Expert Systems with Applications 39 (2012) 10512–10520

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Apparel sizing using trimmed PAM and OWA operators

M.V. Ibáñez [a,*], G. Vinué [b], S. Alemany [c], A. Simó [a], I. Epifanio [a], J. Domingo [d], G. Ayala [b]

[a] Department of Mathematics, Universitat Jaume I, Castellón, Spain
[b] Department of Statistics and O.R., University of Valencia, Valencia, Spain
[c] Biomechanics Institute of Valencia, Universidad Politécnica de Valencia, Valencia, Spain
[d] Department of Informatics, University of Valencia, Valencia, Spain

ARTICLE INFO

Keywords:
Anthropometric data
Sizing systems
Trimmed k-medoids
OWA operators

ABSTRACT

This paper is concerned with apparel sizing system design. One of the most important issues in the apparel development process is to define a sizing system that provides a good fit to the majority of the population. A sizing system classifies a specific population into homogeneous subgroups based on some key body dimensions. Standard sizing systems range linearly from very small to very large. However, anthropometric measures do not grow linearly with size, so they can not accommodate all body types. It is important to determine each class in the sizing system based on a real prototype that is as representative as possible of each class. In this paper we propose a methodology to develop an efficient apparel sizing system based on clustering techniques jointly with OWA operators. Our approach is a natural extension and improvement of the methodology proposed by McCulloch, Paal, and Ashdown (1998), and we apply it to the anthropometric database obtained from a anthropometric survey of the Spanish female population, performed during 2006.

1. Introduction

The development of ready to wear (RTW) cloth requires an estimation of body measures of the target population to generate sizing charts, patterns on a basic size and grading parameters. However, most apparel manufacturers create and adjust their own size charts by trial and error using small customer surveys, mainly models representing the basic size, plus analysis of sales and returned merchandising reports (Chen et al., 2009b). Nevertheless, the growing relocation of the pattern and production activities and the poor level of application of sizing standards are producing one of the main clothing complaints: the lack of fitting.

There are several local and international standards proposing a regulation of the sizing system based on key anthropometric measures, but the lack of common rules and criteria is one of the drawbacks for their implementation. In this context, 'vanity sizing' grows as a common practice among clothing companies. With this strategy, companies often adjust the measurement specifications for each size based on a sale strategy designed to make consumers, especially women, feel better about fitting into smaller sizes (Fan, Yu, & Hunter, 2004, 2007), and therefore prompting them to buy more. The method we propose is aimed at helping difficult customers to find the correct size in different companies. In fact, nowadays, the correct size selection is the main obstacle to large scale online garment sales because it is difficult to find the fit garment from the general size information.

A sizing system classifies a specific population into homogeneous subgroups based on some key body dimensions (Chunga, Lina, & Wang, 2007). The major dilemma is to decide into how many size groups should the population be divided, in order to optimize benefits and user satisfaction. Most of the standard sizing charts propose sizes based on intervals over just one anthropometric dimension. Current standards consider the low correlation between some key dimensions and use bivariate distributions to define a sizing chart and cross tabulation to select the sizes covering the highest percentage of population. For lower limb garments, European Committee for Standardization (2002) propose the combination of three anthropometric dimensions (waist girth, hip girth and stature) leading to a significant increase of the number of sizes. This decreases the profit for the companies since they have to reorganize their production lines and make them more complex. Moreover, correlations between anthropometric measures show a great variability on body proportion. It is not possible to cover so different body morphologies with these kind of models. That is why, multivariate approaches have been proposed to develop sizing systems. Principal components are often used to reduce the dimension of anthropometric data sets, and the two first principal components are used to generate bivariate distributions (Chen et al., 2009; Gupta and Gangadhar, 2004; Hsu, 2009a, 2009b; Luximon, Zhang, Luximon, Xiao, 2011; Salusso-Deonier, DeLong,

* Corresponding author.
E-mail addresses: mibanez@mat.uji.es (M.V. Ibáñez), guillermo.vinue@uv.es (G. Vinué), sandra.alemany@ibv.upv.es (S. Alemany), simo@mat.uji.es (A. Simó), epifanio@mat.uji.es (I. Epifanio), juan.domingo@uv.es (J. Domingo), guillermo.ayala@uv.es (G. Ayala).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.02.127

Martin, Krohn, 1985, 1986). As an alternative to bivariate distributions, clustering techniques using partitioning methods, like k-means algorithms, group the population into morphologies using the complete set of anthropometric variables as inputs (Chunga et al., 2007; Ng, Ashdown, & Chan, 2007; Zheng, Yu, & Fan, 2007). A large scale implementation of this statistical approach using data mining and decision trees was proposed in Hsu and Wang (2005) and Bagherzadeh, Latifi, and Faramarzi (2010). Different alternative approaches, based on optimization algorithms, were first proposed by 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. (1998) modified this approach by focusing the problem on the quality of fit instead of on the sales. The sizes were determined by means of a nonlinear optimization problem. The objective function measured the misfit between a person and the prototype, using a particular dissimilarity measure and removing from the data set a prefixed proportion of the sample. In this paper, we are going to follow this idea. In fact, our paper has been conceived as an extension of the work of McCulloch et al. (1998).

All the multivariate approaches based on optimization algorithms, need to define an objective function. These functions basically measure the misfit between a feature vector from a given person and a model or prototype by combining the misfit observed for each feature. It is clear that discrepancies in certain features (or dimensions) are more critical than others. It is important to get a meaningful combination of these discrepancies. In this sense, the analytic hierarchy process (AHP) proposed in Saaty (1980), tries to convert subjective assessments of relative importance into a set of overall scores or weights. AHP is one of the more widely applied multi-attribute decision making methods. Applied to the customized garment design process, Chen et al. (2009b) propose ordered weighted averaging operators (OWA) jointly with fuzzy methods, to model the easy allowance of the 2D patterns. The weights of the OWA operators can be used to adjust the compromise between the style of garments and the general comfort sensation of wearers.

Fitting RTW clothes is a problem for both customer and apparel industry (Fan et al., 2004). For this reason during last years both national administrations and industrial groups of the clothing sector have been fostering national anthropometric surveys in different countries: USA, UK, France, Australia, Spain and Germany among others. These studies show that there is a high percentage of population with difficulties to find proper fit cloth. Anthropometric studies carried out up to date show high percentages of population with fitting problems. Studies carried out in UK Smith (2007) and Germany Chunga et al. (2007), show a 60% and 50% respectively of customers who say to have difficulty in finding proper clothes. In the same way, an anthropometric study performed in USA Faust and Carrier (2010) to update the sizing ASTM standards also concluded that a 54% of the population was not satisfied with the fitting of the ready to wear (RTW) cloth (Bye, LaBat, McKinney, & Kim, 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 contribute to promote new anthropometric surveys. As a result, broad anthropometric databases are available and constitute valuable information to improve garment fitting adapted to the body shape of the population starting from the definition of an optimized sizing system.

In this way, a national 3D anthropometric survey of the female population was conducted in Spain in 2006 by the Spanish Ministry of Health. The aim of this survey was to generate anthropometric data from the female population addressed to the clothing industry. In this study, a sample of 10.415 Spanish females from 12 to 70 years old randomly selected was measured using a 3D body scanner and 95 anthropometric measures were obtained (Anthropometric survey).

In this paper, we propose a methodology that combines some of these approaches in order to develop a more efficient apparel sizing system that can increase accommodation of the population. We apply it to the anthropometric survey data of the Spanish female population (Anthropometric survey). Our approach is close to that of McCulloch et al. (1998). However, there are two main differences. First, when looking for the k prototypes, we use a trimmed k-medoid clustering method i.e. a trimmed version of the Partitioning Around Medoids (PAM) algorithm, instead of the continuous optimization problem proposed by McCulloch et al. (1998). So, our aim is to look for medoids i.e. for typical persons within the sample, which means that our final prototypes will be real persons of the data set. Additionally, we take into account that an apparel sizing system is intended to cover only what we could call standard population, leaving out those individuals who might be considered outliers respect to a set of measurements. For this reason we propose the use of a trimmed version of PAM procedure. Second, the dissimilarity measure proposed by McCulloch et al. (1998), is merely based on the sum of squared discrepancies over each individual feature. We propose to modify this dissimilarity measure by taking into account to the user, using an OWA operator.

The outline of the paper is as follows: Section 2 proposes the methodology. The description of our data set is given in Section 3. The application of our procedure to the anthropometric database of Spanish women is given in Section 4. Conclusions and possible further developments conclude the paper in Section 5.

2. Methodology

When we talk about an apparel sizing system, our target population is not the whole population. An apparel sizing system is intended to cover only that we could call standard population, leaving out those individuals who might be considered as outliers regarding to a set of measurements.

As it has been stated in the introduction, the methodology that we propose is based on two basic ideas: the use of a trimmed version of the k-medoids algorithm and the use of OWA operators to combine the individual discrepancies proposed by McCulloch et al. (1998). Our aim in this section is to explain these ideas in a detailed way.

2.1. Trimmed k-medoids

A classical partitioning cluster method is the well-known k-means method. However, the k-means method is not a robust procedure, and their results can be influenced by outliers and extreme data, or bridging points between clusters. Trimmed k-means is one way of increasing robustness of the k-means which combines the k-means main idea with a impartial trimming procedure García-Escudero and Gordaliza (1999) in such a way that a proportion α (between 0 and 1) of observations are trimmed. It is analogous to k-means but the proportion α of observations is discarded by the own procedure so the trimmed observations are self-determined by the data.

Let $x_1, \ldots, x_n$ be n observations of dimension p. Let k be the number of groups. The k-means method searches for a set of k points, $m_1^*, \ldots, m_k^*$, the centroids, verifying

$$\{m_1^*, \ldots, m_k^*\} = argmin_{m_1,\ldots,m_k} \frac{1}{n} \sum_{i=1}^{n} \inf_{1 \leqslant j \leqslant k} \|x_i - m_j\|^2, \tag{1}$$

and each point x_i is assigned to its closest center m_j^*. Given k and the trimming size α, trimmed k-means searches k points, $m_1^*, \ldots, m_k^*$ such that

$$\{m_1^*,\ldots,m_k^*\} = argmin_{\mathbf{Y}}, \{m_1,\ldots,m_k\} \frac{1}{\lceil n(1-\alpha)\rceil} \times \sum_{x_i \in \mathbf{Y}} \inf_{1\leqslant j\leqslant k} \|x_i - m_j\|^2, \tag{2}$$

where $\mathbf{Y}$ ranges on subsets of $x_1,\ldots,x_n$ containing $\lceil n(1-\alpha)\rceil$ data points ($\lceil\cdot\rceil$ denotes the integer part of a given value). Each non-trimmed point x_i is assigned to its closest centroid m_j. An algorithm for computing trimmed $k-means$ can be found in Garcıa-Escudero, Gordaliza, and Matrán (2003), and it is available as part of the R package R Development Core Team (2009, 2010).

Instead of using trimmed k-means, we will use a modified version, the trimmed k-medoids, joining the best of the k-medoids and trimmed k-means algorithms. The k-medoids algorithm is based on finding k representative subjects (also known as medoids (Kaufman & Rousseeuw, 1990)) from the data set in such a way that the sum of the within cluster dissimilarities is minimized, instead of minimizing the squared distances as in k-means. Methods based on the minimization of sums (or averages) of dissimilarities (the so-called L^1 methods) are much more robust to outliers than methods based on sums of squares, such as k-means. Note also that the centroids from the k-means do not have to be one of the subjects in the original data set. This has been one of our principal motivations for selecting the trimmed k-medoid method, because medoids are representative subjects in the clusters, very useful in our application. Another reason was the possibility of applying the k-medoid to data described only by dissimilarities. The medoids always exist, even when the data can be related only by a collection of dissimilarities. We just have to compute the dissimilarities between our subjects, there is no need to calculate cluster centers or centroids.

Trimmed k-medoids is analogous to k-medoids but a proportion α of observations is discarded by the own procedure (the trimmed observations are self-determined by the data as before). Furthermore, trimmed k-medoids are analogous to trimmed k-means. Let $d(x_i,x_j)$ be the dissimilarity between subjects i and j. For a given k and a trimming proportion α, trimmed k-medoids searches k subjects of the data, $x_{i_1}^*,\ldots,x_{i_k}^*$ such that

$$\left\{x_{i_1}^*,\ldots,x_{i_k}^*\right\} = argmin_{\mathbf{Y},x_{i_1},\ldots,x_{i_k}} \frac{1}{\lceil n(1-\alpha)\rceil} \sum_{x_i\in\mathbf{Y}} \inf_{1\leqslant j\leqslant k} d(x_i,x_{i_j}), \tag{3}$$

where $\mathbf{Y}$ ranges on subsets of $x_1,\ldots,x_n$ containing $\lceil n(1-\alpha)\rceil$ data points, and $\lceil\cdot\rceil$ denotes the integer part of a given value. Each non-trimmed point x_i is assigned to its closest medoid $x_{i_j}^*$. The algorithm of García García-Escudero et al. (2003) can be easily adapted for computing trimmed k-medoids. The detailed algorithm is given in Algorithm 1.

Note that the medoid of a group can be computed with function *pam* (with $k = 1$ for each group) from the R package, Maechler (2010).

Summarizing, we can describe the algorithm as:

1. Select k starting points that will serve as seed medoids.
2. Assume that $x_{i_1},\ldots,x_{i_k}$ are the k medoids obtained in the previous iteration:
   (a) Assign each observation to its nearest medoid:
   $$d_i = \min_{j=1,\ldots k} d(x_i,x_{i_j}),\quad i=1,\ldots,n,$$
   and keep the set H having the $\lceil n(1-\alpha)\rceil$ observations with lowest d_i's.
   (b) Split H into $H = \{H_1,\ldots,H_k\}$ where the points in H_j are those closer to x_{i_j} than to any of the other medoids.
   (c) The medoid x_{i_j} for the next iteration will be the medoid of observations belonging to group H_j.
3. Repeat the step 2 a few times. After these iterations, compute the final evaluation function.

This algorithm is repeated a few times and the best solution is preserved, see Algorithm 1.

Algorithm 1. An algorithm for trimmed k-medoids

Set k, number of groups; ns, (for instance, $ns = 10$) and nr (for instance, $nr = 100$).
Select k starting points that will serve as seed medoids (e.g., draw at random k subjects from the whole data set).
for $r = 1 \to nr$ **do**
  for $s = 1 \to ns$ **do**
    Assume that $x_{i_1},\ldots,x_{i_k}$ are the k medoids obtained in the previous iteration.
    Assign each observation to its nearest medoid:

$$d_i = \min_{j=1,\ldots k} d(x_i,x_{i_j}),\quad i=1,\ldots,n,$$

    and keep the set H having the $\lceil n(1-\alpha)\rceil$ observations with lowest d_i's.
    Split H into $H = \{H_1,\ldots,H_k\}$ where the points in H_j are those closer to x_{i_j} than to any of the other medoids.
    The medoid x_{i_j} for the next iteration will be the medoid of observations belonging to group H_j.
    Compute

$$F_0 = \frac{1}{\lceil n(1-\alpha)\rceil} \sum_{j=1}^{k} \sum_{x_i\in H_j} d(x_i,x_{i_j}). \tag{4}$$

    if $s == 1$ **then**
      $F_1 = F_0$.
      Set M the set of medoids associated to F_0.
    else
      if $F_1 > F_0$ **then**
        $F_1 = F_0$.
        Set M the set of medoids associated to F_0.
      end if
    end if
  end for
  if$r == 1$ **then**
    $F_2 = F_1$.
    Set M the set of medoids associated to F_1.
  else
    if $F_2 > F_1$ **then**
      $F_2 = F_1$.
      Set M the set of medoids associated to F_1.
    end if
  end if
endfor
return M and F_2.

Let us see in the next section, the dissimilarity measure used.

2.2. Dissimilarity measure

As it was said before, the dissimilarity used to quantify the misfit between an individual and the prototype is a key ingredient to obtain an efficient sizing system. Let us start by introducing some notation. Each individual in the data set is represented by a feature vector of size p of their body measurements, $x = (x_1,\ldots,x_p)$, and $d_i(x,y)$ denotes the dissimilarity in the ith feature between individuals x and y.

We propose to take into account the basic ideas stated in McCulloch et al. (1998) to define the distance functions. First, they argue that fit is better predicted by proportional rather than absolute differences between individual and prototype features. Second, that there is an interval where there is no difference between the values x_i and y_i probably because the fit is perfect although the values are different. Third, that the distance is not symmetric (a garment which is too small may not affect fit in the same way as one which is too large). In particular, for a given value of $|x_i - y_i|$, the distance may be smaller if $x_i < y_i$ than if $x_i > y_i$. Finally, that dissimilarities in certain dimensions are more critical to fit than others. As McCulloch et al. (1998) state, there are a wide variety of functional forms which satisfy the above requirements, but we will continue using the one they propose, and define:

$$d_i(x_i, y_i) = \begin{cases} a_i^l\left(ln(y_i) - b_i^l - ln(x_i)\right), & \text{if } ln(x_i) < ln(y_i) - b_i^l \\ 0, & \text{if } ln(y_i) - b_i^l < ln(x_i) < ln(y_i) + b_i^h \\ a_i^h\left(ln(x_i) - b_i^h - ln(y_i)\right), & \text{if } ln(x_i) > ln(y_i) + b_i^h \end{cases} \quad (5)$$

where a_i^l, b_i^l, a_i^h and b_i^h are constants for each dimension. In this specification, the b_i represents the range in which fit is judged to be perfect and the a_i reflects the rate at which fit deteriorates outside this range. This distance function, illustrated in Fig. 1, satisfies the criteria before mentioned, and allows a great deal of flexibility through the choice of parameter values.

Once defined the dissimilarity for each feature, McCulloch et al. (1998) propose to define the global dissimilarity between individuals x and y as a sum of squared discrepancies over each of the p measurements.

$$d(x, y) = \sum_{i=1}^{p} (d_i(x_i, y_i))^2 \quad (6)$$

Although it could be more natural to consider

$$d(x, y) = \max_i d_i(x_i, y_i) \quad (7)$$

because this distance would consider the worse fit from the point of view of each feature. When the distance is defined as in Eq. (6), the different dissimilarities $d_i(x_i,y_i)$'s are being *aggregated*, and in our opinion, a lot of possibilities can be opened by looking at the problem under this point of view. In particular, an Ordered Weighted Average operator can be used to aggregate $d_i = d_i(x_i,y_i)$.

A brief introduction to OWA operators is exposed in the following subsection.

2.3. Ordered weighted averages

These operators were introduced in Yager (1988). An OWA operator of dimension p is a mapping $f : \mathbb{R}^p \to \mathbb{R}$ with an associated weighting vector $W = (w_1, \ldots, w_p)$ such that $\sum_{i=1}^{p} w_j = 1$ and where

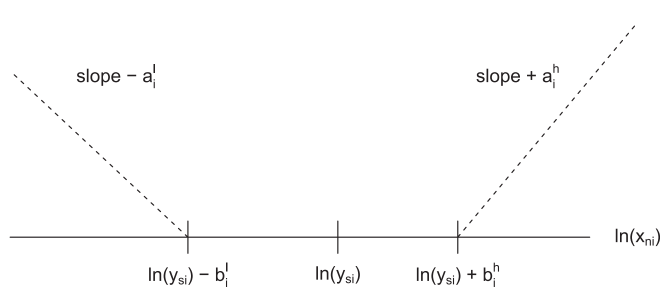

Fig. 1. This plot, based on McCulloch et al., 1998, illustrates the defined dissimilarity and represents the degree of misfit between the medoids and each individual for the *i*th dimension.

$f(d_1, \ldots, d_p) = \sum_{j=1}^{p} w_j b_j$ where b_j is the j-th largest element of the collection of aggregated objects $d_1, \ldots, d_p$. The particular cases shown in Table 1 can better illustrate the idea underlying OWA operators.

As OWA operators are bounded by the max and min operators, Yager (1988) introduced a quantity called *orness* to measure the degree to which the aggregation is like a min *or* max operation:

$$\text{orness}(W) = \frac{1}{p-1} \sum_{i=1}^{p} (p - i) w_i. \quad (8)$$

We have used a simple procedure to generate the set of weights $W = (w_1, \ldots, w_p)$. They are obtained as a mixture of the binomial $Bi(p-1, 1.5\text{–}2\cdot\text{orness})$ and the discrete uniform probability distributions, that is to say, $w_i = \lambda \cdot \pi_i + (1 - \lambda) \cdot \frac{1}{p}$, where π_i is the binomial probability for each $i = 0, \ldots, p-1$, see León, Zuccarello, Ayala, de Ves, and Domingo (2007).

Remarkable advantages of this choice are its flexibility and simplicity: the weights are easily obtained and are also easy to interpret. In addition, our practical experiments have shown that it works well for this case.

3. Our data

A sample of 10.415 Spanish females from 12 to 70 years old randomly selected from the official Postcode Address File was measured using a 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 ten seconds performing a sweep of the body. From the 3D mesh, 95 anthropometric measures were calculated semi-automatically combining automatic measures based on geometric characteristic points with a manual review. Women were asked to wear a standard white garment, a swimming hut, a top and a short that were designed and scaled in 5 sizes, in order to harmonize the measurements. The design of the garment was based on the standard ISO 20685.

In addition to physical measurements other qualitative measures were collected such as women satisfaction with their bodies. They were also asked about their size in the current Spanish sizing system. Because of the lack of consistency and rigor in our current sizing system, the answers to this question were in some cases numerical and in other qualitative: small, large, etc. and in all the cases were considered as an approximation to the real size.

Not all of the anthropometric variables are useful for establishing the sizing system. From these 95 body measurements the five most relevant features in the garment development were obtained. They were chosen for different reasons. First, we follow the recommendations of experts. Second, they are commonly used in the literature about sizing system design. Finally, they appear in the European Normative to sizing system (European Committee for Standardization, 2002). These variables are: *Bust circumference*, *Chest circumference*, *Neck to ground length*, *Waist circumference* and *Hip circumference*. Taking into account the European normative, we will consider *Bust circumference* as the principal dimension to define the size and the other four measures as secondary

Table 1
Illustrating examples of OWA aggregation values.

W	$f(d_1, \ldots, d_n)$
$(1,0,\ldots,0)$	$\max_i d_i$
$(0,0,\ldots,1)$	$\min_i d_i$
$(\frac{1}{n}, \frac{1}{n}, \ldots, \frac{1}{n})$	$\frac{1}{n}\sum_{j=i}^{n} d_i.$

Table 2
Summary statistics for the five variables considered.

Measurement (cm)	Minimum	First quantile	Median	Mean	Third quantile	Maximum
Neck to ground length	116.4	132.9	136.8	137	140.8	161.9
Bust circumference	73	87.4	93.3	95.02	100.7	145.7
Chest circumference	45.91	90.78	96.37	97.92	103.7	150.30
Waist circumference	58.60	75.6	83.10	84.98	92.40	167.6
Hip circumference	72.8	98.3	103.3	104.9	109.9	170.8

Table 3
Constants that define the distance function in Eq. (5).

	a_i^l	a_i^h
Chest circumference	7.5	22.5
Bust circumference	8.3	25
Neck to ground length	9.5	28.5
Waist circumference	6.7	20
Hip circumference	8.3	25

dimensions. Jointly to these main features, other additional features could be used to describe each size.

Finally, a selection of 6013 women was done for this study, leaving out some categories, namely pregnant women, women who declare to be breast feeding at the time, those who have undergone any type of cosmetic surgery (breast augmentation, liposuction, breast reduction, etc.), and the ones younger than 20 or older than 65. So, our data set contained finally five anthropometric body measurements of 6013 Spanish women. The summary statistics of these five variables can be seen in Table 2.

4. Results

The data set was firstly segmented into twelve subsets (classes), taking into account *bust circumference* values according to the sizes defined in the European Normative to sizing system European Committee for Standardization, 2002.The trimmed k-medoids algorithm (Section 2.1), was applied to each segment with $k = 3$ clusters, and a total of 36 sizes were obtained.

The number of random initializations was 600, with seven steps per initialization. The proportion of trimmed sample was prefixed to $\alpha = 0.01$ per segment. Regarding to the constants that define the metric (Eq. (5)), their values were chosen taking into account:

a. As in McCulloch et al., 1998, a person's feature being larger than the prototype's one was penalized three times more than that being smaller $\left(b_i^l = 3b_i^h \text{ and } a_i^l = 3a_i^h\right)$.
b. The dissimilarity consistent with a perfect fit $\left(b_i^l\right)$ was chosen within each segment to cover all the range of values of each measurement in such a way that all the individuals would be perfectly fitted in exactly one size, i.e. for each segment j, $b_i^l = \frac{3 \cdot Range(\{x_{j_1 i}, \ldots, x_{j_n i}\})}{4k}$, where $k = 3$ is the number of clusters.
c. The values of a_i^h were chosen, as in McCulloch et al., 1998, to reflect our judgment about the relative rate at which increasing discrepancies in these measurements deteriorate fit, they are given in Table 3.

On the other hand, the value of orness was 0.7. As has been explained in subSection 2.3, this value represents an aggregation of the individual dissimilarities, getting a compromise between their minimum and their maximum. We chose a value close to one to

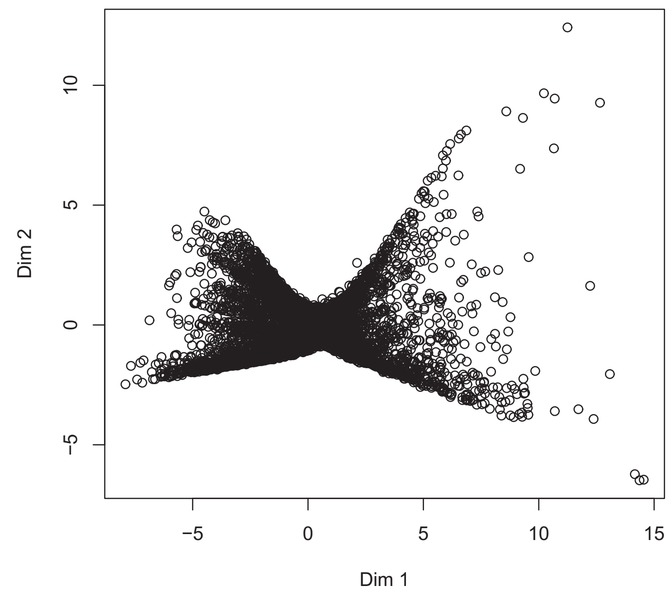

Fig. 2. Two dimensional representation of woman dissimilarities (as explained in Section 2.2) by classical multidimensional scaling.

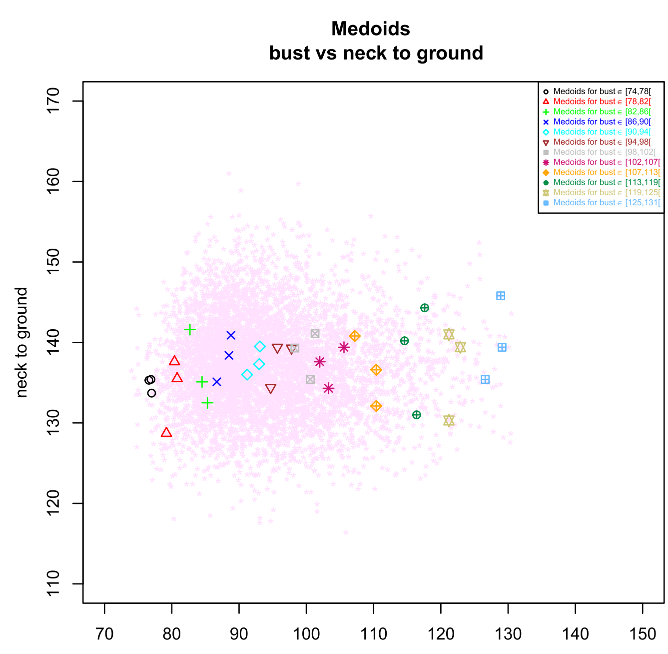

Fig. 3. Bust vs neck to ground for each one of medoids. [82,86] medoids are represented with a green cross, while [94,98] medoids are represented with a brown facing down triangle. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

highlight high dissimilarity values in any of the considered measurements.

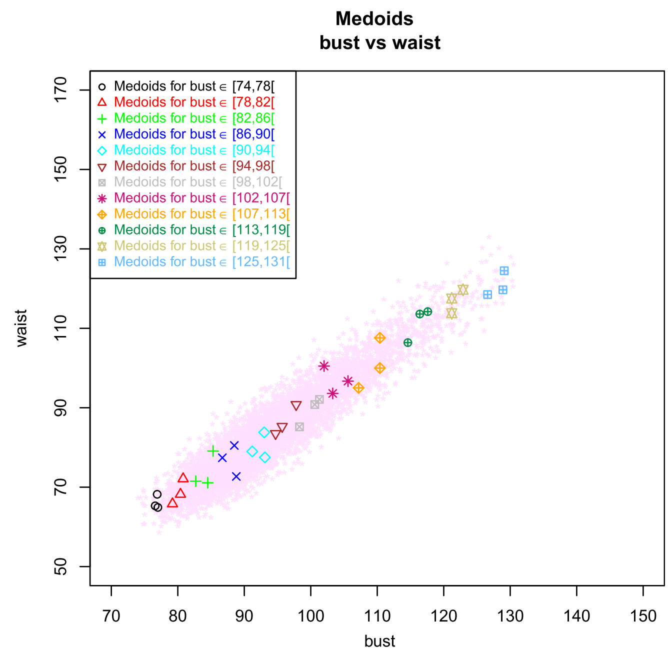

Fig. 4. Bust vs waist for each one of medoids. [82,86] medoids are represented with a green cross, while [94,98] medoids are represented with a brown facing down triangle. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Medoids measurements for bust size [82,86[.

Woman code	Chest	Neck to ground	Waist	Hip	Bust	Hip-waist	Bust-waist
CANDE021	88.6283	132.5	79.1	99.1	85.3	20	6.2
SEVI132	88.6745	141.6	71.5	98.4	82.7	26.9	11.2
LLEID074	87.5182	135.1	71.1	96.1	84.5	20	13.4

4.1. Visualizing of dissimilarities

We have summarized (and represented in Fig. 2) the dissimilarities of our data in two dimensions by means of Classical Multidimensional Scaling. Multidimensional scaling takes a set of dissimilarities and returns a set of points such that the Euclidean distances between the points are approximately equal to their dissimilarities. We have used the function *cmdscale* from R R Development Core Team, 2009. As it can be seen in Fig. 2, there are no separated groups, but a distribution of points covering some area of the feature space. Note that this figure summarizes a lot of information in only two dimensions, and that the dissimilarity proposed in Section 2.2 is not a metric, therefore this graphic should be taken with caution, as an exploratory tool.

4.2. Experimental results

In order to illustrate our results, Figs. 3 and 4 show the scatter plots of bust circumference against neck to ground (Fig. 3) and bust

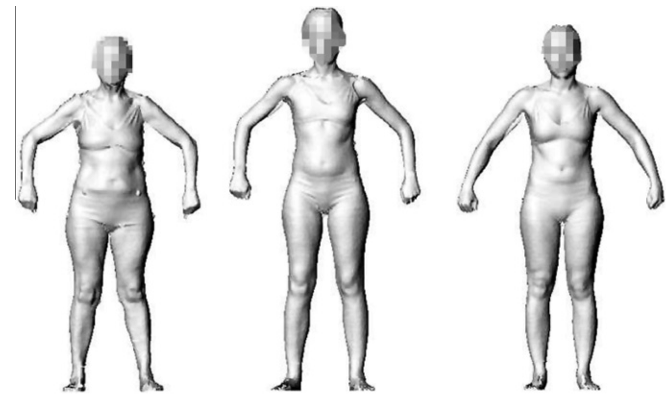

Fig. 5. Front body shape of medoids for size [82,86] (left to right, CANDE021, SEVI132 and LLEID074).

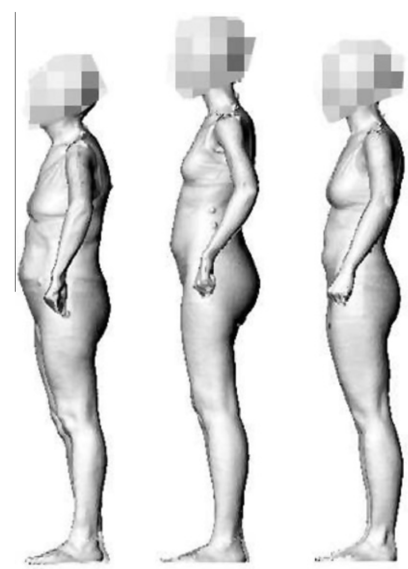

Fig. 6. Lateral body shape of medoids for size [82,86] (left to right, CANDE021, SEVI132 and LLEID074).

circumference against waist (Fig. 4), jointly with the three medoids obtained for each class. The distribution of medoids in both figures show different patterns for each bust range. For example, let us analyze the medoids obtained for women belonging to two particular bust circumference intervals: [82,86[and [94,98[. Identification codes and main measurements of these medoids are detailed in Tables 4 and 5. As it can be seen, medoids in range [94,98[point out the need of only two sizes for length (medoids JAEN075 and CANDE068, have similar neck to ground measures) while medoids in range [82,86[show a greater dispersion along this variable, pointing out the adequacy of three sizes with different lengths for this bust range. The same medoids show an opposite pattern regarding the waist measurements. For bust range [82,86[, medoids SEVI132 and LLEID074, have similar waist

Table 5
Medoids measurements for bust size [94,98[.

Woman code	Chest	Neck to ground	Waist	Hip	Bust	Hip-waist	Bust-waist
SILLE034	96.9951	134.4	83.5	102.5	94.7	19	11.2
JAEN075	101.129	139.3	90.8	108.5	97.8	17.7	7
CANDE068	99.0432	139.4	85.3	104.5	95.7	19.2	10.4

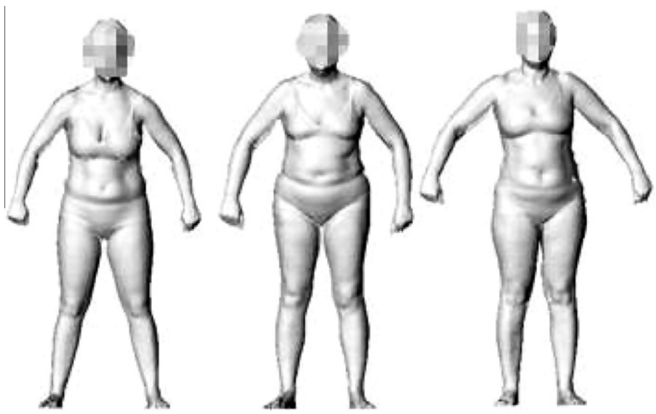

Fig. 7. Front body shape of medoids for size [94,98] (left to right, SILLE034, JAEN075 and CANDE068).

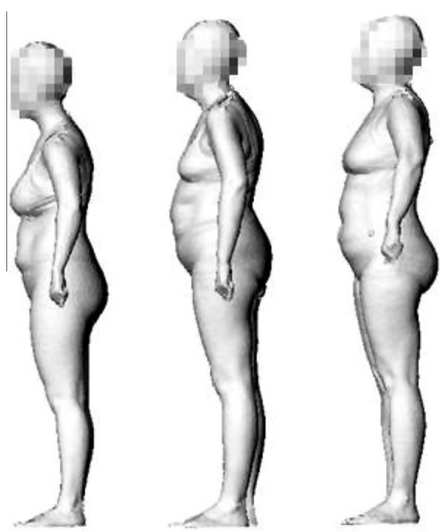

Fig. 8. Lateral body shape of medoids for size [94,98] (left to right, SILLE034, JAEN075 and CANDE068).

circumference while the three medoids of range [94,98[show quite different values for this variable. So, dissimilarity in range [94,98[is more affected by waist, while in range [82,86[the variability of neck to ground predominates.

Figs. 5 and 6 show the body shape of the medoids obtained for the class defined by bust size [82,86]. As it can also be seen in Table 4, SEVI132 and LLEID074 have similar bust-waist proportion and similar waist circumference, while their respective heights differ. In the same way, Figs. 7 and 8 show the body shape of the three medoids for the bust sizes [94,98[. JAEN075 and CANDE068 have similar neck to ground measurement (Table 5), but show a different shape in the belly area affecting the measure of the waist and therefore giving different proportions between bust and waist.

Finally, we would like to check the goodness of our methodology and the improvement in the garment fit, if the 36 sizes defined by our medoids were considered instead of those defined by the

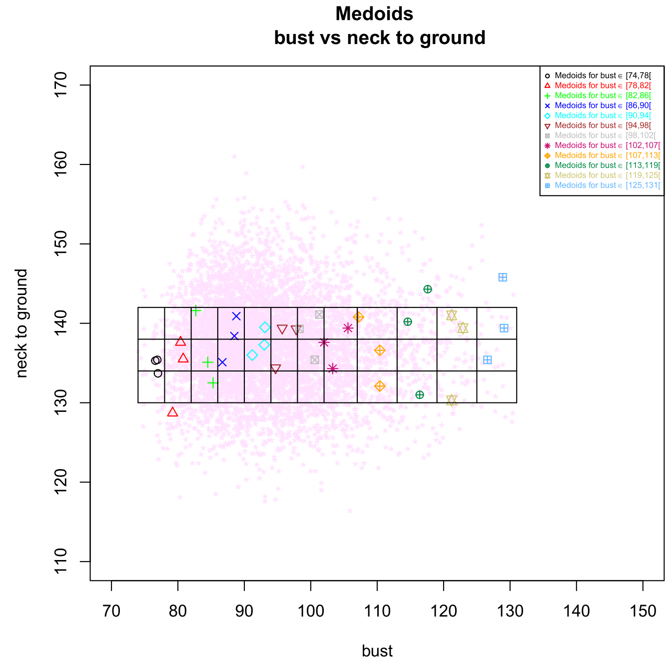

Fig. 9. Bust vs Neck to ground, jointly with our medoids and the prototypes defined by the European Normative.

European Normative to sizing system European Committee for Standardization, 2002. This normative establishes 12 sizes according with the combinations of the bust, waist and hip measurements detailed in Table 6, and does not fix neither chest nor height standard measurements. Anyway, given the high correlation observed between bust and chest measurements in the women of our data set, we can approximate the chest measures through a linear regression analysis, taking the bust measures as independent variable. So, from the bust measurements detailed in the Normative, the chest measures can be approximated. The obtained values are also shown in Table 6. On the other hand, as the measurement form neck to ground shows no correlation with the other considered variables, we will take as neck to ground measures for the standard sizing system, the values 132, 136 and 140 cm because those are the most repeated measurements, and in our opinion are the measurements which best cover our data set (see Fig. 9). So our aim at this point is to compare the adequacy of the sizing system defined from the medoids obtained in our work, with that defined by 36 prototypes resulting to consider the 12 groups detailed in Table 6 and 3 different neck to ground measurements per group. Figs. 9 and 10 show two different scatter plots jointly with our medoids and the corresponding measurements of the prototypes obtained following the considerations of the European Normative. In both graphics, prototypes would be located in the center of the corresponding boxes.

Finally, Fig. 11 shows the cumulative distribution functions for the dissimilarities between all the women and the medoids obtained with our method and for the dissimilarities between all the women and the standard prototypes defined by the European Normative to sizing system. In both cases, distances and dissimilarities have been computed by using the dissimilarity function

Table 6
Measurement to define the sizes on the European Normative to sizing system.

Bust	76	80	84	88	92	96	100	104	116	122	128	134
Waist	60	64	68	72	76	80	84	88	94	100	106	112
Hip	84	88	92	96	100	104	108	112	117	122	127	132
Chest	79.50	83.38	87.26	91.14	95.02	98.90	102.78	106.66	112.46	118.30	124.12	129.94

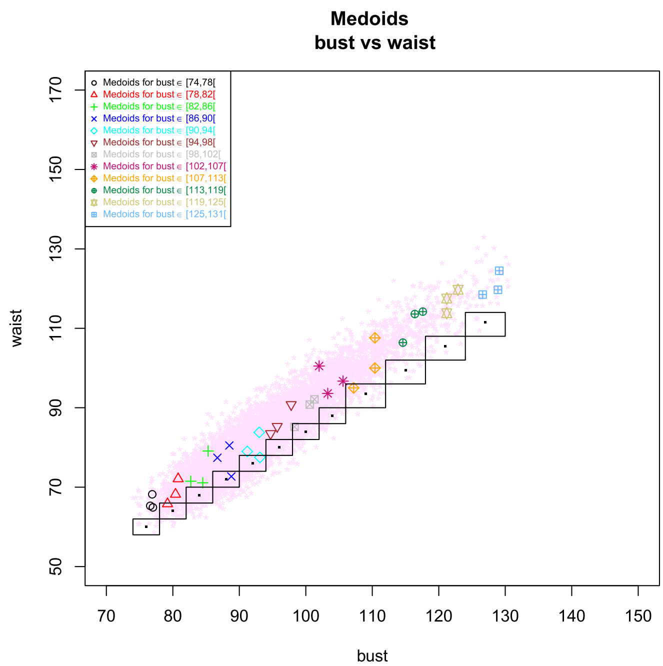

Fig. 10. Bust vs waist, jointly with our medoids and the prototypes defined by the European Normative.

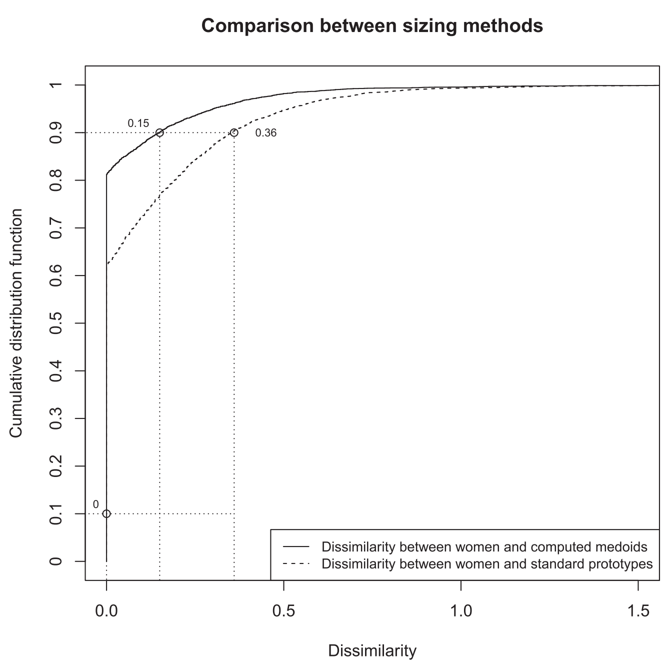

Fig. 11. Cumulative distribution function for the dissimilarities between women and computed medoids and for the dissimilarities between women and standard prototypes.

stated in Section 2.2. Cumulative distribution functions show the probability associated with the fact "dissimilarities less or equal than a certain value".

As we can see in Fig. 11, there is a percentage of population (rounding 60%), which gets a perfect fit according with our dissimilarity criteria in both sizing systems. With our sizing system, this percentage increases until 80%. Women measurements are closer to their corresponding medoids computed with our method, because the corresponding cumulative distribution function increases faster than the cumulative distribution function for the standard system.

This type of plot can also be used to identify the expected range of the dissimilarities, that is to say, the values between the 10 and 90*th* percentiles. In this case, the range for the dissimilarities between women and computed medoids is [0,0.15], while the range for the dissimilarities between women and standard prototypes is [0,0.36], so dissimilarities with respect to the standard prototypes are greater than the dissimilarities with respect to the new computed medoids.

For all of these reasons, this plot serves to confirm that our method builds more reasonable sizes in which the women are more accommodated.

5. Conclusions

There are two approaches in the literature to define a sizing system: traditional step-wise sizing and optimization methods. Traditional methodologies are based on segmentation of bivariant distributions of two independent variables, typically stature and waist for lower garment and stature and chest/bust for upper garment. The benefit of the traditional method is the easy way to communicate the size to consumers. On the contrary, variability of other principal anthropometric dimensions is not considered and, in consequence, a large part of the population feels no properly accommodated on the existing size system. Optimization methods try to find the minimum number of sizes that can cover the maximum percentage of population. However, the resulting sizing distribution based on multiple body dimensions presents several difficulties for a consumers find their proper size. Our study combines both approaches: the pre-segmentation based on bust, which is the primary dimension for upper garment fitting and patterning, provides a first easy input to choose the size, while the resulting morphotypes for each bust size optimize sizing using the main anthropometric dissimilarities.

A methodology to develop an apparel size system has been introduced and applied to a a recently obtained Anthropometric data base of Spanish women. The core of our approach is to segment the data set using a principal dimension (Bust circumference) and apply a trimmed-*k*-medoids algorithm with the number of sizes fixed within each class. We fix, too, a re-accommodating rate and define the discrepancy between individuals and prototypes using OWA operators. This approach has several advantages over currently used systems. Among those stated in McCulloch et al., 1998, ours makes simultaneously the selection of individual discommodities, the derivation of prototypes, and the assignment of individuals to size classes but additionally, the prototypes are more realistic because they correspond with real women of the data set. On the other hand, the use of OWA operators has resulted in a more realistic dissimilarity measure between individuals and prototypes.

Acknowledgements

This paper has been partially supported by grants TIN2009–14392-C02–01, TIN2009–14392-C02–02, GV/2011/004 and P1.1A2009–02. We would like also to thank the Biomechanics Institute of Valencia for providing us the data set, and to the Spanish "Ministerio de Sanidad y Consumo" for having promoted and coordinated the "Anthropometric Study of the Female Population in Spain".

References

Ashdown, S. (2007). *Sizing in clothing: Developing effective sizing systems for ready-to-wear clothing*. Woodhead Publishing in Textiles.

Bagherzadeh, R., Latifi, M., & Faramarzi, A. (2010). Employing a three-stage data mining procedure to develop sizing system. *World Applied Sciences Journal, 8*(8), 923–929.

Bye, E., LaBat, K., McKinney, E., & Kim, D.-E. (2008). Optimized pattern grading. *International Journal of Clothing Science and Technology, 20*(2), 79–92.

Chen, W., Zhuang, Z., Benson, S., Du, L., Yu, D., Landsittel, D., et al. (2009a). New respirator fit test panels representing the current chinese civilian workers. *The Annals of Occupational Hygiene, 53*(3), 297–305.

Chen, Y., Zeng, X., Happiette, M., Bruniaux, P., Ngb, R., & Yu, W. (2009b). Optimisation of garment design using fuzzy logic and sensory evaluation techniques. *Engineering Applications of Artificial Intelligence, 22*, 272–282.

Chunga, M., Lina, H., & Wang, M.-J. J. (2007). The development of sizing systems for taiwanese elementary- and high-school students. *International Journal of Industrial Ergonomics, 37*, 707–716.

European Committee for Standardization (2002). European Standard EN 13402-2: Size system of clothing. Primary and secondary dimensions.

Fan, J., Yu, W., & Hunter, L. (2004). *Clothing apperance and fit: Science and technology*. Woodhead Publishing in Textiles.

Faust, M.-E., & Carrier, S. (2010). Women's wear sizing: A new labelling system. *Journal of Fashion Marketing and Management, 14*(1), 88–126.

García-Escudero, L. A., & Gordaliza, A. (1999). Robustness properties of k means and trimmed k means. *Journal of the American Statistical Association, 94*(447), 956–969.

García-Escudero, L. A., Gordaliza, A., & Matrán, C. (2003). Trimming tools in exploratory data analysis. *Journal of Computational and Graphical Statistics, 12*(2), 434–449.

Gupta, D., & Gangadhar, B. (2004). A statistical model for developing body size charts for garments. *International Journal of Clothing Science and Technology, 16*(5), 458–469.

Hsu, C.-H. (2009a). Data mining to improve industrial standards and enhance production and marketing: An empirical study in apparel industry. *Expert Systems with Applications, 36*, 4185–4191.

Hsu, C.-H. (2009b). Developing accurate industrial standards to facilitate production in apparel manufacturing based on anthropometric data. *Human Factors and Ergonomics in Manufacturing, 19*(3), 199–211.

Hsu, C.-H., & Wang, M.-J. J. (2005). Using decision tree-based data mining to establish a sizing system for the manufacture of garments. *The International Journal of Advanced Manufacturing T echnology, 26*, 669–674.

Iscar, A.M., Escudero, L.A.G., Fritz, H. (2010). tclust: Robust trimmed clustering. R package version 1.0-3. URL http://CRAN.R-project.org/package=tclust.

Kaufman, L., & Rousseeuw, P. (1990). *Finding groups in data: An introduction to cluster analysis*. New York: John Wiley.

León, T., Zuccarello, P., Ayala, G., de Ves, E., & Domingo, J. (2007). Applying logistic regression to relevance feedback in image retrieval systems. *Pattern Recognition, 40*, 2621–2632.

Luximon, A., Zhang, Y., Luximon, Y., & Xiao, M. (2011). Sizing and grading for wearable products. *Computer-Aided Design*.

Maechler, M., (2010). Cluster analysis, extended original from P. Rousseeuw, A. Struyf and M. Hubert. URL http://CRAN.R-project.org/package=cluster.

McCulloch, C., Paal, B., & Ashdown, S. (1998). An optimization approach to apparel sizing. *Journal of the Operational Research Society, 49*, 492–499.

Ng, R., Ashdown, S.P., & Chan, A., (2007). Intelligent size table generation. In: Proceedings of the Asian Textile Conference (ATC), 9th Asian Textile Conference, Taiwan.

R Development Core Team, (2009). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0. URL http://www.R-project.org.

Saaty, T. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. McGraw-Hill.

Salusso-Deonier, C., DeLong, M., Martin, F., & Krohn, K. (1985–1986). A multivariate method of classifying body form variation for women's pparel. Clothing and Textiles Research Journal 4 (1), 38–45.

Smith, D.C., 2007. Process, fit and appearance analysis of three-dimensional to two-dimensional automatic pattern unwrapping technology. Thesis submitted to the Graduate Faculty of North Carolina State University.

Tryfos, P. (1986). An integer programming approach to the apparel sizing problem. *The Journal of the Operational Research Society, 37*(10), 1001–1006.

Yager, R. (1988). On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Transactions on Systems Man Cybernet, 18*, 183–190.

Zheng, R., Yu, W., & Fan, J. (2007). Development of a new chinese bra sizing system based on breast anthropometric measurements. *International Journal of Industrial Ergonomics, 37*, 697–705.