have been used in the literature to create a sizing system:

- Simple mathematical techniques such as classification of two variables or statistical techniques using correlation coefficients (Otieno & Fairhurst, 2000).
- Multivariate techniques such as PCA (Gupta & Gangadhar, 2004).
- Computing techniques such as linear programming or the non-linear optimization (McCulloch, Paal, & Ashdown, 1998; Tryfos, 1986).
- Data mining techniques such as clustering analysis or tree decision (Cottle, 2012).
- Artificial intelligence techniques including genetic algorithms, neural networks and fuzzy logic (Hsu, Tsai, & Lee, 2010; Ng, Ashdown, & Chan, 2007).

Many correlations have been established between measurements of human body in order to understand human body evolution. These correlations are generally used to define the current sizing systems. But the evolution of morphologies generated by junk food, stress, genetics and lack of physical exercises, strongly modifies the morphological shapes and makes these sizing systems where the population is classified into linear body sizes, not suitable.

Consequently, the wealth of literature in the fields of clustering and 3D shape descriptors, leads us to implement a specific methodology for the classification of human morphologies from 3D scans.

The consideration of 3D data instead of measurements, is essential for a better characterization of the morphologies, especially in case of fitting garments. Indeed, a classification of 3D morphologies should enable to extract the main morphotypes of a population and thus to define a better more suitable sizing systems for each groups of morphology.

The choice of the signature or descriptor is crucial to highlight the relevant features of a 3D object. For instance, in this study the comparison of 3D bodies scanned in the same posture requires a very sensitive signature on areas which characterize the morphology and make to a comfortable garment.

In computer vision and pattern recognition, many types of descriptors have been proposed to characterize intrinsic features of a 3D object for clustering purposes (Kwon, Kang, & Bae, 2014; Mehmood, Damarla, & Sabatier, 2012). These descriptors can be divided into two categories: “2D” and “3D”. 2D methods rely on several 2D projections in various viewing angles, which have been soundly selected, to describe the shape of a 3D object. However, in order to take into account of the features of the whole 3D object, 3D methods are generally preferred.

Biasotti, Giorgi, Marini, Spagnuolo, and Falcidieno (2006) present a comparative evaluation study for 3D shape classification. The classification performances are evaluated against a set of popular 3D global descriptors, using a dataset consisting of 14 classes where each class is made of up to 20 objects. In this comparative study, four shape descriptors (the spherical harmonics, the light-field descriptor, the Multi-resolution Reeb graph and the Extended Reeb graph) and five supervised classifiers were experimented.

This study provides interesting results of different descriptors for classification problems. However, the database used for their comparison is composed from very heterogeneous objects. It is thus difficult to conclude about the discriminant capacity of the descriptors.

Many 3D object descriptors for human shapes have also been implemented for different applications.

Wuhrer, Pishchulin, Brunton, Shu, and Lang (2014) proposed a statistical shape space which is posture-invariant to model body shape variation and a skeleton-based deformation to model posture variation. Their method enables to estimate the human body shape and posture specifically for virtual change rooms.

In literature, the investigation of human shape retrieval in different postures is very productive in term of generation of shape descriptors (Pickup et al., 2014). Indeed, different methods have been developed for this purpose, among them are:

- Simple measure such as mesh surfaces and skeleton driven conical forms based on Euclidean distances (Elad & Kimmel, 2003; Yan, Hu, Martin, & Yang, 2008).
- Heat kernel methods (Bronstein & Kokkinos, 2010; Sun, Ovsjanikov, & Guibas, 2009).
- Spectral descriptors such as spectral grapg wavelet signature the spectral geometry based framework developed by (Li, Godil, & Johan, 2014).
- Local feature descriptors such as the point feature histogram based methods (Rusu, Marton, Blodow, & Beetz, 2008).
- Shape description based on histogram of area projection transform proposed by Giachetti and Lovato (2012).
- Bag of features approach (Bronstein, Bronstein, Guibas, & Ovsjanikov, 2011) or dictionary learning methods (Mairal, Bach, Ponce, & Sapiro, 2009).
- Hybrid shape descriptor such as the method proposed by Li et al. (2014) which associate a geodesic distance based global features and a curvature based local feature.
- 3 level shape descriptor which combines a low level descriptor based on heat kernel, a middle level descriptor based on bag of feature method and high level descriptor using deep learning approach (Hinton, Osindero, & Teh, 2006).

However, for our human shape clustering from body scan data (with almost similar posture) the above shape descriptors which perform well in other applications, could have a too low discriminating capacity from the garment fitting point of view. It should be noted that the shape descriptor is the key point to reach the objective of this paper. Therefore the main contribution of this work aims to define a shape descriptor suitable for the morphology clustering.A suitable shape descriptor with a high discriminant capacity should enable a more efficient and easiest clustering process. Thus, we consider that the choice of clustering method has an minor impact on the results.

The global geodesic shape distribution proposed in Hamza and Krim (2006) is very interesting since this method is invariant to the small posture variations which could exist between two human scans and takes into account the whole 3D object. Furthermore, the number and the location of the reference points (or starting points) can be used as parameters to increase the discriminant capacity of the descriptor on required areas. Indeed as mentioned earlier, the comparison of human morphologies requires a higher discriminating power to detect difference in specific areas of the body, while the general 3D form stays quite similar. Thus, we propose an original method which associates the geodesic shape distribution and a selection of anthropometric points to highlight the relevant zones of interactions between the body and the garment.

This paper is structured as follows. The next section presents our methodology. In Section 3, we describe the experimental tests carried out on a 3D scan database of a population sample. Finally, we conclude in Section 4 by summarizing our results and discussing issues for future work.

## 2. Methodology

The French sizing survey, realized in 2003, has shown that the usual measurement charts should be revised since the morphology of the population has considerably changed. Two major issues about the well-being of clothing have arisen from this survey (Fig. 1):

- Firstly: a measurement chart does not exactly reflect the morphology as shown in Fig. 1.
- Secondly: the value of a perimeter (ex: hip girth) does not give the distribution in volume of the body.

The establishment of a clothing sizing system requires accurate and large anthropometric databases. The development of new technologies enables companies or laboratories to collect anthropometric data using non-contact body scanner. This technology eliminates the greatest hindrance to anthropometric surveys. Indeed 3D scanning offers a technique to capture the body dimensions in a fast and reproducible way (Lim, Istook, & Chun, 2011). Thus the methodology proposed in this study relies on the acquisition of 3D human body with a body-scanner. From these 3D data, our method consists of 5 steps as illustrated in(Fig. 2).

Therefore, the proposed method has to highlight the body shape similarities which are relevant for the garment fit. To reach this aim, we implemented an original and efficient 3D clustering using 3D shape descriptor which has a high discriminant capacity of the areas previously mentioned.

Automatic detection of 3D human body dissimilarity is a very important factor for human morphology analysis. The 3D Shape descriptor used in this study is based on geodesic distribution. The calculation of the geodesic shape distribution is performed with a combination of reference anthropometrics points placed on the surfaces of 3D torsos.

The main challenge is to carry out a clustering system for human morphologies suitable for the apparel industry. Therefore, the proposed method has to point out the body shape similarities which are relevant for the garment fit, i.e. the shapes of waist, hip, bust, etc. The first four steps of this method can be listed as follows:

1. The 3D body scan data are cleaned and the head, arms and legs are deleted in order to only extract the 3D torso.
2. The torsos are normalized using the minimal bounding sphere.
3. The 3D descriptor is computed with the geodesic shape distribution for each normalized torso.
4. Finally, a clustering method is applied to the geodesic shape distribution to extract the morphotypes (centroids of the clusters).

### 2.1. Data acquisition and cleaning

The 3D scans of human bodies are obtained from a Vitus 3D Body scanner. As with any body scanner, pre-processing steps (fill holes, remove noise, smoothing and optimizing the mesh) are required to obtain a body scan suitable for further processing. All the cleaning steps are automatically achieved with the *meshfix toolbox* developed by Attene and Falcidieno(2006,(200). In order to generate 3D objects which are rigorously comparable between each other, we only take into account the torso of the body scan (Domingo et al., 2014). Indeed, the differences of faces and spacing of arms and legs would involve dissimilarities between bodies which are not relevant for the morphology comparison. Besides, the main measurements of a garment are related to the torso fitting (waist, hip, chest,...). The arms and legs could be considered

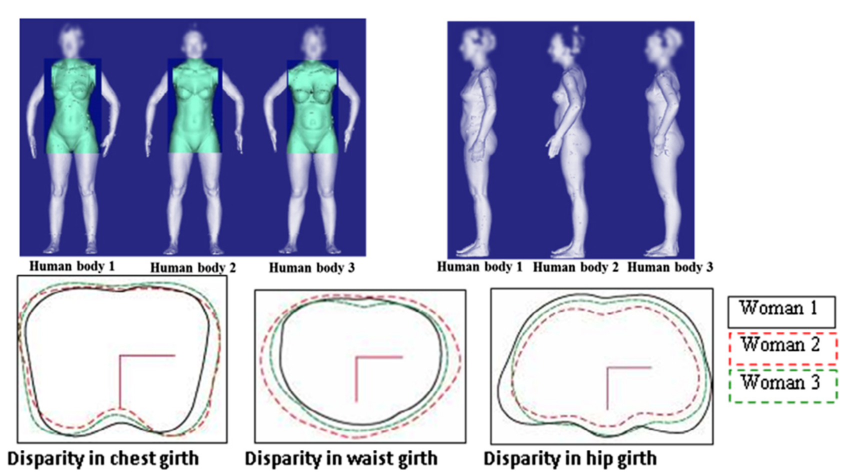



**Fig. 1.** Difference between 3 women with the same commercial size and identical drop.


**Fig. 2.** Proposed 3D morphology clustering from 3D scans to define new sizing system.

as secondary measurements because the garment should easily have some alterations for the sleeves or pant legs. Then, the bodies are automatically segmented with section planes located at anthropometric points with the *iso2mesh Matlab toolbox* developed by Fang and Boas(2009,(200). The location of the anthropometric points should follow a strict procedure to ensure the reliability of the data to be compared. Finally, the torso surface is meshed in order to optimize the size and the number of mesh, and respect the compatibility between torsos (Fig. 3).

### 2.2. Data normalization

The normalization is crucial to accurately compare the shape of the 3D torsos without taking into account the stature or other measurements. To normalize the 3D torsos, we choose to implement the minimal bounding sphere method with the algorithm of Gärtner (1999) for its precision and fast processing time.

This algorithm enables to find a translation $T_{x,y,z} = (t_x, t_y, t_z)$ and a scale $s \in R^+$ to center every 3D object inside a sphere of radius $r = 1$ in such a way that the maximum distance between the sphere center and the mesh vertices is $r$ (Fig. 4). The Gärtner algorithm computes the normalized vertex $(x_n, y_n, z_n)$ from an original vertex $(x, y, z)$ as follows:

$$x_n = \frac{x - c_{x,s}}{d_s}, y_n = \frac{y - c_{y,s}}{d_s}, z_n = \frac{z - c_{z,s}}{d_s} \tag{1}$$

with $d_s$ the sphere diameter and $c_{x,s},\ c_{y,s},\ c_{z,s}$ the coordinates of the sphere center.

### 2.3. Geodesic shape descriptor

As previously explained, the selected descriptor has to be very sensitive on dissimilarities which enable to differentiate morphologies such as differentiation between the shapes of the waist, the hip and the bust.

Geodesic path and distribution of geodesic distances present interesting properties in term of shape description and especially for non-rigid shape description. In addition to its rotational, translational and scale invariance, the geodesic shape description, is also robust to re-sampling, simplification and has a low sensibility to posture variations.

Thus, the descriptor, used in this paper, is the distribution of the geodesic distances between reference points (or starting points) and all points on the mesh of the 3D torso. The geodesic distances between a reference point and all other vertices of the mesh are computed with the well-known Dijkstra's algorithm (Cormen,

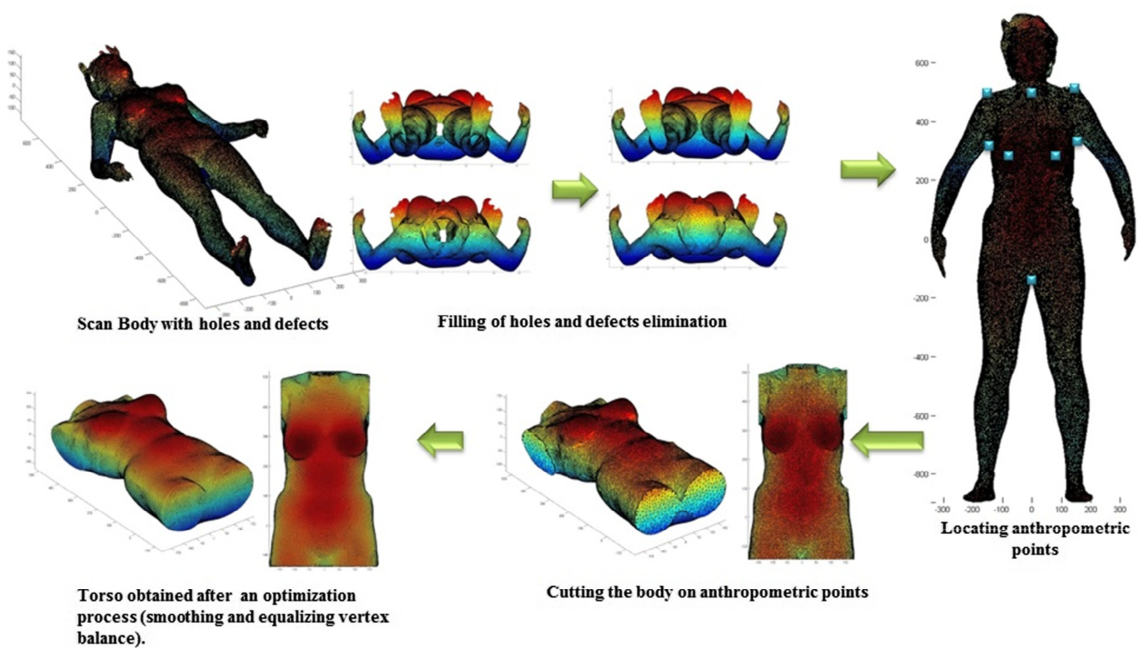



**Fig. 3.** Automatic treatment process of torsos from bodyscan.

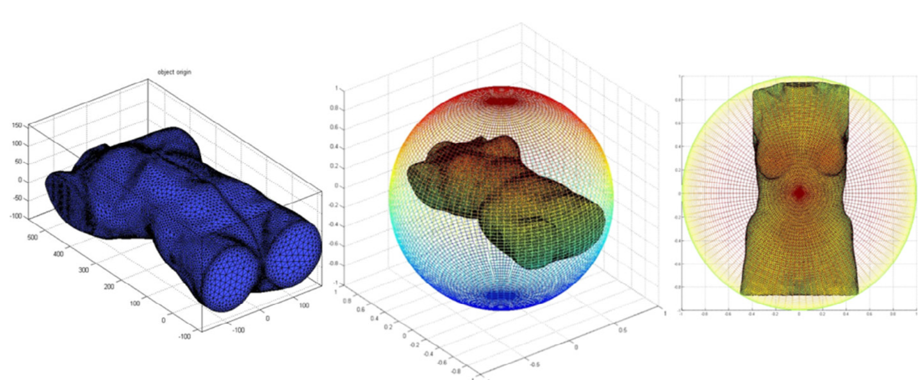


**Fig. 4.** Normalization with the minimal bounding sphere.

2009). The geodesic shape distributions are then obtained with the kernel density function (Zelinka, 2011). This descriptor enables us to increase the discriminating level on the targeted areas by optimizing the location of the reference points. Indeed, the number and location of reference points obviously impact the discriminating capacity of the descriptor. According to the objective of the clustering, i.e. find the morphotype of a population for the sizing apparel system, it seems obvious that the reference points should be defined from anthropometry points and relevant points for the garment design.

### 2.4. Selection of reference points

A descriptor based on geodesic distribution is very sensitive to the locations of reference points. Thus, it is possible to find the combination (number and location) of reference points which optimizes the discriminating capacity of the descriptor for a set of 3D morphologies.

To this end, the following experiment is implemented. Three reference torsos are generated from the same parametric mannequin (Hamad et al., 14th) commonly used in a company. The advantage of using this mannequin is that it has the ability to change the stature and other measurements independently with control parameters, which allows us to artificially create three torsos corresponding to the traditional shapes HOAXY defined by Duffy (1987): the pyramid shape or A, the hourglass shape or X and tabular shape or H.

The objective is to set up the reference points in such way that the geodesic shape distribution is the more discriminant for the 3 torsos, i.e. the distribution curves are the more dissimilar.

Each torso is represented as a meshed surface with the same size of triangles and it is normalized with the minimal bounding sphere. To compare the geodesic shape distributions and, hence, to measure the performance of the proposed solution, we used euclidean distance.

To restrict the solution space, we limit the location of the reference points to the 11 anthropometric points which are the more relevant for garment design (Fig. 5): neck point, left and right waist points, left and right hip points, left and right under bust points, middle chest point and projected point on the back, front and back abdominal points. Considering the symmetry of the points on the chest, the abdominal, the waist, the hip and the under bust, a solution can be coded as a combination of 6 bits as represented in Fig. 6. By taking into account the size of the solution space which becomes equal to 26, we exhaustively explore and evaluate all the possible combinations for the 3 reference torsos as illustrated in Fig. 7. The best solution is the combination which leads to maximum sum of Euclidean distances between the 3 geodesic shape distributions.

This optimal combination of reference points is then used for the computation of the geodesic shape distribution in the whole database.

| b1 | b2 | b3 | b4 | b5 | b6 |
|---|---|---|---|---|---|

bi = 0 means that the point (or pair of points) is not selected
bi = 1 means that the point (or pair of points) is selected

b1 = neck point
b2 = chest points
b3 = abdominal points
b4 = under bust points
b5 = waist points
b6 = hip points

**Fig. 6.** Coding of a solution for the selection of the reference points.

### 2.5. Clustering

Then 3D Clustering is performed on the database of geodesics distributions.

Clustering is an unsupervised way of data grouping using a measure of similarity. It is a common technique for statistical data analysis used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics. There are various methods and different ways to organize unlabelled feature vectors and to produce clusters (Bezdek, 1981; Fraley & Raftery, 1998; Kohonen, 2001; Ruspini, 1969). At this step, the aim is to cluster bodies with similar descriptor into the same group which represent a morphotype.

#### 2.5.1. Clustering quality

The quality of the clustering is a compromise between too many clusters (bad separability) and not enough clusters (bad compactness). Then, the final cluster number is determined and is a crucial parameter of the clustering quality. The clustering was evaluated by Davies and Bouldin (1979) defined as:

$$DB = \frac{1}{k}\sum_{i=1}^{k} max_{i\neq j}(D_{i,j}) \quad (2)$$

with $D_{i,j}$ the within-to-between cluster distance ratio for the $i$th and $j$th clusters.

$$D_{i,j} = \frac{\bar{d}_i + \bar{d}_j}{d_{i,j}} \quad (3)$$

with

$\bar{d}_i$ the average distance between each point in the cluster $i$ and the centroid of the cluster $i$.

$\bar{d}_j$ the average distance between each point in the cluster $j$ and the centroid of the cluster $j$.

$d_{i,j}$ the Euclidean distance between the centroids of the *ith* and *jth* clusters.

The maximum value of $D_{i,j}$ represents the worst-case within-to-between cluster ratio for the cluster $i$. The optimal clustering solution is the smallest Davies-Bouldin value.

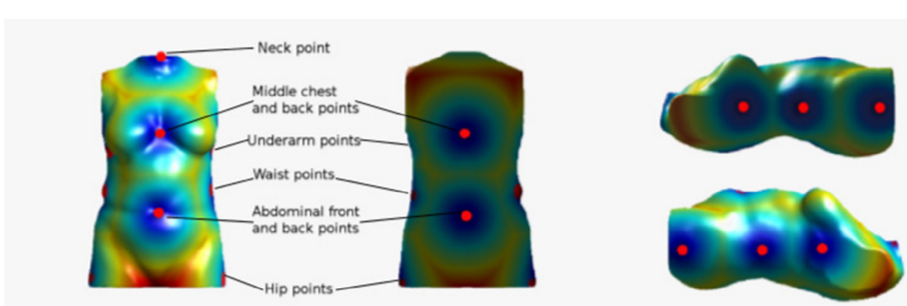



**Fig. 5.** The 11 selected reference points for the computation of the geodesic distances.

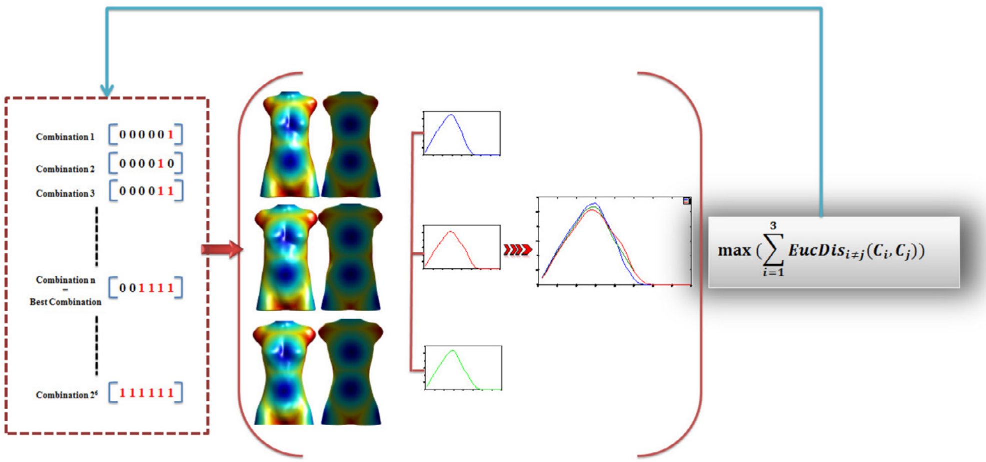



**Fig. 7.** Optimization of the reference points on the three reference torsos.

#### 2.5.2. Kmeans clustering method

The most common partitioning clustering algorithm is kmeans algorithm, where each cluster is represented by the mean value of the objects in the cluster. One advantage of the partitioning clustering is that the procedure is dynamic, i.e., data points can move from one cluster to another. The other advantage is that some a priori knowledge, such as cluster shapes, can be incorporated in the clustering. But this method haq well-known drawbacks such as the difficulty to find clusters of arbitrary shapes, the number of clusters have to be prefixed and is sometimes hard to determine and the final clusters are dependent of the initialization and problems of local optima can arise.

Despite these drawbacks, the k-means method is implemented on the whole geodesic shape distributions and aims to partition these curves into k clusters ($k$ = 2–20). In order to avoid convergence towards local optima, induced by the centroids aleatory initialization, we have replicated the procedure 500 times for each value of $k$. From the Davies-Bouldin index presented in Section 2.5.1, the optimal number of cluster is calculated. However, the convergence of the K-mean algorithm remains very difficult despite the large number of replications. Indeed, if the best result on all the experiments carried out is obtained for 3 classes, the aleatory initialization of the centroids generates significant variations of the partition and consequently the optimal number of classes and the optical value of Davies-Bouldin index. In order to make the method more robust for the initialization of the centroids, the implementation of a two-level classification appears pertinent.

#### 2.5.3. Two-level approach

The clustering method used in this study has to be robust in term of convergence. Thus a two-level approach which has been used successfully for several decades on many applications, has been developed. (Fig. 8). The first level is composed of a SOM network which forms a 2D map of the data. At this level, a large set of prototypes which is much larger than the expected number of clusters, is

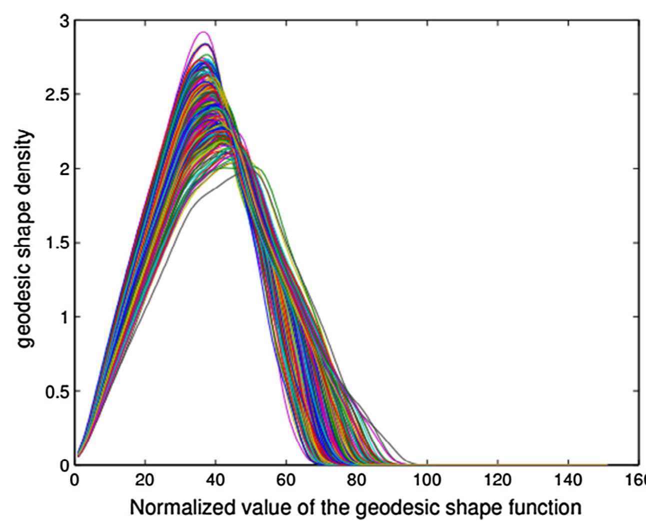



**Fig. 9.** Geodesic shape distribution of the 500 normalized torsos.

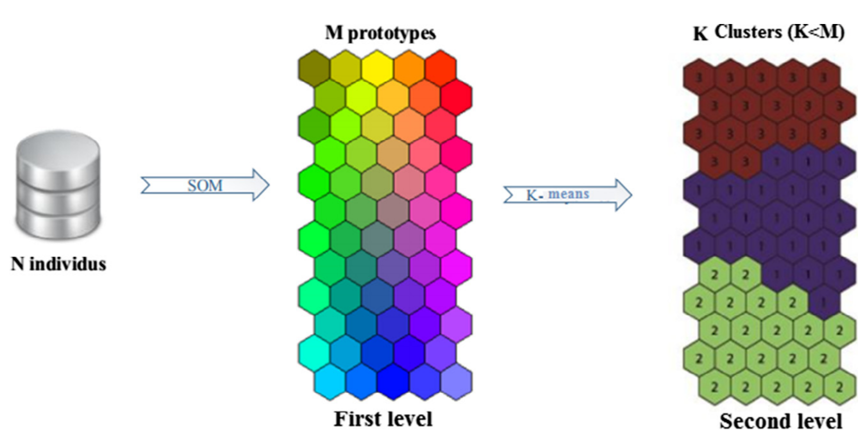



**Fig. 8.** The two-level clustering method.

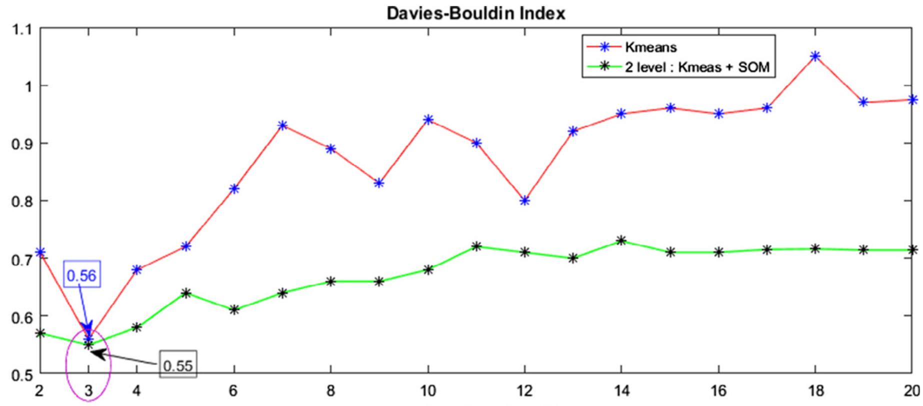



Fig. 10. The Davies-Bouldin index with K-means method.

formed by using the SOM (Self Organizing Map). The second level is composed of a second procedure which clusters the SOM outputs.

The main benefits of this method are: the reduction of the computational cost, the noise reduction and the robustness to the random initialization process. The SOM can be combined with many other clustering methods like K-means (Vesanto & Alhoniemi, 2000).

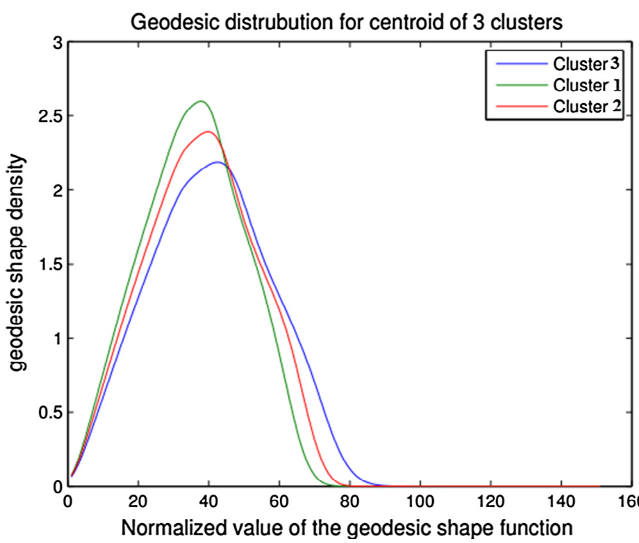



Fig. 11. Geodesic shape distribution of the centroids of the 3 clusters.

It could be noted that the clustering performs at the second level is much more simplify since the SOM has already structured the data on the map (Fig. 8).

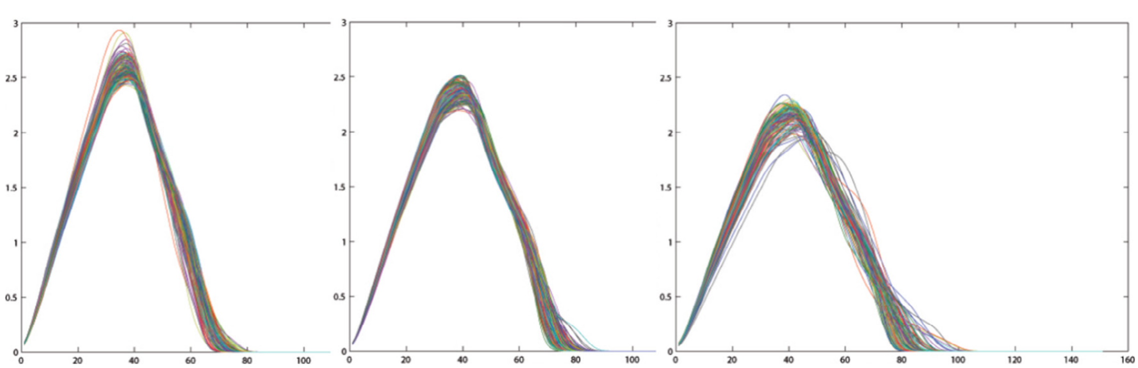
### 2.6. Morphological evolution

The result of 3D clustering has been linked with previous works on adaptive morphotypes to create 3D adaptive morphotype mannequins. Therefore, the parametrized model morphotype is based on a model surface representation defined from many sections of curves derived from a scanned human body representing the morphotype of each cluster. The concept of model set morphotype occurs in the choice and position of these curves, their settings, relationship between them and data from sizing survey.

3D morphologies clustering method give us morphological clusters represented by morphotypes. Based on these results, we can define a set of equations representing the linear regression of the key measurements (chest girth, waist girth, hip girth...) as a function of the height of a person. Thus, the evolution of the human body becomes a linear function of its height. Indeed, in the apparel industry, the gradation of garments is based on linear relationships between different measures of lengths and circumferences. Thus, the evolution of the human body is formulated by the following equation:

$$girth_i = a * height + b \tag{4}$$

where the coefficients $a$ and $b$ are the different for each clusters resulting from our 3D clustering method.



(a) Cluster 1 (b) Cluster 2 (c) Cluster 3

Fig. 12. Quality of clustering using the Davies-Bouldin index.

Hamad et al. present a solution for modeling the body shape variations with the correlation between the body shape and body size. The obtained models is adaptive and follow various morphologies in synchronization with different international sizing survey data.

Reverse engineering and modeling software are used to generate a 3D mannequin from scanned data of the subject and then, to extract sectional curves (Hamad et al., 14th). Sectional curves are imported into an available 3D CAD system which includes tools for 3D: lines and curves drawing. The obtained mannequins and equations can be then used to generate suitable sizing systems according to the desired range of sizes.

**Table 1**
Measurement chart from the 3 obtained morphotypes.

| Coefficients | Cluster 1 | | Cluster 2 | | Cluster 3 | |
|---|---|---|---|---|---|---|
| | *a* | *b* | *a* | *b* | *a* | *b* |
| Neck girth | 0.210 | 2794 | 0.116 | 20,056 | 0.249 | 5086 |
| Armpits girth | 0.336 | 39,520 | 0.688 | −17,032 | 1.268 | −87,946 |
| Chest girth | 0.338 | 35,175 | 0.436 | 21,329 | 0.633 | 12,565 |
| Underbust girth | 0.232 | 37,737 | 0.321 | 22,623 | 0.485 | 16,311 |
| Waist girth | 0.292 | 18,90 | 0.385 | 19,721 | 1.002 | −52,425 |
| Hip girth | 0.633 | −8666 | 0.479 | 20,490 | 0.505 | 27,970 |
| Thigh girth | 0.336 | −6364 | 0.423 | −16,067 | 0.427 | −16,423 |
| Knee girth | 0.207 | −1277 | 0.222 | −5642 | 0.950 | −115,001 |
| Calf girth | 0.011 | 30,295 | 0.140 | 7985 | 0.455 | −39,164 |
| Ankle girth | 0.116 | 3253 | 0.089 | 9185 | 0.275 | −20,823 |

## 3. Experimental results and discussion

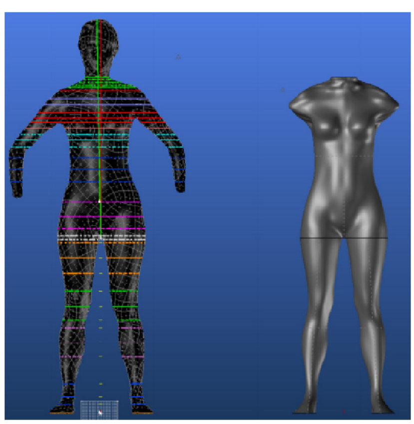
The evolution of morphologies over time can be considered as slow, namely several decades are required to note significant changes. Therefore, the measurement survey are arranged every 20 or 30 years and the last one was conducted in 2003 in France. The data used in this experiment are restricted to female between 20 and 40 year-old. For this limited range, 500 records has be considered as representative by the French Institute of Textiles and Clothing (IFTH). These data include the 3D cloud points and the coordinates of anthropometric points automatically detected by the Vitus Smart 3D body scanner with Human Solutions software. The coordinates of anthropometric points are required to enable the automatic process of location and segmentation described in previous section.

The obtained geodesic shape distributions of the 500 torsos are illustrated in Fig. 9.

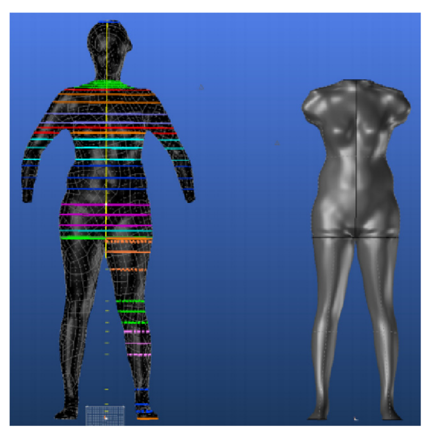
The two-level clustering procedure (first level: SOM and second level: k-means) is implemented on these 500 distributions and aims to separate these curves into k clusters ($k = 2$–20). A comparison with at least one naive method is implemented and compared with the two-level clustering procedure.

### 3.1. Optimal number of neurons and optimal number of clusters

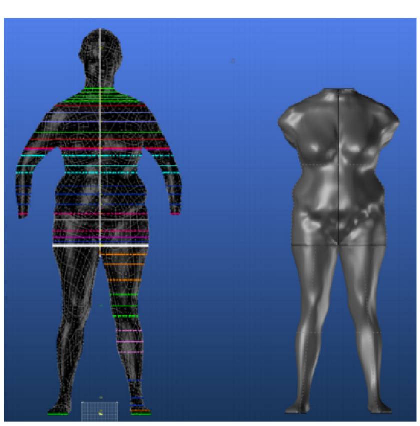
To determine the number of neurons of the SOM the output layer, we applied the following formula given by (Garcia & Gonzlez, 2004): $m = 5\sqrt{n}$ where $m$ is the number of map units



*(a) Morphotype 1*



*(b) Morphotype 2*



*(c) Morphotype 3*

**Fig. 13.** Morphotypes and their adaptive mannequins.

**Table 2**
New sizing system.

| Height (cm) | Morphotype 1 | | | Morphotype 2 | | | Morphotype 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | 150 | 160 | 175 | 150 | 160 | 175 | 150 | 160 | 175 |
| Neck girth | 34.37 | 36.48 | 39.64 | 37.50 | 38.67 | 40.41 | 42.5 | 44.99 | 48.75 |
| Armpits girth | 90.05 | 93.42 | 98.47 | 86.25 | 93.13 | 103.46 | 102.3 | 114.9 | 134.02 |
| Chest girth | 85.95 | 89.34 | 94.42 | 86.75 | 91.10 | 97.64 | 107.6 | 113.9 | 123.5 |
| Underbust girth | 72.66 | 74.99 | 78.48 | 70.84 | 74.06 | 78.88 | 89.14 | 93.9 | 101.28 |
| Waist girth | 62.73 | 65.66 | 70.04 | 77.60 | 81.46 | 87.25 | 97.97 | 107.9 | 123.03 |
| Hip girth | 86.29 | 92.62 | 102.11 | 92.46 | 97.25 | 104.45 | 103.8 | 108.8 | 116.46 |
| Thigh girth | 44.11 | 47.47 | 52.52 | 47.43 | 51.67 | 58.02 | 47.72 | 51.9 | 58.41 |
| Knee girth | 29.84 | 31.91 | 35.03 | 27.86 | 29.90 | 33.23 | 34.81 | 36.9 | 40.03 |
| Calf girth | 32.03 | 32.15 | 32.3 | 29.13 | 30.54 | 32.65 | 31.51 | 33.71 | 37.01 |
| Ankle girth | 20.67 | 21.83 | 23.57 | 22.56 | 23.45 | 24.79 | 22.18 | 23.29 | 24.95 |

and $n$ is the number of samples of the training data. To calculate the ratio between the number of rows $r$ and the number of columns $c$, we calculate the square root of the ratio between the two biggest eigenvalues ($e1$ and $e2$) of the training data: $\frac{r}{c} = \sqrt{\frac{e_1}{e_2}}, e_1 > e_2$. Thus, the number of map units are $m = 90,\ r = 30$ and $c = 3$. The 90 prototypes, obtained with a hexagonal topology characterize many morphologies types.

Then, the k-means clustering is performed on the 90 prototypes. To find the optimal number of clusters, we compute Davies and Bouldin (1979) to evaluate the obtained clustering. According to this criteria, 3 clusters are achieved for the given population (Fig. 10).

### 3.2. Clustering result

The centroids of theses 3 clusters, presented in Fig. 11, are obviously different. This result reflects the good separability of the 3 clusters and demonstrates the good discriminating power of our descriptor. The geodesic shape distributions of the 3 clusters are presented in Fig. 12(a), (b) and (c). It should be noted that the three clusters look compact. This reflects the good homogeneity within-cluster of torsos belonging to the same cluster. The correlations have been established between measures of human body in order to understand human evolution of the body.

Table 1 represents the coefficients *a* et *b* of the evolution Eqs. (4) for the three clusters. These coefficients enable to control the morphological contours of the 3 morphotype mannequins which are representative of the studied population. These three morphotypes corresponding to the 3 centroids of the clusters and their adaptive mannequins are given in Fig. 13(a), (b) and (c).

To deduce the new sizing system, we adjust each morphotype mannequin to the base height (160 cm) and the height of two extrema (150 cm and 175 cm) in according with the methods currently used by the Textile-Apparel-Industry to design and validate clothing collections. Thus, Table 2 represents our new system with the measurements of principal contours required to design and produce garment.

## 4. Conclusion

The apparel industry is very specific and requires up-to-date sizing systems to propose for instance suitable system for virtual try-on to their consumer. The aim of this study is threefold:

- To identify the main morphotypes in a given population with an automatic clustering method for human morphology from 3D scans.
- To define a suitable discriminant 3D descriptor in order to detect the main features of the human morphology.
- To define resulting adaptive morphotypes to define a new sizing system usable for instance for virtual try-on.

The proposed method allows for automated processing of 3D scans and computation of their geodesic shape description. This descriptor is optimized to ensure the highest discriminating capacity.

From this descriptor, we find an optimal number of 3 clusters corresponding to 3 morphotypes on a database of 500 female scans. The clustering procedure is carried out with a two-level method which is composed of a SOM network and a k-means clustering. However, it should be interesting to check the viability and accuracy of the method on a larger database. Moreover many others potential classification techniques should be tested and evaluated on different databases. The automatic morphotype generation from the centroid of the cluster is also an enhancement to investigate in future works.

This methodology, associated with previous works on adaptive morphotypes (Hamad et al., 14th), could significantly improve the sizing systems of apparel companies. Furthermore, combined with adaptive garments (Thomassey & Bruniaux, 2013), it opens new opportunities to progress towards the full digital tailor process.

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