A STATISTICAL APPROACH TO BUILD 3D PROTOTYPES FROM A 3D ANTHROPOMETRIC SURVEY OF THE SPANISH FEMALE POPULATION

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Abstract: Fitting cloth is a problem for both the customer and the apparel industry, but analysis of anthropometric data can be useful to define better sizing systems. In 2006, the Spanish Ministry of Health coordinated a study to obtain 3D anthropometric data of the Spanish women. Our aim in this work is to develop a statistical methodology to define prototypes based on the 3D clouds of points obtained from 3D scans of a great number of women and apply it to the 3D anthropometric survey of the Spanish female population. To build the prototypes, 3D images will be built, and after registration, homologous 2D sections will be averaged, and a 3D "mean" shape will be reconstructed from them.

1 INTRODUCTION

In 2006, the Spanish Ministry of Health coordinated a study to obtain anthropometric data of the Spanish women. Its aim was to provide real and consistent measures to apparel designers in order to normalize the sizing system. The final purpose is to increase the protection of consumers and to help in the treatment of alimentary mental disorders.

A sizing system classifies a specific population into homogeneous subgroups based on some corporal dimensions (Chunga et al., 2007). There are several local and international standards proposing a regulation of the sizing system based on key anthropometric measures, but the lack of common criteria is one of the drawbacks for their implementation. Most of them propose size systems by taking into account just a single anthropometric dimension, although more elaborated systems use distributions of two or three variables to define a sizing chart and cross-tabs to select the size system covering the highest percentage of the population. Anyway, anthropometric measures show a great variability on body proportions, and it is not possible to cover all the different body morphotypes with this kind of models. That is why, multivariate approaches have been proposed to develop sizing systems. Principal components analysis are often used to reduce the dimension of our anthropometric data set, and the two first principal components are used to generate bivariate distributions (Chen et al., 2009; Hsu, 2009; Luximon et al., 2011; Gupta and Gangadhar, 2004; Hsu, 2009; Salusso-Deonier et al., 1986). As an alternative to bivariate distributions, the cluster techniques using partitioning methods like k-means algorithms, group the population into morphologies using the complete set of anthropometric variables as input (Chunga et al., 2007; Zheng et al., 2007; Ng, R. and Ashdown, S.P. and Chan, A., 2007). A large scale implantation of this statistical approach using data mining and decision trees, has been proposed in Hsu and Bagherzadeh et al. (Hsu and Wang, 2005; Bagherzadeh et al., 2010). Different alternative approaches based on optimization algorithms were first proposed by Tryfos (Tryfos, 1986), who used integer programming to partition the body dimension space into a discrete set of sizes by choosing the size system to optimize the sales of garment. Later on, McCulloch et al (McCulloch et al., 1998) modified this approach by focusing the problem on the quality of fit instead of on the sales.

Since fitting cloth is a problem for both the customer and the apparel industry (Fan et al., 2004), na-

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tional anthropometric surveys have been carried out in the latest years in different countries (USA, UK, France, Australia and Germany among others). These studies show that a high percentage of population has fitting problems with the cloth. Studies developed in the UK (Smith, 2007) and Germany (Chunga et al., 2007) show that 60% and 50% respectively of customers manifest to have difficulty in finding clothes that fit them properly. In the same way, an anthropometric study done in USA (Faust and Carrier, 2010) to update the sizing ASTM standards also concluded that 54% of the population was not satisfied with the fitting of the ready to wear (RTW) cloth (Bye et al., 2008). Additionally, from the technological point of view, new 3D body scanning techniques constitute a step forward in the way of conducting and analyzing anthropometric data and can contribute to promote new anthropometric surveys to obtain more accurate measurements (Simmons and C.Istook, 2003).

In this paper we propose a statistical methodology to define prototypes based on the 3D cloud of points obtained from 3D scans of the body of a sufficient number of women and then we apply it to the 3D anthropometric survey of the Spanish female population. Another work who have been working following this idea can be found in (Haslera et al., 2009).

From the 3D cloud of points of each woman, a 3D image of a 3D shape can be built. After registration of these 3D images, a fixed number of 2D cross sections can be obtained for each woman. Each of these sections coincides with an anatomically relevant point detected in each shape. Each set of corresponding sections for all women can be considered as a sample of a Random compact closed set whose mean set can be computed. A random closed set is a popular probabilistic model for shapes with a growing interest in the Computer Science and in particular in the Computer Vision literature. Its formal definition jointly with many examples of this concept can be found in (Stoyan et al., 1995; Matheron, 1975; Cressie, 1993). Different definitions of the mean set of a random compact set can also be found in the literature (Stoyan and Stoyan, 1994; Baddeley and Molchanov, 1998; Simó et al., 2004). In this paper the Baddeley-Molchanov definition of mean set will be used. Finally, each prototype will be obtained as the 3D-reconstruction of a complete body using these cross section means.

The description of our data set and is given in section 2.1. The computational details to obtain and process the images and the definition of Baddeley-Molchanov mean are explained in section 2.2. Section 3 illustrates the results of the application of our methodologies to the anthropometric database of Spanish women. Some conclusions and possible further developments conclude the paper in section 4.

2 MATERIALS AND METHODS

2.1 Data Set

A sample of 10415 Spanish females from 18 to 70 years old were randomly selected. They were scanned by using the Vitus Smart 3D body scanner from Human Solutions, a non-intrusive laser system formed by four columns allocating the optic system, which moves from the head to the feet in about ten seconds performing a sweep of the body. Several cameras capture images and associated software provided by the scanner manufacturers, makes a triangulation that allows the knowledge of the 3D spatial location of a great amount of points on the body surface. These points are grouped in triangles forming a mesh which is stored as a file in Stereo-Lithography format (.stl).

Standard white garments were used to harmonize the measurements, and seven small wooden half-spheres were attached to the body surface on anatomically relevant points. One of them was fixed on the third neck vertebra, two more over the left and right clavicles, a couple of them on the low waist and high waist in the right side, and the corresponding pair on the left side. These marks were automatically detected by the software from the mesh of points, and their coordinates are stored in a separated file in .xml format.

2.2 Methodology

As a first step, a 3D binary image is produced from the collection of points located on the surface of each woman scanned. Running through the vertical axis of the body (z-axis), the image is divided into thin slices. The points that belong to each slice are enclosed by their convex hull (Rosenfeld and Kak, 1982) which is then filled.

Some special cases must be taken into account: when a horizontal plane cuts not only the trunk but also the arms we would wish not a convex hull enclosing the three shapes but one for each of them. This is tackled by imposing limits to the point coordinates which are considered: only those into a parallelepiped (box) limited by certain proportions of body height and width are considered. Using proportions assures us that this limitation is valid for all individuals, since the box does not need to be too tight to separate appropriately the arms from the main body.

This method does not provides a global 3D convex hull, neither a prefect fit because human body sections are not always convex. Nevertheless, more accurate methods to reconstruct the shape would have need many ad-hoc adjustments and would have been too prone to error with a so wide spectrum of cases. We think that approximation by height-section convex hull is enough for the purpose of this work.

Once the 3D matrix of voxels is available, each shape is rotated 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 and the inertia matrix is calculated and diagonalized. The diagonalizing 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 dimension the matrix to hold the result of the mean shape.

The last step in our data ”preprocessing” is to obtain the 2D cross sections of each 3D aligned shape. Six anatomical fixed points are identified on the women’s body surface and a pre-stated number of 2D cross sections are extracted between each pair of them for all women.

The different cross sections will be considered as realizations of random compact sets (Stoyan et al., 1995; Matheron, 1975; Cressie, 1993). So we will have a random compact set corresponding to each level, and the sample mean of these cross sections will give us a natural way to define each prototype. The 3D reconstruction of these 2D means would lead us to obtain the desired prototype.

Different definitions of the mean set of a random compact set can be found in the literature, the most important ones being the Aumann mean (Stoyan and Stoyan, 1994), the Vorob’ev mean (Stoyan and Stoyan, 1994) and the Baddeley-Molchanov mean (Baddeley and Molchanov, 1998), with the Baddeley-Molchanov mean being the most flexible one. A brief review of the Baddeley-Molchanov definition of mean set is given below.

Let Φ be a random compact set on $\Re^2$. Let $\mathcal{F}'$ be the space of non-empty closed sets with hit-miss topology (see (Matheron, 1975)) and let $d : \Re^2 \times \mathcal{F}' \to \Re$ be a generalized distance function i.e. a lower semi-continuous function with respect to the first argument and measurable with respect to the second argument in such a way that the two following requirements are fulfilled: (i) If $F_1 \subset F_2$ then $d(x,F_1) \geq d(x,F_2)$ for all x in $\Re^2$, and (ii) $F = \{x : d(x,F) \leq 0\}$. Let m be a metric (or pseudo-metric) on the family of distance functions and let m_W be the restriction of m to W (a certain compact set, here a window). Suppose that $d(x,\Phi)$ is integrable for all x and we define the mean distance function $d^*(x) = Ed(x,\Phi)$. Let $\Phi(\varepsilon) = \{x \in W : d^*(x) \leq \varepsilon\}$ with $\varepsilon \in \Re$ and let $\varepsilon^* = argmin_\varepsilon\, m_W(\Phi(\varepsilon), d^*)$. The Baddeley-Molchanov mean of Φ, $E_{bm}\Phi$, is the set $\Phi(\varepsilon^*)$.

Let Φ_i with $i = 1,\ldots,n$ be a random sample of the random set Φ, i.e. a collection of independent and identically distributed (as Φ) random sets. The estimation of $E_{bm}\Phi$ results from the empirical distance average defined as

$$\hat{d}^*(x) = \frac{1}{n}\sum_{i=1}^{n} d(x,\Phi_i). \qquad (1)$$

In our case we have m samples of m random sets Φ_j $j = 1,\ldots,m$, corresponding to each cross section of the body of the woman, and the procedure to compute the m sample mean sets $E_{bm}\Phi_j$, $j = 1,\ldots,m$ would be very complex and would require a lot of computation.

Alternatively, Lewis et al. in (Lewis et al., 1999) propose a different empirical approximation to the Baddeley-Molchanov mean set. They suggest to use another ”discrepancy criteria” when choosing the optimal threshold, namely the ε^* that minimizes

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

where $A(\Phi)$ denotes the area of Φ. The optimal threshold ε^* is then the value that makes more similar the area of $\bar{\Phi}(\varepsilon^*)$ 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.

3 RESULTS

Our main aim is to show a methodology to get prototypes for the different sizes, so, as an illustration, we have segmented our data set in different groups, getting a prototype for each of them. Pregnant women, those who are breast feeding at the time, who have undergone any type of cosmetic surgery (breast augmentation, liposuction, breast reduction, etc), who are younger of 20 or older than 65 , are deleted from the data set for this study. According with the European regulation, the European sizing system is built by taking into account girth and height measurement ranges. So nine sizes are usually defined for the bust measurement and another nine sizes for the height (Table 1).

Table 1: Standard size coding according with the bust and height dimensions (in cm).

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

Instead of segmenting the population according with the 81 possible combinations of these bust and height codes, we segment the population in a lower quantity of groups, maintaining the nine groups for the bust measurement, by defining just three height groups (Table2)

Table 2: Height groups (in cm).

Code	1	2	3
Height	<162	[162 - 174)	≥ 174

As bust and height are the corporal dimensions used to segment the population, in order to get accurate prototypes, instead of working with the whole body, a region of interest comprising the trunk of the women, is isolated for our study, and prototypes will be built to fit this region. Fig 1 shows, as an example the prototype built for those women whose bust ranges between 74 and 82 cm, and whose height is under 162 cm. In fig 2 different views of the same prototype are also shown.

4 CONCLUSIONS

A new statistical methodology has been developed to build prototypes from 3D anthropometric data. From a 3D cloud of points, a 3D image of a 3D shape has been built and registered to get homogeneous volumes. Once a group of women sharing similar anthro-

Figure 1: Prototype for the segment of women with a bust measurement ranging between 74 and 82 cm, and whose height is under 162 cm.

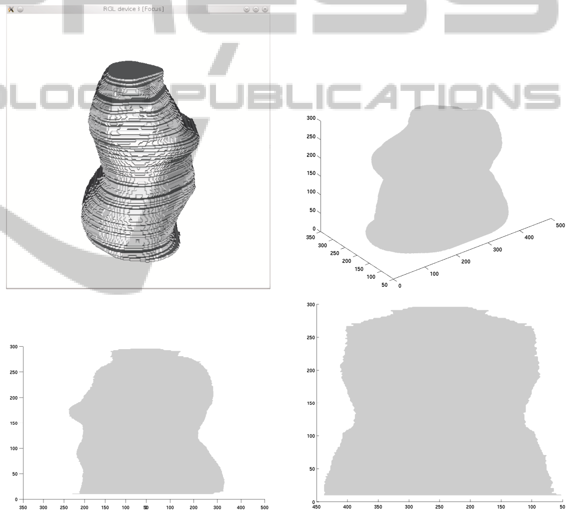

Figure 2: Different views of a prototype.

pometric measurements is selected, their 3D ”mean shape” is a valuable information for apparel industry. Our contribution in this work has been to build this 3D ”mean shape”. From 2D cross sections of these 3D aligned shapes, we have computed the sample (Baddeley - Molchanov) mean of each homological section. The 3D reconstruction of these 2D means allows us to obtain the desired prototype. In our opinion, to average the 2D homologous sections has allowed us to build prototypes that reproduce in a quite accurate way the shape (and proportions) of the woman’s body. Our aim for future works is to work directly with the 3D volumes to obtain 3D ”mean shapes”.

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