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Modeling of female human body shapes for apparel design based on cross mean sets ☆

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ABSTRACT

This paper is concerned with a method to build prototypes of human bodies that can be used for apparel design. One of the most important issues in the apparel development process is to define a sizing system to provide a good fitting for the majority of the population. Since anthropometric measures do not present the same linear growth with size in each dimension, it is very important to find a prototype that represents as accurately as possible each class in the sizing system. In this paper we propose a method based on the concept of random compact mean set to define prototypes in apparel design. From a cloud of 3D points obtained with a 3D scanner a solid that represents the human body is obtained. 2D cross sections of this solid are extracted at certain heights corresponding to key points of the body. These different cross-sections can be seen as a realization of a random compact set in the plane. A very popular definition on mean set is applied to each sample of 2D cross sections, and finally the prototype is obtained as the 3D reconstruction of these 2D mean sections. As a real example, the proposed methodology is applied to the 3D database obtained from a anthropometric survey of the Spanish female population conducted in this country in 2006.

1. Introduction

Anthropometry data is a fundamental information used in the design process of products and environments to assure ergonomics and provide a better comfort (Pheasant, 1996). In the particular case of the clothing industry, designers and pattern makers use mannequins for representing the main anthropometry of a basic size, which is then scaled proportionally to cover most of the population.

The primary anthropometric information used by clothing designers consists of size tables that list the mean values for each size of the main anthropometric measures. These tables exist for upper and lower garment. Additionally, physical mannequins based on these anthropometric dimensions are used to test the garment fitting during the pattern development process. Most of this information has been developed by the designers' own experience or it is based on a beauty canon far from the real shape of the greatest percentage of population (Fan, Yu, & Hunter, 2004).

For the last years, new technology for body scanning has emerged, as reported in Daanen and Haar (2013), and user's fitting problems with mass production of clothing has promoted new sizing surveys to update anthropometric data of the population in different countries (USA, UK, France, Australia, Spain and Germany) Rissiek and Trieb (2010). Most of these studies have mainly addressed apparel applications (Alemany et al., 2010; Carrier & Faust, 2009; Unspecified author, 2004). So far, most of the research studies that have been done are focused on the analysis of these data for their application in apparel design (Gillies, Ballin, & Cs'aji, 2004; Simmons, Istook, & Devarajan, 2004; Sul & Kang, 2010; Wang, 2005).

Although a lot of anthropometric information exists, most of it is just available as static aggregated data published on books and scientific articles (Peebles et al., 1998; Unspecified author, 2011). This provides useful information for studying population changes but was never either reliable or sufficient for designers and ergonomics engineers to apply appropriately. The extended use of computer aided design promotes the development of many tools that use information from anthropometry measures to create virtual

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3D models of humans. These models can be added to any virtual environment or workspace, to assess ergonomics, comfort and performance (Duffy, 2009). There are two types of 3D human body models: digital human models (DHM) and avatars.

DHM are parametric body models, which simulate body proportions, postures, reach ranges and motions of a user population to analyze classic ergonomics concerning postures, envelopes and reaches applied to their interaction with virtual environments, mainly in automotive and work place design (Blanchonett, 2010; van der Meulen & Seidl, 2007). DHM use 1D anthropometric scaling by applying regression equations to create a family of mannequins. Percentiles of anthropometric measures could be introduced in the parametric model to create mannequins representing the mean body, the 5% percentile or the 95% percentile of a specific population. Interesting examples of this approach using clustering techniques are found in Ibáñez et al. (2012) where the authors apply trimmed k-medoids and OWA (ordered-weighted average) operators and in Vinué, León, Alemany, and Ayala (2014) in which the clustering technique is hierarchical PAM (partitions around medoids). The univariate characteristic of these approaches is a severe limitation that requires a careful use; the combination of anthropometric dimensions, even in the same range of percentiles, will lead to an unknown percentage of the given population that cannot be accommodated (Zehener, Meindl, & Hudson, 1993), And they will easily produce an unreal body type totally unsuitable for ergonomic design. Additionally, shape information of the body is not considered. The main difference with our approach is obviously the data reduction: as it will be explained later, we work with all the body shape considered as a solid without using the numerical parameters that could be extracted from it.

An alternative is the use of multivariate methods. Robinette and McConville (1981) proposed the use of the principal component analysis, which reduces the number of anthropometric variables grouping and ranking it by the percentage of variability explained by each one. Using the plot of the first and second component, a circle can be imposed including the desired percentage of population, typically 95%. The center of this circle is used as a mean body representation for the principal anthropometric variability. Some points distributed over the boundary of this circle, are selected as representative cases to describe anthropometric variability. More recent examples of the use of PCA or related characteristics are Luximon, Zhang, Luximon, and Xiao (2012) that applies their methodology only to feet, and (Wuhrer, Shu, & Xi, 2012) that applies to a whole body, even in different poses. However, the use of actual cases instead of models to represent the anthropometric mean of a population and their boundary variability, presents an important problem: singularities in the body shape related to personal characteristics, with lower weight in the principal component representation, will influence product design and assessment. Again, the difference with this proposal is that PCA changes the representation space before model construction whereas we operate all the time with the original shapes.

Other alternative also based on anthropometric measures consists of using archetypes. Archetypal analysis assumes that there are several ‘‘pure’’ individuals who are on the ‘‘edges’’ of the data, and all others individuals are considered to be mixtures of these pure types. Archetypal analysis estimates the convex hull of a data set, and therefore favors features that constitute representative ‘‘corners’’ of the data, which are precisely the archetypes. This comments, and some advantages in a comparative analysis with Principal Component Analysis (PCA) is detailed in Epifanio, Vinué, and Alemany (2013).

In the case of avatars, the main specification is to provide a realistic visual representation. Commercial applications are focused on virtual try-on for apparel (commercial products from firms like Vidya, Browzwear or Optitex). They give priority to an aesthetic appearance, leading to unreal 3D body shapes. The parametric avatars, which enable to introduce specific anthropometric measures, use deformation methods that are not based on statistical distributions.

In this context, recent emerging research relying on 3D body shape analysis aims to generate 3D statistical body models from large 3D body databases. Different authors, analyzed human shape variability using a volumetric representation of 3D human bodies and applied a principal component analysis to the volumetric data to extract dominant components of shape variability for a target population (Azouz, Rioux, Shu, & Lepage, 2006; Seo & Magnenat-Thalmann, 2003; Xi, Guo, & Shu, 2011). As a result, through visualization, they showed the main modes of human shape variation. It is important to note, that the development of shape descriptors that can efficiently represent the human body shape and size at different levels of detail is still under research (van der Meulen & Seidl, 2007).

Also included in this line we must mention the approaches that start from the data provided by 3D scanners and build with them the prototypical human model. Almost all of them take the values of the body surface points, or a mesh of polygons that have the points as vertexes, as representation primitives; some of them build a Point Distribution Model (PDM) like Ruto, Lee, and Buxton (2006) and others make use of polygons/normal vectors, as in Allen, Curless, and Popović (2003) and Anguelov et al. (2005) or Hasler, Stoll, Sunkel, Rosenhahn, and Seidel (2009). In both cases correspondences are established between the different cases, which allows the generation of a mean model that, if done with the subjects of a given group, can be taken as the mean shape of that group. More recently other work have elaborated and improved these ideas, like Hsiao and Chen (2013) and Huang, Mok, Kwok, and Au (2012) or Baek and Lee (2012). Some of them even take into account deformability of the surface patches used to model the body surface so that characteristics of the cloth material can be incorporated to visualize a realistic representation of the fit of a given cloth to a given body. These approaches differ from ours in the obvious fact of using surfaces instead of volume as their main primitives. This brings some advantages, like the availability of a well established framework (differential geometry) to model and deform the surfaces but also what it is, from our point of view, an inconvenient: the lack of well studied statistical methods to work with the parameters that define the surfaces whose statistical distributions are totally unknown. Nevertheless, notice that our method does not exclude the use of surface-based methods at a later state: having the shape as a volume, the surface can be extracted, modeled with B-splines or other of the methods proposed by the aforementioned works and used to make realistic garment fitting.

Finally, it is worth to mention too some works that build the 3D model (using surfaces, even this is not intrinsic to their approach) using only relevant points extracted from the projections of the body scanner on lateral and frontal planes. These are Lin and Wang (2011, 2012); we have applied similar ideas (see Section 3.2 and in particular, Figs. 1 and 2). These methods can be very useful if a scanner is not available (even a simpler arrangement should be built to take the image of projections) but suffer the risk of loosing valuable.

In this work we present also an approach to generate a 3D body shape using a statistical methodology to define prototypes based on 3D clouds of points obtained with a 3D scan. The proposed method is applied to the 3D anthropometric survey of the Spanish female population. The difference with the aforementioned approaches that work with the surface points is that we work with volumes (a grid of voxels) from which slices are extracted only as a mean the make the method computationally feasible. In some of the surface based methods the shapes to be averaged are aligned

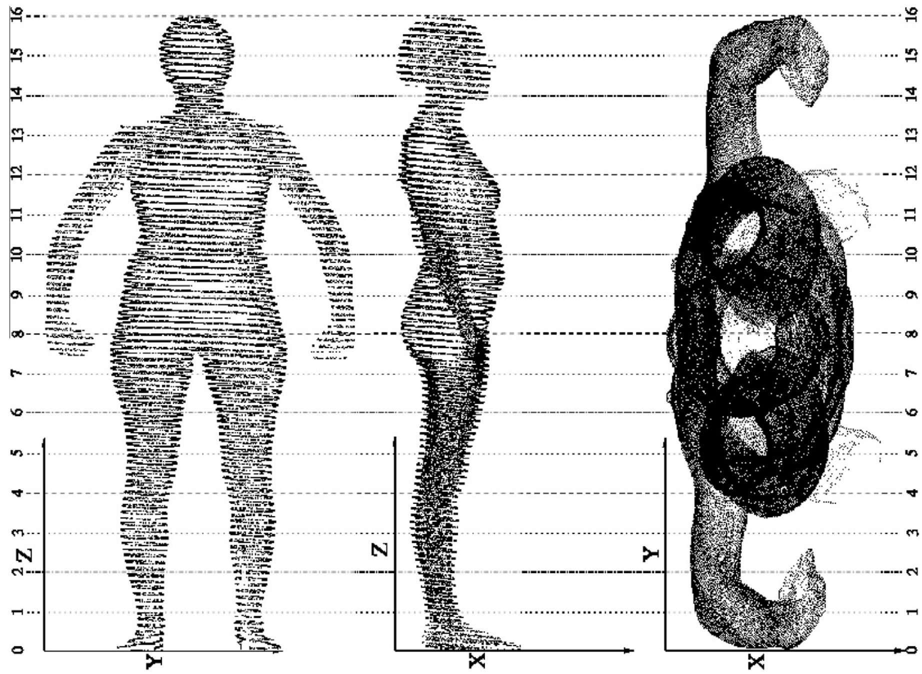

Fig. 1. Projections on the coordinate planes.

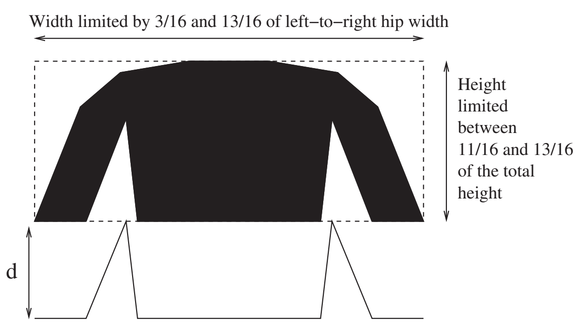

Fig. 2. Rectangle used to find armpits.

to each other, first by aligning their centroids and then executing a generalized Procrustes algorithm; after that, techniques of Principal Component Analysis (PCA) can be applied to reduce the number of points that constitute the PDM, but this is not compulsory. Nevertheless, it is done to reduce the complexity of Iterative Closest Point algorithms (ICP) that must be applied in order to fit a new shape to the model through deformation. Our approach starts by making a gross alignment of the shapes, too (centroid and main inertia axes) but immediately forget the limit surface and works with all the points of the volume considering them as the realization of a random compact set. This increases the amount of memory needed but avoids from the very beginning problems like surface hole filling (that is solved by surface based approaches by using the smoothed mean model) and also avoids the need to register the surfaces which is not usually an easy task (for instance, in Allen et al. (2003) authors propose a fitting function based on data error, smoothness error and marker error that must be minimized using two levels of resolution). But is also true that these surface-based methods can cope with a great variety of poses.

In fact, the main point is that the final objective is quite different for these approaches: the first of them essentially aims to get a model that can be deformed to produce a realistic view of a wide range of shapes (a thing very difficult to get within our framework) whereas the main goal of our approach is to extract the behavior of a previously existing group to get a prototype that best describes the group. This is more difficult to be done with surface-based approaches since they use deformation that alter the original shapes. In any case, we do not claim our method to be intrinsically superior to surface-based approaches but we consider interesting to try out to enrich the range of available tools.

The outline of the paper is as follows. A general view of our data set and the chosen methodology is given in Section 2. Section 3 gives a detailed description of each step of the method with the data and algorithms used. Section 4 shows the results of applying our methodology to the anthropometric database of Spanish women, and some conclusions and further work ends the paper in Section 6.

2. Summary of the approach

The Spanish Ministry of Health conducted in 2006 a national 3D anthropometric survey of the female population. The aim of this survey was to help apparel designers by providing real and consistent measures to aid in the normalization of the sizing system. The final purpose was to increase the protection of consumers and to help in the treatment of alimentary mental disorders. Each women that participated in the study was measured using a 3D body scanner. This scanner provides a cloud of about 200,000 points whose 3D coordinates are stored. These are the raw data from which we start.

The main objective of this work is to define a prototype of the trunk shape of the female population. In order to get accurate prototypes, sizing systems traditionally classify a specific population into homogeneous subgroups based on body dimensions (Chunga, Lina, & Wang, 2007), being bust and height the corporal dimensions more commonly used. As stated before, in the work presented in this paper, instead of working with the whole body, we will work with a region of interest comprising the trunk of the women. For this purpose we will isolate this region from each scan, and prototypes will be built to fit it.

From the 3D cloud of points provided by the scanner a 3D image of a 3D shape is built and after the alignment of the 3D images, 2D cross sections will be obtained for each woman at several heights of the human body. Two kinds of points are chosen to do the cross sections, the first kind comprises only six important anatomical points located between the nape of the neck and the crotch. Then, several sets of slices equally spaced between each pair of consecutive anatomical points will be defined. They are listed in Section 3.4. Of course, the extracted cross sections for a given woman are not independent, but homologous section for different women are considered to be independent realizations of a random process and therefore meaningful conclusions can be drawn from their study with the appropriate statistical tools.

Formally, each sample of a 2D cross sections can be considered as a sample of a Random compact closed set in $\Re^2$ and the concept of mean set will be applied to each of these cross sections. A random closed set is a very popular probabilistic model for shapes that has a growing interest in Computer Science and in particular in Computer Vision literature. The formal definition with many examples of this concept can be found in Cressie (1993), Matheron (1975) and Stoyan, Kendall, and Mecke (1995). Different definitions of the mean set of a random compact set can be found in the literature (Baddeley & Molchanov, 1998; Molchanov, 2005; Simo, De Ves, & Ayala, 2004; Stoyan & Stoyan, 1994). In this paper the Baddeley–Molchanov definition of mean set will be used. Finally, the prototype will be obtained from the reconstruction of these cross section means.

In using this approximation, we are assuming that the greatest source of variability (within each size) is horizontal, i.e. the biggest and most important differences between women into a size are due to differences in their horizontal cross sections. This a natural and logical assumption, and it allows us to work with 2D data instead of 3D volumes which, as we will argue later, would represent an excessively heavy computational task.

3. Materials and methods

Our methodology is divided into five main steps, which are detailed in the rest of this section, preceded by Section 3.1 which describes the data set.

1. A 3D binary image is obtained from the collection of points located on the surface of each scanned person. The computational details are given in Section 3.2.
2. The 3D images are aligned in a meaningful way in order to be able to average them (Section 3.3).
3. From each 3D image a set of 2D cross sections is obtained (Section 3.4).
4. Homologous 2D cross sections of different women are averaged using a definition of random compact mean set (Section 3.5).
5. Finally, the 3D prototype is reconstructed from the 2D mean sets (Section 3.6).

3.1. Our data set

As stated before, our raw data comes from the anthropometric survey conducted in 2006 by the Spanish ministry of Health. A sample of 10,415 Spanish females ranging from 18 to 70 year old randomly selected from the official Postcode Address File was measured using The Vitus Smart 3D body scanner from Human Solutions (see reference H. S. Company).

In order to harmonize the measurement process, standard white garment, consisting of a swimming hut, a top and a short, was designed and scaled five sizes. The design of the garment was based on the standard ISO 20685 (ISO, 2010). This International Standard addresses protocols for the use of 3-D surface-scanning systems in the acquisition of human body shape data and measurements defined in ISO 7250-1 that can be extracted from 3D scans. The intent of ISO 20685 is to ensure comparability of body measurements as specified by ISO 7250-1 but measured with the aid of 3-D body scanners rather than with traditional anthropometric instruments.

Also, seven small wooden half-spheres, which are not reflective, and are easily detected by the software of the scanner, were attached to the body surface using double-side adherent tape. The spheres were attached on seven anatomically relevant points: one of them was fixed at the third neck vertebra, one over the left clavicle and its corresponding on the right clavicle, a couple at the low waist and high waist in the right side, and the corresponding pair at the left side.

From these seven landmarks, other points manually requested by the human operator in addition to others automatically detected from the mesh of points are written in a .xml format file. It contains the coordinates of many relevant points together with 95 anthropometric measures, some of them automatically calculated and others obtained through user intervention in the form of path marking.

Furthermore, other qualitative measures such as the women satisfaction with her body or diet habits were collected. Women were also asked about their size in the current Spanish sizing system. Due to the lack of consistency and rigor in the current sizing system in Spain, the answers of this question were in some cases numerical and in other cases qualitative: small, large, etc. being in all the cases only an approximation.

From the sample of 10,415 Spanish females, some scans were rejected due to problems with the software during the scanning process. Finally, a selection of 5,799 women was done. Pregnant women; those who declare to be breast feeding at the time; who have undergone any type of cosmetic surgery (breast augmentation, liposuction, breast reduction, etc.), and the ones younger than 20 or older than 65, were removed from the data set for this study.

For each case 160 body measures (the 95 anthropometric ones plus the additional information) are directly available but others had to be calculated using the shape. Also, our approach to mean shapes needs the data not as a surface mesh but as a volume composed by voxels (3D pixels). This imposed us the need of developing algorithms and software to transform the clouds of points into filled 3D volumes, as will be explained in the next section.

3.2. From 3D points to a 3D image

As stated in the introduction, instead of working with the whole body of each woman, our aim is to build prototypes from the women trunks, so we will need to get a 3D binary image of this region for each woman. In this section, we explain the method used to produce a 3D binary image from a collection of points located on the surface of the scanned person.

Point coordinates, as provided by the software into the .stl file, are floating point numbers. Sampling them to fill a regular 3D matrix of voxels might cause a loss of precision. The voxel size must be taken sufficiently small so as to be comparable to the precision of the scanner. Our program allows to choose this parameter and the rest of this study is done with cubic isotropic voxels of 1 mm side.

Once sampled at the selected resolution, we have a digital representation whose data structure is a cubic matrix of binary voxels. The method now runs through the vertical axis of the body (z-axis) dividing it into thin slices. The points that belong to each slice are enclosed by their convex hull which is then filled. It is a simple and very robust method, whose steps are detailed in Algorithm 1.

Algorithm 1. From 3D point sets to 3D binary image

Set the caliber of the horizontal cross section: δ.
Set the minimum and the maximum of the vertical axis: h_{min} and h_{max}.
for i= h_{min}, h_{max} with step δ **do**
  Select the points with coordinate: $z \in [h_{min} + (i-1)\delta, h_{min} + i\delta], S$.
  The point set S is projected over the horizontal plane giving a 2D set, $\mathcal{P}(S) = Ps$
  The convex hull of Ps is evaluated, $co(Ps)$.
  The convex hull $co(Ps)$ is filled.
end for

Algorithms for calculating the convex hull of a set of points and for filling a polygon are common in computer graphics with many implementations available. We have used the one given in Šonka, Hlaváč, and Boyle (1993). For our problem in hand, some special cases must be taken into account. The first case happens when a horizontal plane cuts not only the trunk but also the arms. In this case the convex hull would also enclose three groups of points: those belonging to the trunk and to each of the two arms. However, we wanted to get only the convex hull of the trunk. This is tackled by imposing limits to the point coordinates which are considered: only those into a prism (box) limited by certain proportions of body height and width are kept. Using proportions assures us that this limitation is valid for all individuals, since the box does not need to be too tight to separate properly arms from main body.

Notice that this method is neither a global 3D convex hull, which would yield little more than a cylinder or cone trunk, nor a perfect fit since human body sections are not always convex. Nevertheless, any method to reconstruct the shape more accurately would have needed many ad hoc adjustments and would have been too prone to errors with such a wide spectrum of cases. We think that the use of height-sections convex hulls is enough for the purpose of this work.

Now we can use algorithms to calculate important anthropometric parameters which are not directly provided by the scanner software. These parameters include the height of the armpits over the floor, the height of the crotch, the lateral limits of the left and right hip and the height of these points, the height of the bust and the perimeter of the chest girth.

Most of these parameters are calculated using projections. Fig. 1 shows our choice for the coordinate axes and the three projections on each coordinate plane: XY, XZ and YZ. Projections are 2D binary images whose analysis will allow us to obtain relevant values. Each projection has a maximum extension in each of its two dimensions; this extension is divided into 16 equal parts so that the algorithms use always 1/16th of the extension as unit of measure. This allows a parametrization of the algorithms independent of the real women dimensions.

The height of the crotch is calculated from the YZ projection: a rectangle is isolated that goes between 3/16 and 13/16 in the Y dimension and between 5/16 and 8/16 in the Z dimension. A 1D array is built that runs along the Y dimension and, for each Y value, stores the Z coordinate of the first non-zero (object) point. This array, considered as a function, has the maximum value for some Y-values at the beginning and end of the rectangle, zero for some values at the left and right leg and non-zero for some values near the center. The maximum value of this central part is taken as the crotch height.

With respect to the height of the armpits, the procedure is similar: using the YZ projection the rectangle to be isolated goes this time again from 3/16 and 13/16 in the Y dimension but now between 11/16 and 13/16 along the Z axis. The obtained shape and the function giving the lowest Z coordinate are represented in Fig. 2. The highest value for each of the two lateral peaks is taken as the height of each armpit and the average of both is returned as the value for this parameter.

The lateral limits of the left and right hip and the height of these points use the same rectangle as the crotch, also in the YZ projection, but this time we look for the leftmost and rightmost points (minimum and maximum value of Y) for which there is any point in its column (Z values for that Y).

The most difficult parameters to calculate are the height of the bust and the perimeter of the chest girth. We will take as bust height the height of the horizontal section with larger perimeter of its convex hull. To find it we start at the value of the Z coordinate formerly obtained for the armpit and descend in intervals of 1 mm, taking slices. The convex hull of the points in each slice is already calculated, since it was used for the reconstruction of the 3D volume, so we simply calculate its perimeter and we get the largest one. This height is used as a reference to obtain the height where the perimeter of the chest girth must be calculated. Indeed, it is taken at the bust height plus 7/10 of the height difference between bust and armpit. The use of convex hull it is consistent with the fact that, when using metric tape to measure on humans, the designer always strains the tape so that not all points of it are directly located on the body surface. It must be noted that calculation of the perimeter with this method, even using the appropriate corrections due to the digital nature of the images, always gives a value higher than the one measured with tape, as we have checked with a sample of real woman. This is an artifact also noticed by Han, Nam, and Choi (2010) so a linear correction based in regression on the real measured cases was applied.

Finally, a region of interest for our study is isolated that comprises the trunk of the women. This will be the union of two parallelepipeds, one for the lower trunk, from the crotch up to the lower waist, and one from there to the neck. Both include the total depth (X coordinate) but the lower one is wider (bigger extension in Y coordinate) going from the left to the right most prominent points of the hip whereas the higher box will be limited in width by the left and right armpit Y coordinates. In that way the arms are left outside but all the trunk is included. See Fig. 3. Notice that all the parameters needed to define this boxes have been

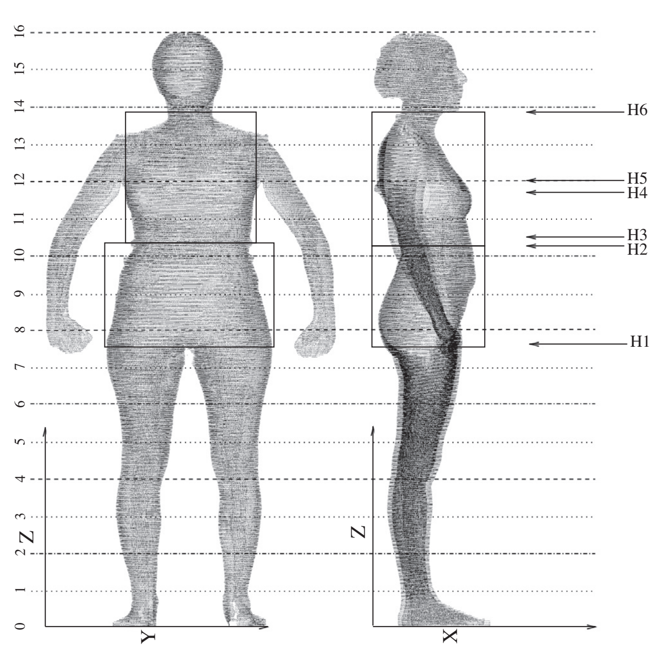

Fig. 3. Boxes to isolate the volume of interest.

previously calculated, except the height of left and right waist and the height of the third neck vertebra, which are given by the software of the scanner helped by little wooden spheres attached to the body with double-side adherent tape.

3.3. Spatial alignment

Once the 3D matrix of voxels is available we will need to align in a meaningful way all the shapes to be compared or averaged. Absolute coordinates cannot be taken as a reliable guidance since placement and posture of the person can change between subjects. The solution we have used is to rotate each shape to place the origin of coordinates at the center of mass of each shape and to make its principal inertia axis coincide with the canonical axis of coordinates. Volumes are supposed to be homogeneous (we do not need to calculate the real center of mass or inertia, just that of the binary shape) and the inertia matrix is calculated and diagonalized. The diagonalization change of basis is taken as the 3D rotation to be applied to each voxel of the shape. Also the minimal enclosing parallelepiped whose faces are parallel to the coordinate planes (enclosing box) is calculated after the rotation. This will be used to know the minimal box that encloses all the shapes which in turn will be used to know the dimensions of the matrix which will hold the result of the mean shape.

3.4. 2D cross sections of each 3D image

The last step in our data preprocessing procedure is to obtain the 2D cross sections of each 3D aligned shape. Six main cut points which have been marked with arrows in Fig. 3 are determined along the trunk of the women, which are arbitrarily numbered as:

1. crotch height (H1)
2. height of the lower waist markers (average of both sides) (H2)
3. height of the upper waist markers (average of both sides) (H3)
4. height of the section where the breasts are more prominent (horizontal distance between chest and back is maximum) (H4)
5. armpit level (average of both sides) (H5)
6. height of the neck marker (H6)

To be able to compare different shapes in a meaningful way we extracted 100 slices from the trunk section. These will be distributed as follows:

	Between points…				
	1–2	2–3	3–4	4–5	5–6
Number of extracted sections	35	5	20	5	35

The total number of slices (100) was taken so that they are close enough to represent appropriately the details of the shapes still keeping a reasonable computational cost. The number of slices in each section is taken approximately proportional to the average thickness of such section. This results in a real separation between slices different for each women, but only slightly different for women belonging to the same group of those we take for the study (see Table 1). By doing this we can establish a correct homology between shapes of different heights taking into account anatomical information. From now on we will denote z_{ij} as the Z-coordinate of section j of woman i, where $j = 1 \dots 100$.

3.5. Mean sets

Following the methodology used so far, for every woman of our sample we have obtained a set of planar sections of her body. From now on m denotes the number of planar sections per woman (as stated before, $m = 100$) and n the number of women to be averaged. Thus, each woman in the sample set is now represented by m compact sets in $\Re^2$.

Table 1
Identification of the groups with larger sample sizes. Section 4 explains in detail how these groups are obtained.

Group label	Bust (cm)	Height (cm)
A	[74–82)	⩽162
B	[74–82)	(162–174)
C	[82–90)	⩽162
D	[82–90)	(162–174)
E	[90–98)	⩽162
F	[90–98)	(162–174)
G	[98–106)	⩽162
H	[98–106)	(162–174)
I	[106–118)	⩽162
J	[106–118)	(162–174)

In this section we focus on one of these planar sections, let it be the jth section. The set of n 2D compact sets can be regarded as a sample from the collection of all possible jth sections of all Spanish woman. Mathematically speaking, they can be regarded as realizations of a *Random compact set*. As an example, in Fig. 4 we can see the same section for 4 women of our data set.

From this standpoint we propose to average the n compact sets using a mathematical definition of random compact mean set, whose foundations are introduced below.

A random compact set, Φ, is essentially a random variable taking values in the space $\mathcal{K}$ of all compact subsets of a complete separable metric space. The formal definition of this concept can be found in Cressie (1993), Matheron (1975), Molchanov (2005) and Stoyan et al. (1995) among others. In this work we focus on the case where the metric space is the Euclidean space $\Re^2$.

Unlike the uniqueness of the definition of the expectation of a real-valued random variable, sets have different features and so, particular definitions of expectations highlight particular features which are important in the chosen context (see Molchanov, 2005). That is why different definitions of the mean set of a random compact set can be found in the literature; three of them are particularly relevant: the Aumann mean (Stoyan & Stoyan, 1994), the Vorob'eV mean (Stoyan & Stoyan, 1994) and the Baddeley–Molchanov mean (Baddeley & Molchanov, 1998). Each of these definitions of mean set is based on the average of a certain random function associated to the random set. The Aumann mean is based

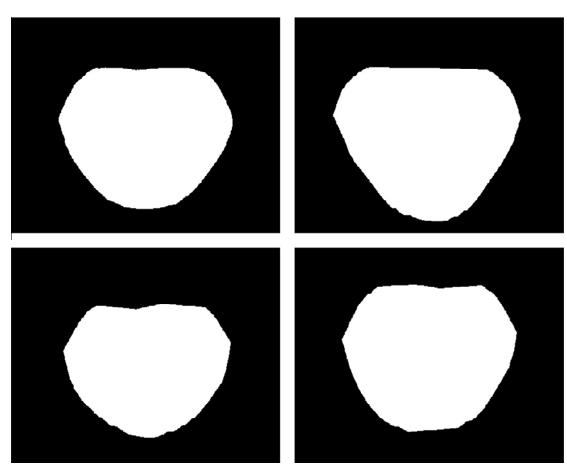

Fig. 4. (a) Compact sets corresponding to the same cross section of the body of 4 women of our data set.

on the *support function* of the set, the Vorob'eV mean on the *coverage function* and the Baddeley–Molchanov on some *distance function*. Other recent definitions of mean set can we found in Jankowski and Stanberry (2010) and Simo et al. (2004).

Among these particularly important mean set definitions, the Baddeley–Molchanov is the most flexible because it provides different results depending on the distance function chosen and so it can be adapted to each specific application. Additionally Baddeley–Molchanov mean can be applied for general compact sets because no restrictions are needed. On the contrary, Aumann mean is only suitable for averaging convex sets i.e. for random compact and convex sets. Regarding the Vorob'eV mean, although it is applicable to non-convex sets, it is not suitable for random sets with zero area.

Regarding our application, Aumann mean cannot be applied because many of the sets considered are not convex. Both Baddeley–Molchanov and Vorob'eV definition of mean set can be used because our observations are sets with positive area. However, the results of our experiments did not produce good results using the Vorob'eV average; indeed, the obtained prototype had a strange visual appearance which, in some cases, did not even have female shape. Consequently, we decided to use the Baddeley–Molchanov definition, despite the difficulty to obtain confidence regions for this (but also for the other) means. Note that the sample mean of distance functions converges to the *population* mean using versions of the central limit theorems for random processes. However, the Baddeley–Molchanov assume a threshold of the this sample mean. The closer result can be found in Jankowski and Stanberry (2010).

A brief review of this definition of mean set is given below. It is also called *distance average*.

Let Φ be a random compact set on $\Re^2$. Let $\mathcal{K}$ be the space of non-empty closed sets and let $d : \Re^2 \times \mathcal{K} \to \Re$ be a distance function, $\triangle$ a metric (or pseudo-metric) on the family of distance functions and $\triangle_W$ the restriction of $\triangle$ to W, a certain compact set (window) (see Molchanov, 2005).

Suppose that $d(x, \Phi)$ is integrable for all x; then, we define the mean distance function as:

$$d^*(x) = Ed(x, \Phi).$$

Let us consider $\Phi(t) = \{x \in W : d^*(x) \leqslant t\}$ with $t \geqslant 0$ and the distance functions $d_t(x) = d(x, \Phi(t))$. The Baddeley–Molchanov mean of $\Phi, E\Phi$, is defined as the thresholded set $\Phi(t_{opt})$, where the 'optimal' threshold t_{opt} is chosen to minimize the $\triangle_W$-distance between d_t and the mean distance function of Φ, i.e. $t_{opt} = argmin_t \triangle_W(d_t, d^*)$.

This is the theoretical definition of the Baddeley–Molchanov mean set. Given Φ_i with $i = 1, \ldots, n$, a random sample of the random set Φ i.e. a collection of independent and identically distributed (as Φ) random sets, the empirical estimation of $E_{bm}\Phi$ is obtained from the empirical distance average defined as

$$\bar{d}(x) = \frac{1}{n}\sum_{i=1}^{n} d(x, \Phi_i). \tag{1}$$

Following the theoretical definition, this empirical distance function should be thresholded at various levels and the sample mean should be defined as the thresholded set at the 'optimal' threshold given by the metric $\triangle$. Baddeley and Molchanov proposed in their paper (Baddeley & Molchanov, 1998) a range of plausible metrics, suggesting to work with the L^2 distance. However, in all the cases, the procedure is very complex and computationally very expensive.

Alternatively, Lewis, Owens, and Baddeley (1999) propose a different empirical approximation to the Baddeley–Molchanov mean set. They suggest to use another 'discrepancy criteria' to choose the optimal threshold, t_{opt}, minimizing:

$$\frac{1}{n}\sum_{i=1}^{n} \|A(\Phi_i) - A(\bar{\Phi}(t))\|,$$

where $A(\Phi)$ denotes the area of Φ. The optimal threshold t_{opt} is then the value for which the area of $\bar{\Phi}(t_{opt})$ is most similar to the average of the areas. This value can be easily determined from the histogram of $\bar{d}$. They call this procedure *area-matching*. This is the one we use for our application.

As mentioned previously, one of the main advantages of the Baddeley–Molchanov mean is that it depends on the chosen distance function, d. Thus we can get different kinds of mean sets using the most appropriate distance function for each application. Baddeley and Molchanov give a list of examples with different distance functions. In our application we use the Euclidean distance function defined as:

$$d(x, \Phi) = inf\{\rho(x, y), y \in \Phi\},$$

where ρ denotes the Euclidean distance in $\Re^2$. It is used because it is the simplest and most natural in our context.

With respect to the intuitive meaning of the mean shape, its explanation requires a clarification of the concept of distance function. For any given planar shape (a set of points), its associated distance function is defined at every point of the plane, either if it belongs to the set or not. In the latter case, the distance function is defined as the distance to the closest point of the set, or equivalently, to the contour of the shape. For points belonging to the set, including its contour, distance function is defined as zero. Therefore, the range of values for the distance function goes from 0 to plus infinite (the points infinitely far away). The distance functions for the four shapes in Fig. 4 are shown in Fig. 5 where brighter mean higher values.

Using the distance function of each case, the mean distance function is estimated as an average of each function, point by point. This function encodes information on which points should belong to the mean shape (those with lower values of the mean distance) but it is not yet a shape (a binary set). It will be transformed into one by thresholding it; several possibilities exist to choose the threshold but the most common, and the one chosen here, consists of taking as threshold the value that makes the area of the resulting shape as similar as possible to the mean of the areas of the original binary sets which are being averaged. The mean distance function of the four sets if Fig. 4 with the value for the threshold superimposed in white, together with the final mean shape, are shown in Fig. 6.

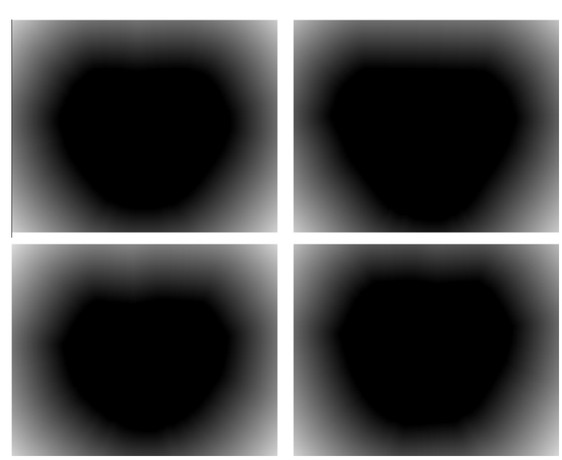

Fig. 5. Distance functions associated to the 4 cases shown in Fig. 4.

The direct use of this definition of mean shape using 3D, even in principle more appropriate, has a computational limitation that prevents us to use it. For each case, the distance function must be calculated; as far as the authors are aware of, the fastest algorithm in three or more dimensions to calculate the distance function is based on the construction of a kd-tree (Bentley, 1975) containing the points in the frontier of the set, ∂S (those which have at least one neighbor in the set and at least one in the background). Then, a depth-fist search on the kd-tree, that can be pruned by a distance threshold, is used to calculate the closest point in ∂S to the point where distance function has to be calculated. We tried two alternative implementations, one of the authors and the one found in the ITK libraries (Ibáñez et al.) due to (Maurer, Qi, & Raghavan, 2003); both spent roughly the same time, about 15 min by each four cases in a modern machine with four nucleus which, given our number of cases (5799), would have become impractical for a real application. Nevertheless, implementation could be highly accelerated using special hardware (Graphic Processing Units, GPUs), a possibility we are currently exploring.

3.6. From planar mean sets to 3D prototypes

Let us recall that our initial data set consisted of m sections ($m = 100$) of n women, following the notation previously introduced $\{\Phi_{ij},\ i = 1,\dots,n\ j = 1,\dots,m\}$ where Φ_{ij} is the cross section of women i at level j. In this section we assume that we have applied the Baddeley–Molchanov mean to each one of these sections and thus we have obtained m 2D mean sets $E\Phi_j, j = 1,\dots,m$. The final step to define the prototype is the 3D reconstruction from these mean sets.

To make the 3D reconstruction, the 2D sets $E\Phi_j$ are stacked keeping a spacing between them proportional to the real average height of the group of women that are averaged. i.e. the 3D prototype will be $\{(x,y,z) : \exists j :\ (x,y) \in E\Phi_j \text{ and } \bar{z}_{j-1} \leqslant z \leqslant \bar{z}_j\}$ where $\bar{z}_j = \sum_{i=1}^{n} \frac{z_{ij}}{n}$. The groups of women are defined in Table 1.

3.7. Summary of the method

The whole chain of operations performed to complete the method can be expressed as the following algorithm:

1. For each case, apply the Algorithm 1 explained in Section 3.2 to generate the cubic matrix of voxels for the shape.
2. For each matrix of voxels, apply the algorithms detailed in Section 3.2 to get the part of the shape included in the union of the two boxes (region of interest) as shown in Fig. 3.
3. For each 3D region of interest, extract 100 slices perpendicular to Z-axis as the 1-voxel height 2D sections of the 3D shape.
4. For each homologous (equally numbered) section of all cases, consider them as realizations of a random compact set and find their Baddeley–Molchanov mean set, as explained in Section 3.5.
5. Pile up all the resulting mean sets along the Z-axis to build the final prototype, at heights as stated in Section 3.6.

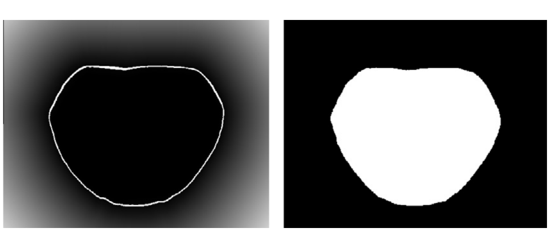

Fig. 6. Mean distance function and Baddeley–Molchanov mean set of sets in Fig. 4.

4. Results

The main goal of this work is to show a methodology that aims at getting prototypes for the different sizes; therefore, as an illustration, we have segmented our data set into different groups, getting a prototype for each of them. The European Normative to sizing system (European Committee for Standarization, 2002) defines a system with 9 sizes for the bust circumference, and another 9 sizes for the height, according with the intervals detailed in Table 2.

According with the European Committee for Standardization (European Committee for Standarization, 2002), sizes are usually defined from the combination of nine height intervals (154–158 cm, 158–162; 162–166; 166–170; 170–174; 174–178; 178–182; 182–186 and 186–190 cm), and another nine bust ranges (74–82 cm; 82–90; 90–98; 98–106; 106–118; 118–131; 131–143; 143–155 and 155–167 cm), so we should carry out a segmentation of our sample set in 81 groups and get a prototype per group. Nevertheless, in this way a large number of groups are completely empty or just contain a few women on them. To build mean sets on larger subsets we have to consider a smaller number of groups with greater sample sizes. Table 3 shows the bust and height measures of the 27 groups proposed together with the number of women in them.

As can be seen in Table 3, 10 out of these 27 groups have quite large sample sizes. As an illustration, the methodology exposed in Section 3 has been applied for building prototypes for these groups. For a better understanding of the results, these ten groups have been labeled with capital letters A,B,C,...J, as detailed in Table 1. Fig. 7 shows the prototypes (mean sets) obtained for each group. As said in Section 3.6, to make the 3D reconstruction the 2D mean sets have been stacked maintaining a spacing between them proportional to the real average height of the group that is being averaged. Different viewpoints for some of the prototypes shown in Fig. 7 are also shown in Fig. 8.

In addition to the prototypes, we have obtained mean sets for each section of interest of the body of women in each group. From each mean section, the contour of the resulting 2D shape can be measured and compared with the mean of the corresponding *"real"* anthropometric measures collected in the data set. As an illustration, Table 4 compares the contour of the resulting mean sets for the sections corresponding to the bust, waist and hip of the women in the different groups, to the mean of their corresponding measures collected in the data set. Confidence sets are also computed from the measures in the data set, and the percentile corresponding to the value obtained from the Baddeley–Molchanov mean is finally shown. Note that in many cases, the mean measures of our contours differ significantly from those obtained from the anthropometric measures. In our opinion, this is due to the fact that our methodology considers each section as a set and therefore the average takes into account the full shape of these sets, whereas

Table 2
Bust and height measurement ranges defined by the European Normative to sizing system. All measures in mm.

Bust. Code	Bust (cm)	Height. Code	Height (cm)
1	74–82	1	154–158
2	82–90	2	158–162
3	90–98	3	162–166
4	98–106	4	166–170
5	106–118	5	170–174
6	118–131	6	174–178
7	131–143	7	178–182
8	143–155	8	182–186
9	155–167	9	186–190

Table 3
Bust and height measurement ranges that used to segment our data set jointly with the number of women on each group. The units are in all cases mm.

Bust (cm)	Height 1 ⩽162 cm	Height 2 [162–174) cm	Height 3 ⩾174 cm
[74–82)	253	97	2
[82–90)	1038	686	31
[90–98)	1074	645	45
[98–106)	784	304	14
[106–118)	468	164	7
[118–131)	121	46	2
[131–143)	14	2	1
[143–155)	0	1	0
[155–167)	0	0	0

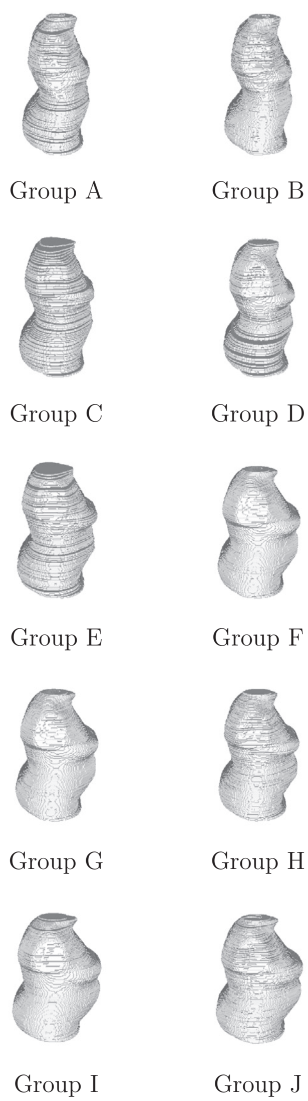

Fig. 7. Prototypes obtained with our methodology for the women groups defined in Table 1.

when the standard anthropometric means are computed, just the perimeters of these sets are considered.

5. Discussion

A interesting fact to be discussed is the difference between anthropometric measures taken on the woman with tape measure and our values. The differences are very likely due to the fact that

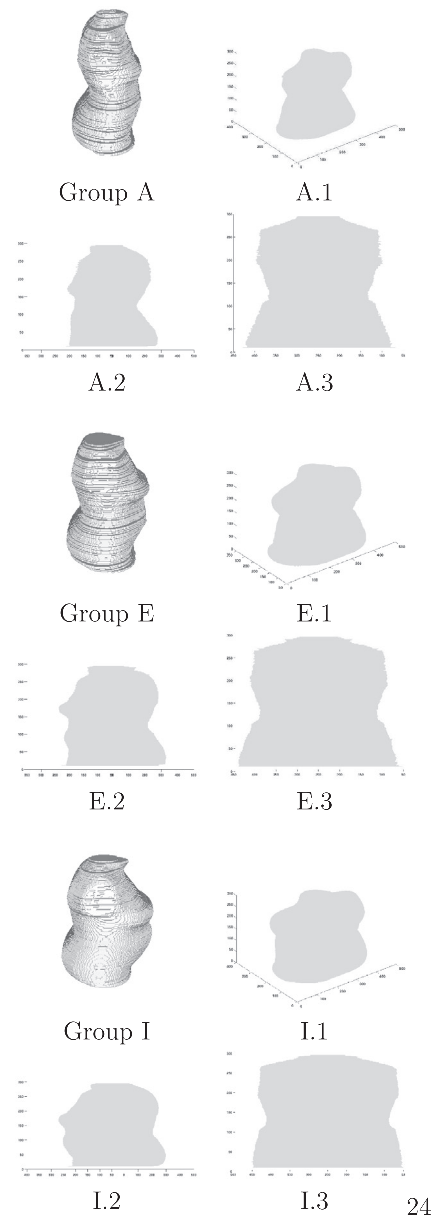

Fig. 8. Some of the prototypes shown in Fig. 7 are now shown from different view points. Viewpoints of Fig. A.1, E.1, and I.1 correspond to an $azimuth = -37.5^0$ and an $elevation = 30^0$; Fig. A.2, E.2 and I.2 to an $azimuth = 60^0$ and an $elevation = 0^0$; and Fig. A.3, E.3 and I.3 to an $azimuth = 180^0$ and an $elevation = 0^0$.

the real measurements were taken by different persons and with a not sufficiently unified criterion. A study with less samples (persons) but with measurements more carefully taken should be more close to settle the question. If measurements are well taken, corrections should be applied to our algorithms to make them coincide; this is a work currently in progress. We guess that the fact of having discrete voxels has introduced some inaccuracy in the calculated lengths.

Another point to be discussed is the roughness of the final model. Piling up slices causes slight sawtooth-shaped surface along the height dimension. This could be minimized either by taking a higher number of slices instead of the 100 we have used or smoothing the final result with a morphological operation like a 3D-opening with a spherical structuring element, essentially with aesthetic purposes. Nevertheless, we have preferred to show the

Table 4
Comparison of the contour of the Baddeley Molchanov mean sets and the corresponding *"real"* mean measures, for three particular sections. All units are given in mm.

Group	B–M	Antrop.	Confidence set	Percentile
Bust				
A	820.16	794.67	[790.71, 798.62]	1
B	829.57	802.42	[795.80, 809.03]	1
C	889.96	863.69	[861.66, 865.71]	0.86
D	888.3	863.29	[860.78, 865.78]	0.84
E	974.72	938.43	[936.32, 940.53]	0.94
F	1048.6	937.70	[934.95, 940.45]	1
G	1048.6	1015.11	[1012.63, 1017.58]	0.88
H	1045	1013.22	[1008.96, 1017.48]	0.83
I	1139.7	1110.34	[1105.69, 1114.98]	0.77
J	1130.3	1114.30	[1106.43, 1122.16]	0.67
Hip				
A	754.38	925.46	[917.46, 933.47]	0
B	758.97	951	[937.59, 964.41]	0
C	803.84	985.24	[980.42, 990.07]	0
D	811.01	998.52	[993.17, 1003.87]	0
E	914.31	1030.43	[1024.59, 1036.26]	0.01
F	999.32	1053.77	[1046.99, 1060.54]	0.16
G	999.32	1073.37	[1066.19, 1080.53]	0.12
H	995.8	1101.91	[1089.57, 1114.26]	0.06
I	1111.1	1154.11	[1142.23, 1165.99]	0.35
J	1099.2	1173.27	[1154.06, 1192.49]	0.16
Waist				
A	660.34	679.67	[672.09, 687.26]	0.30
B	676	692.34	[677.67, 707.01]	0.42
C	729.7	751.21	[746.88, 755.55]	0.33
D	733.6	738.70	[733.55, 743.85]	0.47
E	822.95	842.05	[837.58, 846.52]	0.32
F	927.86	823.12	[817.20, 829.04]	0.98
G	927.86	930.59	[925.42, 935.77]	0.47
H	894.55	919.94	[910.05, 929.83]	0.31
I	1028.5	1039.82	[1031.72, 1047.92]	0.46
J	1012.5	1028.57	[1014.53, 1042.62]	0.46

results without any post-processing to get the anthropometric measures for comparison without alteration.

Regarding the utility of the method, having a 3D virtual prototype of the body shape has become specially important for computer graphics and specially for computer-aided design industry. Also, 3D prototypes can be of great help for developing an accurate and rapid garment design (like a swimming suit) for different ranges of sizes. In the same way, for the design of certain ergonomic furniture prototypes, body shapes that capture the main real body dimensions are also of interest.

6. Conclusions

The major contributions of this paper are threefold. Firstly, anthropometric 3D human body analysis has undergone a major scientific and technological development in recent years, including research studies in digital human models, avatars and archetypal analysis. However, the transfer of this knowledge to the industry has had minimum impact due to the lack of knowledge about the relationship between the anthropometry of the user, the apparel design and the final adjustment. This knowledge has hardly been addressed from a scientific perspective. The problem has been addressed for the first time in this article from a innovative mathematical perspective.

A novel statistical methodology to define prototypes in apparel design has been introduced, providing a new tool to help on the support decision-making processes in textile industry; getting accurate prototypes is one of the most important issues in the apparel development process, they guarantee a suitable fitting for a range size and a successful garment design.

Secondly, current methodologies on prototypes design are mainly based on resuming the body of each woman with a set of 1D anthropometric measurements. Unlike these methodologies, in this paper, a statistical and computational method has been developed to build prototypes from 3D anthropometric data that takes into account information of the shape of each woman's body. In our opinion, this captures much better the concept of shape the apparel designers look for. It is more valuable for garment design since it is useful to build 3D mannequins than cannot only provide the measures listed in tables but also any other that the designer may require. Other recent approaches based on 3D anthropometric data works with 3D surface points, too. The difference with our approach is that we work with volumes, and we analyze them without using deformations that alter the original shape. Additionally, only a few statistical methods can work with the parameters that define the surfaces and they are quite complex.

Finally, as the shape of the prototype has to represent women shapes for a segment of the population, our approach is based on the mathematical definition of mean shape which, to our knowledge, has been never used before in this context.

In a Euclidean space, there is a clear and unique concept of mean which corresponds to the arithmetic average of realizations. However, the concept of an average or *mean* shape is not trivial and allows different definitions. In particular, we have proposed to use the Baddeley–Molchanov mean set. Baddeley–Molchanov mean set is one of the most flexible definitions of mean set as it can be adapted to each specific application depending on the distance considered. Our particular choice allows to consider the volume of the women and to emphasize differences between women in their horizontal cross sections, which is natural and logical in the apparel design context.

In addition to the prototypes, we have obtained mean sets for each section of interest of the body of the women in each group. These sections can also be used to get more accurate estimates of the contour measures.

7. Further work

It is envisaged to extend this work in several ways. In this work 2D cross sections have been extracted at key points at selected heights from a 3D solid. In future work, instead of extracting 2D cross sections we plan to work directly with the 3D solid. This 3D solid can be seen as a realization of a compact set. A prototype of a female human shape can be obtained by a applying a popular definition of mean set. In that way we can also get a prototype than better synthesizes the average body shape for a range of sizes.

It also of interest for the apparel industry to represent the variation of the 3D body shapes around the mean set (prototype) which allow more feasibility on the design of clothes. For this purpose, in a future work we plan to introduce confidence regions or set intervals that generalize the concept of confidence intervals widely used in classical statistics. Confidence sets can provide a guideline to deform the encapsulated structure of the body (mean set), within statistically justified bounds with a level of confidence. The introduction of confidence sets not only allow to guide the design of clothes but also the statistics learned from the population can be used to generate virtual populations for studies of simulation (virtual body models or mannequins) using computer aided and/or computer graphics tools. Such virtual populations can be controlled by designers either to statistically match an existing population, to increase the sample size, to generate extreme cases (body shapes) or to study the influence of certain parameters related to body shape, on the design of clothes.

As future work, we are developing a computer user interface for interactive body models. The main purpose of this interface will be to help online costumers to find their size by matching their own body model with a certain prototype. Once the prototype has been found this could be deformed within certain limits using the confidence regions as well as providing a level of confidence to the costumer. The level of confidence could interpreted as a personalized level of "fitting" for clothes.

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