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Online 3d Unsupervised and 2d Supervised Classification in Clients' Pattern Recognition

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Abstract

This paper presents the first phase of the process of building an intelligent platform for an e-commerce application. Its first step is consumer's morphology recognition which is an important stage in the process of 3D virtual try-on online. Using this platform will improve garment fit and will decrease return rates which affect the e-commerce sector. A robust strategy was developed to get the consumer's silhouette and link it with 3D database by a 2.5D shape descriptors. This method has been tested on the morphologies of women. The database used is composed of 500 scans of woman bodies from the French Sizing Survey conducted in 2006 by the French Institute of Textile and Clothing. The results show a proven efficiency because our method is a good comprise between big data analysis and space dimension reduction.

Keywords: E-commerce; Morphology pattern recognition; 2D classification; 2D image analysis; 3D clustering; SOM; K-means; Silhouette extraction

Introduction

Recently, owing to the outstanding advantages of price, rapidity, and facility, the e-commerce is an emerging trend embracing almost all sectors of manufacturing industries. Compared to other industries, the development of garment's e-commerce is much slower due to certain limitations arising out of the specificity of the garment purchasing process. From the consumers' and producers' perspective, the restrictions concern mostly: detection of the morphological features of a single person, correspondence between the consumers' measurements and the proper garment size, consumer sensory evaluation and 3D virtual try-on visualization. Those issues are important from the consumers' and producers' perspective and have to be resolved by the manufacturers. From their perspective, a proper technology has to be provided, and all processes involved in the garment retail services must form a coherent whole.

Furthermore, according to the new trends in the trade of goods and services, namely the trend of products' personalization, the on-line platform has to provide fashionable and comfortable garments. This achievement can be realized through the use of co-design and 3D virtual try-on of the products. In this approach, it is important to remember that the body being a three-dimensional object is the final form of dressing for clothes. Thus the fitting of the garment in a 3D environment is most similar to the process of real try-on and can be done just by profound knowledge of the 3D body representation.

Despite the virtual try-on showing a correct fit on a standardized morphology, the client receives a garment not according to their morphology. It misguides the client and causes its general disappointment and financial loss. This practice is the primary factor which generates the high return rates of purchased clothes.

Methodology

The work presented in this paper is a part of a global project aimed at creating an online co-design intelligent platform with integration of 3D garment designs. We endeavour to find a solution to the technological gap: detection of the 3D morphological features of the consumer. This constraint for online garment retail may be overcome by exploring the morphological knowledge obtained from national measurement campaigns and their relevancy to the existing products. This morphological knowledge has to be directly connected to the consumer's measurements and their morphology features. That is the first problem to solve in online garment retail. Attaining precise body measurements ensures a high quality of service and consumer satisfaction. Seeing the need and growing interest of apparel brands we focused on the improvement of the measuring methodology of the garment in e-commerce. There is no automatic and robust method which analyses the human morphology in all its complexity in an e-commerce environment. This complexity leads segmentation of the body to analyse specific shapes function of the e-commerce application deeply. Also, different authors use clustering and pattern recognition algorithms [1-5]

Attaining body measurements online can be resolved in two ways; either by consumers input or via the external capturing device. More and more platforms in e- commerce applications ask the customers to send their morphological data to choose a garment's size which supposed to suit them. Depending on the brand strategy, these data can be a set of traditional measurements taken by the client himself (waist, hip, chest, crotch length, etc.) according to a well-defined protocol or a morphological profile (stature, weight, age) that extrapolates the previous measures from significant morphological database. Nonetheless, ill-fitted garments are still frequent, because a 2D analysis has not taken into account the 3D body shape. Also, whatever the case is, using limited measurements is not sufficient to represent a human shape, even though such measurements are taken correctly by the client [6-8].

Another solution to providing the client's body measurements is a

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non-contact method and can be given by the external image capturing device. It is undoubtedly true the most relevant body measurements tool are the 3D scanners, as it was used in many international measuring campaigns. However, we are searching for a solution which is available for all in an online environment. Therefore it cannot be used in our research as a measuring tool. The number of non-contact size tools available for all online users is limited to the computer's internal or external cameras or the smartphone.

To support the reliability of the method this work judiciously uses 2D and 3D measurement technologies to detect the morphology of an individual consumer online. The first step consisted in using the scanner to classify the 3D morphologies of a target population and to extract the morphotypes representing the centroids of each cluster. Then, a 2D measurement taken by camera made it possible to obtain the silhouette of a customer from two different viewpoints (anterior view, lateral view). It is by comparing the silhouettes extracted from the different morphotypes and those of the client that we were able to identify its morphology, and then its measurements by its stature.

It is important to look at fashion retail from the global perspective and keep in mind that the proper classification of consumers' body dimensions is a first and necessary step to obtaining a final product which is a well-fitted garment. To define the 3D and 2D shape descriptors respectively to the 3D classification of the population and the 2D detection of the client, an anthropometry and morphology analysis must be realized. We recognize the need to create from scratch a strategy for planning the creation of clothing in an online environment in favor of a future manufacturing system to maintain proper functionality [9]. This paper is a first step in the process.

Anthropometry and Morphology Analysis

Anthropometry is the methodical measurement of the human body to determine its physical dimensions and the proportion of its parts among different ages and races or groups [10,11]. Otieno in his work underlines three issues which have to be undertaken by clothing anthropometrics: firstly; an adequate way of measuring the body; secondly, analysis of significant data for size charts; thirdly, use of size charts to assure the consumers' satisfaction with clothing [11].

In this context, a robust anthropometric measurements database is the focal point of developing reliable size charts and morphology classification. That statistical information is used in product optimization. Nevertheless, it is not clear how the anthropometric data are analysed, and confusion has risen by the apparel industry [10]. Additionally, there is no strictly defined procedure by which the database of the anthropometric measurements is used to estimate a representative sample. Also, most of the anthropometric measurements in the database come from old measurement surveys, which have not been updated and do not represent the current population [12]. Each industry can establish their standards for creating size charts and size gradations, which will be accurate if it in a correct way follows real consumers' dimensions and easily can be recognized by all the target population.

Consequently, another issue arising from the omission of updated anthropometric data input is related to the models which are used to design basic clothing patterns. For a vast majority of apparel brands, there is a wooden dummy with the hourglass morphology decided as being perfect and highly most representative. For example in the USA, this fitted just 8% of all female figures [12,13]. There is a broad variety of body shapes (morphotypes). Most of the population cannot find well-fitted garments in the market, which is the main reason of returns rates generated by the individual consumer [14]. On the stage of developing garment size's specification, it is the producer who is responsible for assuring their target customers with the well-fitted garment.

A means to improve the situation is to search the individual customer morphotypes based on a database of current 3D morphotypes which fits into mass customization model.

Industry describes the morphology by dividing the body based on figure types or shape categories. These two defined notions are sometimes used alternately but, indeed, they both represent two different approaches to body description. Figure types are based on the height and the drop value, which is a subtraction between hip and bust circumference, and are used mostly to create the size charts [15]. Shape categories, however, are often utilized by the stylist to advise the style of a garment dedicated to the particular silhouette. The common shape categories are Triangle, 'V' or inverted triangle, "H" or Rectangle, "X" or Hourglass, "O" or Oval [13,16,17]. To identify body shape the most relevant way is to make a "body graph" [17]. It is a manual and time-consuming process, but the results are reliable.

Another way of defining the body shape is by using the calculated well-matched trio, that is body circumference bust, waist, and hips circumference or by using the hierarchical clustering method as it was made for the French Sizing Campaign [18,19]. The method depends on the proper use of the input data taking into account the specificity of what might occur in a specific application.

The way of making a division into a particular type or shape is related to the 'pattern industry' aimed for a specific garment [20]. So it is not uniform across the apparel industry and may vary from brand to brand, from country to country [21]. It means that to describe individual morphology, either based on its type or shape; there is no single unified methodology. Till now there is no software able to classify bodies into morphology clusters automatically [20].

It is a great challenge to group the anthropometric measurements into clusters and to classify them. However, also, a big challenge is to allocate the newly measured body into the pre-defined cluster. The automatic methods of taking body measurements used to classify the body shape in an online environment have limitations, and they must rely on pre-built clusters' database.

Silhouette Extraction by 2d Image Modelling

In the online environment, there is a lack of a method for the assignment of a new client to an existing database that would result in its 3D counterpart creation. Different scientific studies show the interest of using the anterior, lateral or both views in the shape recognition process for the purpose of feature points extraction [5,22,23] or 3D body reconstruction [24-29]. However, most of this research does not have the perspective in developing 3D garment on such virtual models. Therefore, in our opinion, the required accuracy is not sufficient. Boisvert et al., show differences in body measurements and reconstructed 3D human shape expressed in a mean error of 11mm [27]. Nevertheless, to our knowledge, none of them were using a current 3D body shape database. Our research focuses on 2D shape determination from anterior and lateral views, based on a comparison with a database of 3D morphologies managed by the morphotypes of each cluster. The need of image processing comes from the limitation of the online environment we will face during the implementation of the morphotypes recognition and during modelling a three-dimensional counterpart of a client.

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To provide the mathematical logic for classification of the new body in relation to the existing database of 3D morphologies, the process of 2D shape descriptors determination has been endorsed to create a gateway between 3D and 2D environment. The combination of two approaches; first, 2D image capture and 2D pattern recognition; and second, 3D morphology classification and morphotypes mannequin creation. It may lead to an improvement of the online morphology identification process, and by this improve matching of garment fit to body. We position this new process of morphology recognition between ready-to-wear and made-to-measure solutions.

Conception Model

To improve similarity between the individual client and his virtual counterpart (avatar), the process of morphology recognition has to rely on the database of the representative morphological population types. From this perspective, an automatization of morphology recognition process provokes great interest in an online garment retail segment. The avatar of the client can be obtained directly from the scanner, but it will involve the necessary computer processing, for example, elimination of noise, holes and other imperfections by using Rapid Form or other software to process 3D scans and by this the expert's' intervention is necessary [30].

Creation of an avatar of the customer by comparing its data from the scanner with a wide database of morphological dimensions is presented in other works and the similar project CAESAR [25,31,32].

The results are impressive, however, stays in contrary to the principles of online sales. The main reason for this is that to deploy scanner on different stores, distributed wisely to be close to the client, is expensive, time-consuming and obliges the client to be present in the warehouse while scanning.

Therefore, inspired by the desire to develop a superior, more cost-effective model, we have created a conceptual schema of our model, which is formulated around two axes of research: 3D unsupervised classification and 2D supervised classification (Figure 1) [33].

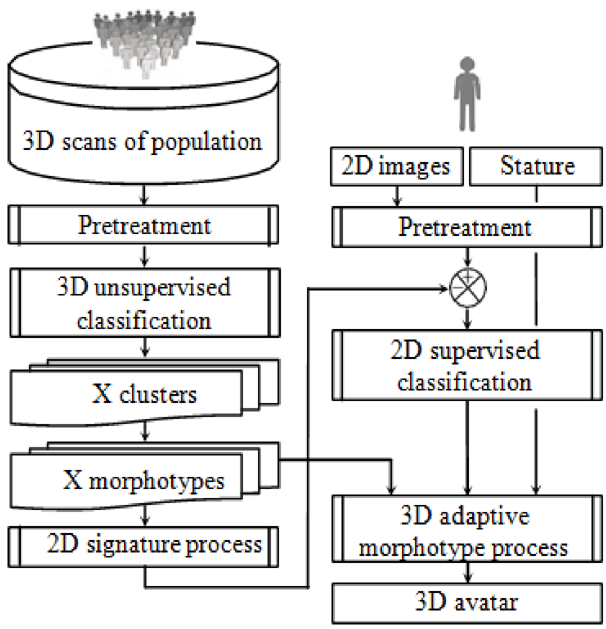

Figure 1: Morphology detection process.

The objective of the first axis is to classify a set of characteristic 3D morphologies of the population. It starts by pretreatment based on Hamad's automatic pre-processing of 3D scans data to extract and standardize the torsos from a group of different morphologies, consistent with the needs of the clothing industry [2,34]. The torsos have been normalized and strictly compared with the stature constraints. The 3D geodesic curves allowed him to describe each 3D torso according to their signature. Then, X clusters are detected by the criteria of the unsupervised 3D classification Davies-Bouldin index [33]. Exploitation of the results of the classification led to the determination of X morphotypes, each of them representing the morphology of a scanned person, the closest to the centroids of each cluster. A process of 3D adaptive morphotypes creation was then applied on each morphotypes to make them adjustable in function depending on a stature parameter. The adjustment of the volume is controlled by the stature following rules extracted from a statistical analysis of each cluster.

The objective of the second axis is the pattern recognition of a new customer by the supervised 2D classification. Working on a 2D scale has a double benefit. The first is economical because it avoids the expensive scanning procedure among retailers. The second is human oriented because the end user can quickly take a picture using a Kinect Microsoft camera, computer camera, smart phone or other accessible tools, which may provide RGB or grayscale images.

Our purpose is to achieve the situation in which the client using the means, as mentioned above, can send by the Internet the lateral and anterior views and a value of stature. The stature is necessary as a reference to establish parametric dimensions of a 3D adaptive morphotype, which is the subject of the next paper. In our work, we focus on torso silhouettes to be coherent with the unsupervised 3D classification data.

A pre-treatment converts different information of silhouettes into standardized torso information. To assign the client to one of the 3D morphotypes required a change of physical space via a 2D signature process. Then, the client is assigned to his specific morphotype by supervised 2D classification. This morphological assignment provides an appropriate choice of the 3D adaptive morphotype and manages the client's avatar by the stature.

D Unsupervised Classification

The foundation of present research is the robustness classification of a target population. Therefore, we have employed the 3D clustering method of the individual morphotypes, which has been developed in Matlab and validated by Hamad et al. [33]. The morphological database is composed of 500 females from the French national measurement campaign conducted in 2006 by IFTH (Institut Français du Textile Habillement).

3D shape pre-processing

The 3D shape pre-processing is composed of three steps: data acquisition, data segmentation, and data normalization. The goal of the first step is to obtain 3D body scan data exploitable for further processing. It consists of filling holes in the hidden zones under arms and in the crotch, removing measurement noises, smoothing and optimizing the mesh by an automatic procedure to clean the body scans. The second step is a segmentation step to create suitable torsos. Taking into account anthropometry and morphology analysis, the bodies are segmented with section planes located at anthropometric points recognized automatically by the body scanner (landmarks on the body). The compatibility between each torso, defined by the size and the number of triangles, is obtained by re-meshing the torsos. The third step represents the 3D object normalization (translating and scaling). For that, we use the minimal bounding sphere method with the algorithm of Gärtner for its precision and fast processing time (Figure 2) [35].

The Gärtner algorithm computes the normalized vertex (xn, yn, zn) from an original vertex (x, y, z) as follows:

$$x_n = \frac{x - c_{x,s}}{d_s};\ y_n = \frac{y - c_{y,s}}{d_s};\ z_n = \frac{z - c_{z,s}}{d_s} \qquad (1)$$

Where,

d_s is the sphere diameter,

$c_{x,s}$, $c_{y,s}$, $c_{z,s}$ is the coordinates of the sphere center.

3D clustering methods

The 3D shape descriptor has to be very sensitive to dissimilarities which enable it to differentiate between morphologies such as the waist, hips, and bust. Geodesic path and distribution of geodesic distances are tools especially interesting in terms of non-rigid shape description and has a low sensibility to posture variations. However, the location of reference points (or starting points) obviously impacts the results and shall be carefully performed. Thus, these reference points should be directly defined by anthropometry properties. The shape descriptor represents the statistical distribution of the geodesic distances between reference points and all points on the 3D torso mesh. The geodesic distances are computed by the well-known Dijkstra's algorithm, the geodesic shape distributions use the kernel density estimation to calculate the probability density function of the data [36,37].

The clustering method used in this study is the straightforward k-means algorithm [38]. The k-means method splits the data set into disjoint clusters from numeric attributes. However, the random initialization of the center of classes (or centroid) and the requirements of several iterations to check the convergence of the algorithm lead to different final clusters. The goal is to find the right compromise between too many clusters (bad separability) and not enough clusters. To find the optimal number of clusters and to evaluate the quality of the obtained clustering, we compute the Davies- Bouldin (DB) criterion clustering evaluation [39]. The Davies-Bouldin criterion is based on a ratio of within-cluster and between-cluster distances, i.e.:

$$DB = \frac{1}{k}\sum_{i=1}^{k} \max_{j \neq i}\{D_{i,j}\}, D_{i,j} = (\overline{d_i} + \overline{d_j}) / \overline{d_{i,j}} \qquad (2)$$

Where,

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

$\overline{d_i}$, the average distance between each point in the cluster i and the centroid of the cluster j

$\overline{d_{i,j}}$, the Euclidean distance between the centroids of the i^{th} and j^{th} clusters

The optimal clustering solution has the smallest Davies-Bouldin index (Figure 3).

Results

Our raw data are taken from the French anthropometric survey. The 500 females were measured using The Vitus Smart 3D body scanner from Human Solutions. The Davies-Bouldin index curve shows that the optimum number of clusters is defined for a value of k=3.

The three torsos and the associated morphotypes are represented in Figure 4.

D Supervised Classification

The goal of this section is to recognize the client online by relying on precedents classified in the morphologies database. For that, 2D supervised classification was used [40]. However, the difficulty is finding a shape descriptor or a similarity function that creates the bridge between the 3D environment of the database and the 2D space of the client in front of its screen.

Identifying one shape from another can be solved by analysing the client's silhouette in relation to that of each morphotype of the database. In this case, to deal with the problem related to the switching from 2D to 3D space, we chose to work in 2.5, i.e. by relying on two images of the client to get closer to the 3D data of the database. In the presented case, the contours extracted from anterior and lateral view, supplemented by the value of a new subject's stature are presented. As it was already specified, the stature will be used, in the next step of research, for the pattern recognition of the morphotype to create the client's avatar.

Image capture protocol

It is considered that to build an accurate system of morphology detection; different conditions must be met. To provide normalized images the subject has to be informed about the protocol of taking the images. For our tests, the distance between the camera and subject was kept as one meter, while the target line is parallel to the ground (or focal plane is perpendicular to the ground). The experiments were carried out using a Kinect RGB camera. The images were framed between the crotch and the 7th cervical with resolution 1280x 960 pixels. Additionally, each subject's height was used as a calibration measure in the morphology reconstruction. It is imperative that the garment

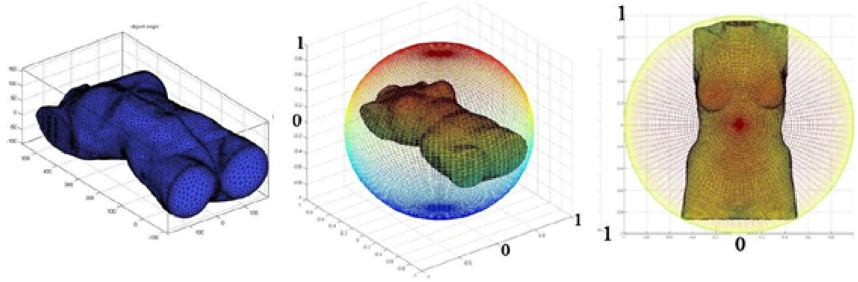

Figure 2: Normalization with the minimum bounding sphere.

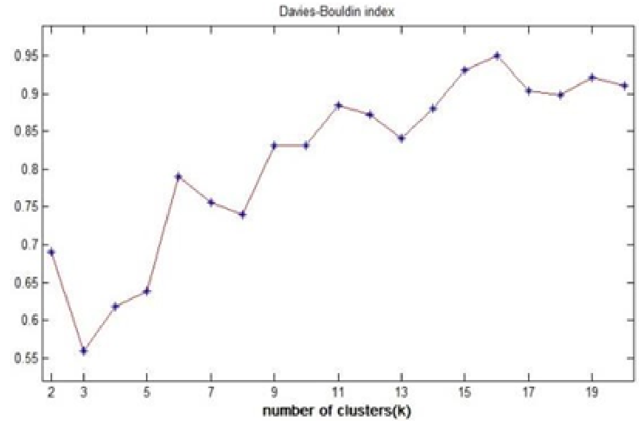

Figure 3: Quality of clustering by Davies-Bouldin index.

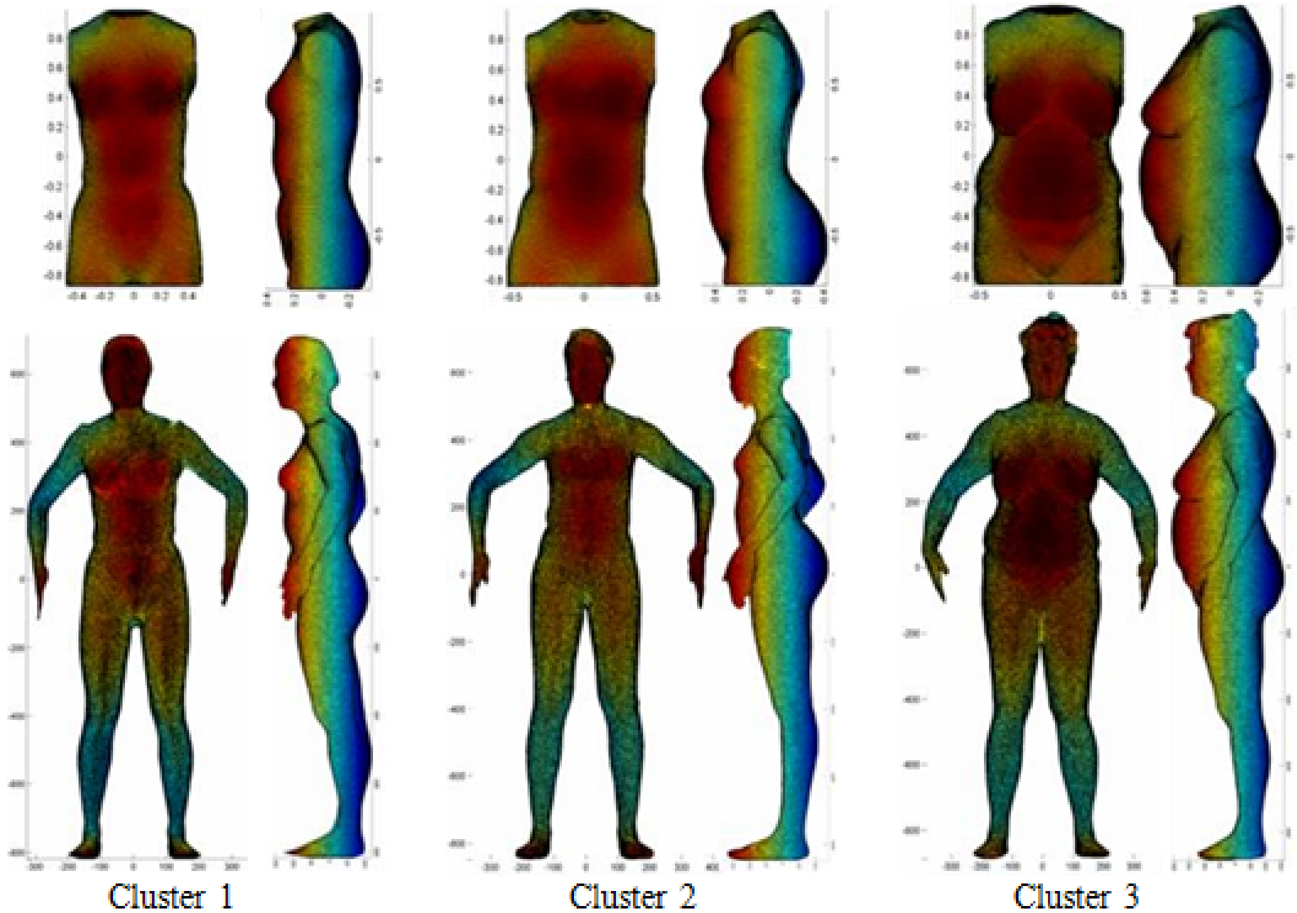

Figure 4: Normalized torsos and morphotypes of the 3 clusters.

be worn close to the body. A black garment on a white background is strongly advised.

2D pre-processing of images

The 2D pre-processing of images is composed of four steps: data acquisition, data segmentation, data normalization and boundary detection of the silhouette. Before seeking the client's morphotype, the images need some pre-processing to be useful. The image's height is reframed between the crotch and the 7th cervical and width to 125% of the width of the hips. From this previous work, the image is converted to grayscale by eliminating hue information and saturation while retaining the luminance (Figure 5a).

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The binary image can now be segmented. Thereby, the image is converted by thresholding. The threshold is defined by the method of Otsu which chooses the threshold to minimize the intraclass variance of black and white pixels [41]. Let the pixels of a given picture be represented in L gray levels [1, 2,…, L]. The number of pixels at level i is denoted by n_i and the total number of pixels $N= n_1 + n_2$. To simplify the discussion, the gray-level histogram (Figure 5b) is normalized and regarded as a probability distribution:

$$p_i = \frac{n_i}{N}, p_i \geq 0, p_1 + p_2 = 1 \tag{3}$$

Then we dichotomize the pixels into two classes C_1 and C_2 (body and background) by a threshold at level k. C_1 denotes pixels with levels [1,.., k], and C_2 denotes pixels with levels [k+1,…, L]. Then the probabilities of class occurrence and the class mean levels, respectively, are given by:

$$w_1 = \Pr(C_1) = \sum_{i=1}^{k} p_i = w(k) \tag{4}$$

$$w_2 = \Pr(C_2) = \sum_{i=k+1}^{L} p_i = 1 - w(k) \tag{5}$$

$$\mu_1 = \frac{\sum_{i=1}^{k} ip_i}{w_1}, \mu_2 == \frac{\sum_{i=1=k}^{L} ip_i}{w_2} \tag{6}$$

The variances of class C_1 and C_2 are provided by:

$$\sigma_1{}^2 = \sum_{i=1}^{k} (i - \mu_1)^2 p_{i/w_1} \tag{7}$$

$$\sigma_2{}^2 = \sum_{i=K+1}^{L} (i - \mu_2)^2 p_{i/w2} \tag{8}$$

Now, the image is separated into two parts (Figure 5c). To improve the comparison between images they have been normalized. In this case, all images are redefined to 600 x 400 for the face images and 600 × 250 for profile images. After this step, the silhouette can be extracted. For the step of the silhouette extraction, which amounts to a contour detection problem, the Sobel's and Prewitt's filter is simultaneously used (Figure 5d and 5e) [42,43]. The operators calculate the gradient of the intensity of each pixel. It shows the largest change from light to dark in the different directions, corresponding to the edges. Each filter uses the matrix [3 × 3] which is convoluted with the image to calculate the horizontal and vertical derivative approximations. Having two images G_x and G_y, and A defined as the source image the computations are as follows:

$$DSC = 2\frac{|X \cap Y|}{|X| + |Y|} \tag{9}$$

With k =1 for Prewitt's operator and k = 2 for Sobel's operator.

At each point, the resulting gradient approximations give the gradient magnitude using:

$$G = \sqrt{G_x{}^2 + G_x{}^2} \tag{10}$$

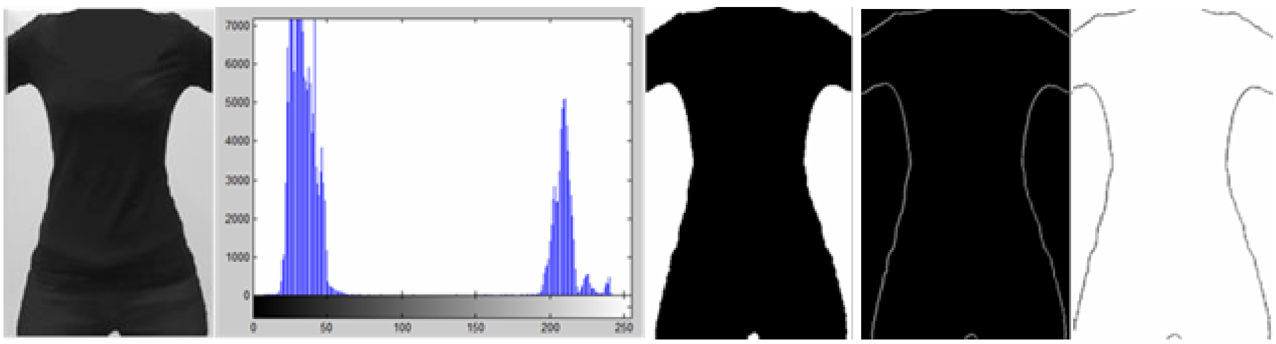
D classifications

The goal of the 2D classification is to assign the client to a cluster trough 2D shape descriptors of their torso. To measure the similarity between the client and the morphotype a similarity function has to be defined. The Dice coefficient also known as Sorensen-Dice or Dice Similarity Coefficient (DSC) is used in this research [44]. It is a statistic tool adapted for comparing the recovery of two samples. In other words, it defines the differences between two groups by reflecting either the presence or absence of certain characteristics. It is widely used in medical imaging and studies of genetic relationships in biology [45,46]. This similarity coefficient *DSC* is presented in the original formula in equation (11)

$$DSC = 2\frac{|X \cap Y|}{|X| + |Y|} \tag{11}$$

Where |X| and |Y| are the two sets of samples considered to be compared to define the value of similarity. It was adapted to meet the requirements of the experiment and will be explained later in the paper. To weight the information coming from the two viewpoints, the DSC is applied to the two images of the anterior and lateral views. The expression of the final similarity τ was:

$$\tau = \frac{(\alpha \times DSC_{anterior} + \beta \times DSC_{lateral})}{\alpha + \beta} \tag{12}$$



(a) (b) (c) (d) (e)

Figure 5: Silhouette extraction process.

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Where α and β were found empirically on a sample of the database.

Pre-processing of 3D into 2D shape descriptors

As aforementioned, the 3D clustering method of morphology shape detection has provided three morphological clusters presented in Figure 2 [2,34]. The morphotypes are assigned to the closest 3D morphology of the centroid of each cluster Figure 6.

Subsequently, the 2D shape descriptors of 3D morphotypes are obtained. The 2D shape descriptors of anterior (av) and lateral (lv) view are shown in Figure 7.

Results and Discussion

Classification evaluation

The quality of our classification is evaluated based on the results of Hamad et al. 3D morphology classification [2,34]. It is particularly relevant since we are interested here in morphology classification within the context of assignment to the 3D morphotypes database. Therefore, fifteen women subjects have been scanned and classified into one of three morphotypes, five for each morphology, with the 3D method [33]. The 2D shape descriptors to each of the images, both for the anterior and the lateral profile, have been determined and correspond to a balanced distribution of the fifteen morphologies in the clusters C1, C2 or C3. Morphology 1 is assigned to cluster C1, morphology 2 to cluster C2 and morphology 3 to cluster C3. Table 1 presents the values of DSC between the fifteen women subjects compared to the morphotypes of each class for anterior and frontal views. The global index of similarity τ is an indicator defining the quality of the classification. The expression α, τ=1.0 and β= 0.7 has been calculated empirically.

An example of comparison is given in Figure 8; violet the test morphology and green, the different morphotypes. This morphology is marked in yellow in Table 1. Green and red colors in the table represent the level of similarity between consumer's measurements and certain morphology. The green color reflects the best matching, and the red color discludes the consumer from certain morphology.

New client classification

The method was tested with a new client following the measurement protocol. The client's comparison results are presented in Figure 9 and give us as the value of similarity index τ the following values: 0.83648 for the morphotype 1, 0.77016 for the morphotype 2, 0.67738 for the morphotype 3. Thus, the morphotype 1 can be assigned to this new client. The estimation of the client's shape can be defined by superimposing two 2D shape descriptors at once. This operation has to be executed between the different morphotype's 2D shape descriptors and subject's 2D shape descriptors. The discrimination of the 2D shape descriptors is solid if it is used with τ representing the DSC weighted between the lateral and anterior views. Depending on the garment, it may be beneficial to give more value to the lateral view than to the anterior view. The 2D descriptor classification method was evaluated through results of 3D clustering classification. Table 1 shows the overall results; the client's morphotype recognition is 75% correct, and the value of τ to validate is close to 0.865. This recognition rate is right because the classification does not use the same descriptor. It can be noted that even when there is an error, there is no confusion in transferring the subject from morphology 1 to morphology 3, which are the two extremes of the morphotypes.

The classification of the new client gives satisfactory results with τ (= 0.836) slightly inferior to 0.865. The others values of τ are distant enough. Many factors could influence a client's shape. The ambiguity may occur mostly owing to the posture. On the anterior view, we observed the tendency of a subject to tilt the shoulders more on one side. Bad posture on the lateral side can cause even more serious inaccuracy. Likewise, the breasts are prone to adapt to the bra shape. Therefore, if the subject has a bra which deforms the breasts, the chest line may overlap with under chest segment of the body. As a result, the contour which is extracted from the lateral view can lead to an inaccurate data reading.

Based on the outcomes two decisions are possible: First, if the new client does not match with any of morphological clusters, the new cluster can be created. Second, if the new customer matches one of the morphological class (e.g. Cluster 2), the adaptive morphotype (PM2) adjusted for the stature of the customer thereby creating an avatar with body dimensions. Thanks to the basic garment pattern for a particular client can be obtained.

Morphology	Anterior profile			Lateral profile			τ		
	C 1	C 2	C 3	C 1	C 2	C 3	C 1	C 2	C 3
1 morphology	0,88419	0,83493	0,71150	0,83405	0,86473	0,80397	0,86354	0,84720	0,74957
	0,84186	0,76497	0,67176	0,86819	0,82292	0,78819	0,85270	0,78883	0,71970
	0,84398	0,76507	0,67753	0,91168	0,82161	0,78338	0,87186	0,78835	0,72112
	0,89886	0,88166	0,78544	0,86785	0,83444	0,77635	0,88609	0,86222	0,78170
	0,87984	0,87017	0,73002	0,80768	0,88705	0,82321	0,85013	0,87712	0,76839
2 morphology	0,83597	0,86623	0,81126	0,82447	0,86314	0,81220	0,83123	0,86496	0,81165
	0,82725	0,80115	0,86973	0,82321	0,88086	0,82205	0,82558	0,83397	0,85009
	0,87163	0,88822	0,79913	0,77180	0,83082	0,77418	0,83052	0,86458	0,78886
	0,81870	0,72490	0,66054	0,86272	0,82293	0,78210	0,83683	0,76526	0,71059
	0,88386	0,88373	0,84645	0,70955	0,83827	0,79736	0,81209	0,86501	0,82624
3 morphology	0,81692	0,79746	0,77690	0,83471	0,91821	0,88488	0,82425	0,84718	0,82136
	0,81458	0,84062	0,90680	0,78138	0,83784	0,80267	0,80091	0,83947	0,86392
	0,84981	0,79177	0,85113	0,73962	0,81781	0,79941	0,80443	0,80249	0,82983
	0,82548	0,85350	0,88105	0,73876	0,84266	0,84582	0,78977	0,84904	0,86654
	0,82702	0,86419	0,88725	0,81302	0,90592	0,88566	0,82125	0,88137	0,88660

Table 1: Similarity index of 15 women's subjects with the three morphotypes.

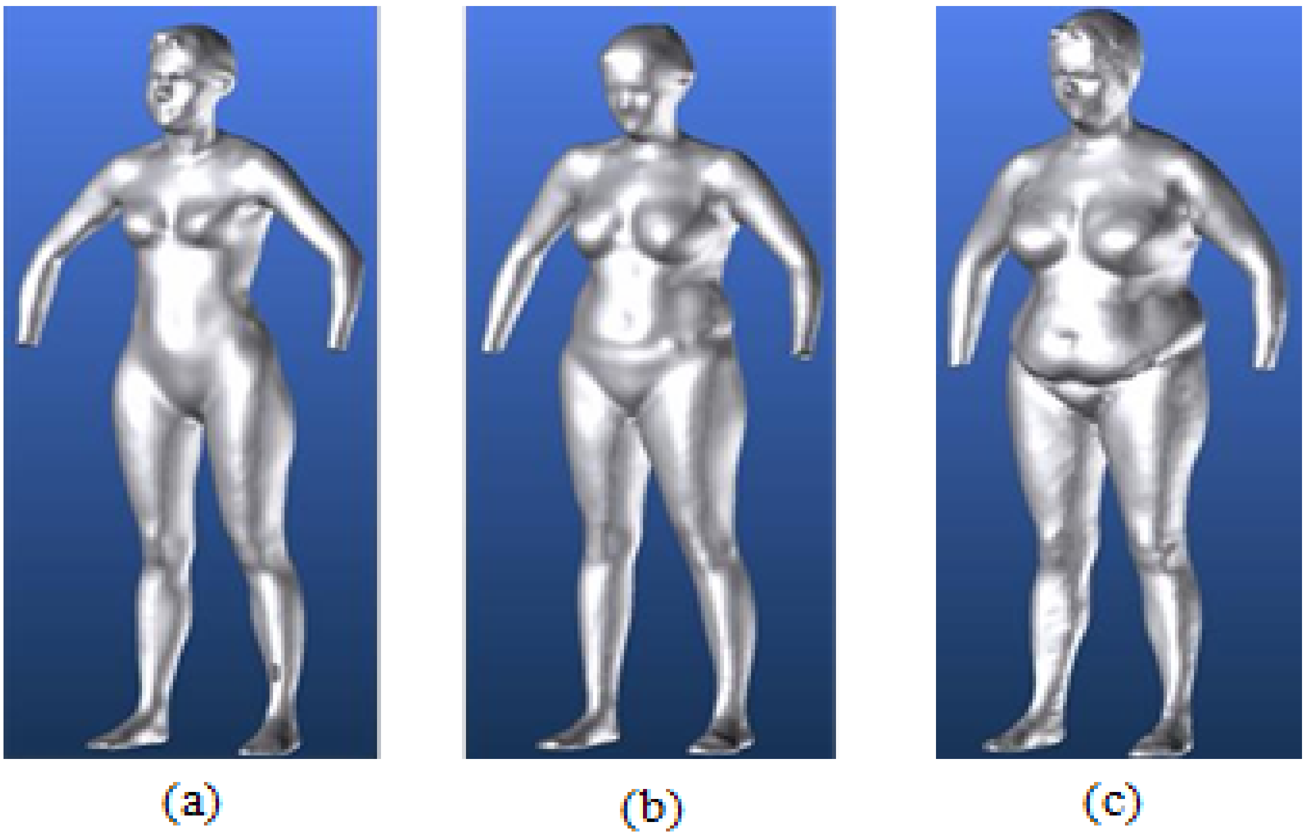


Figure 6: 3D morphotypes for the cluster 1: (a), 2: (b), 3: (c).

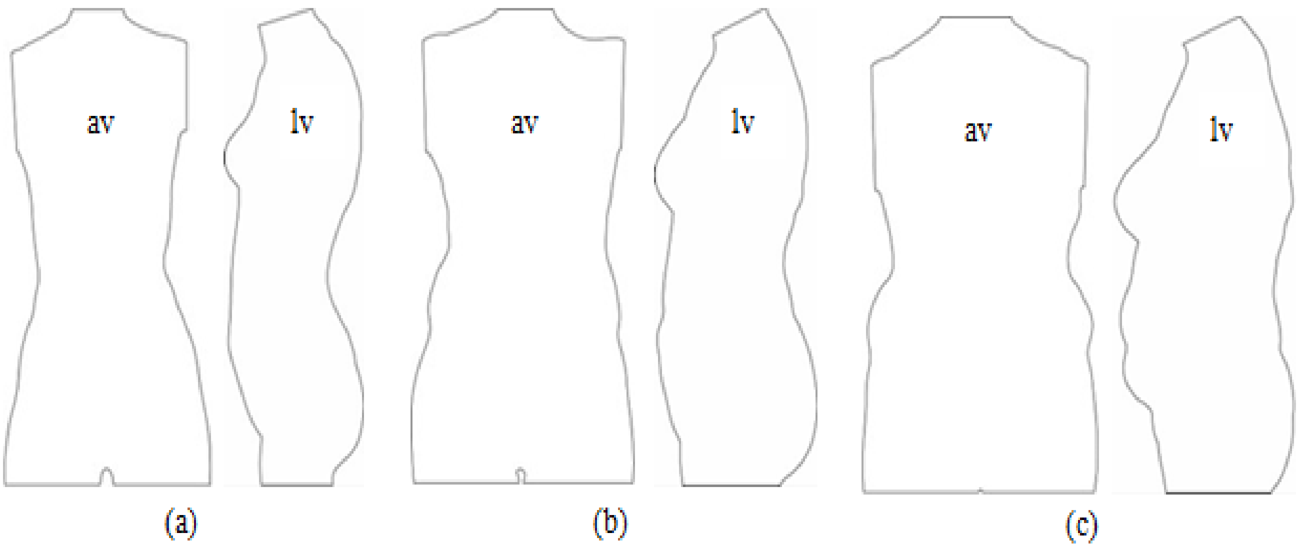
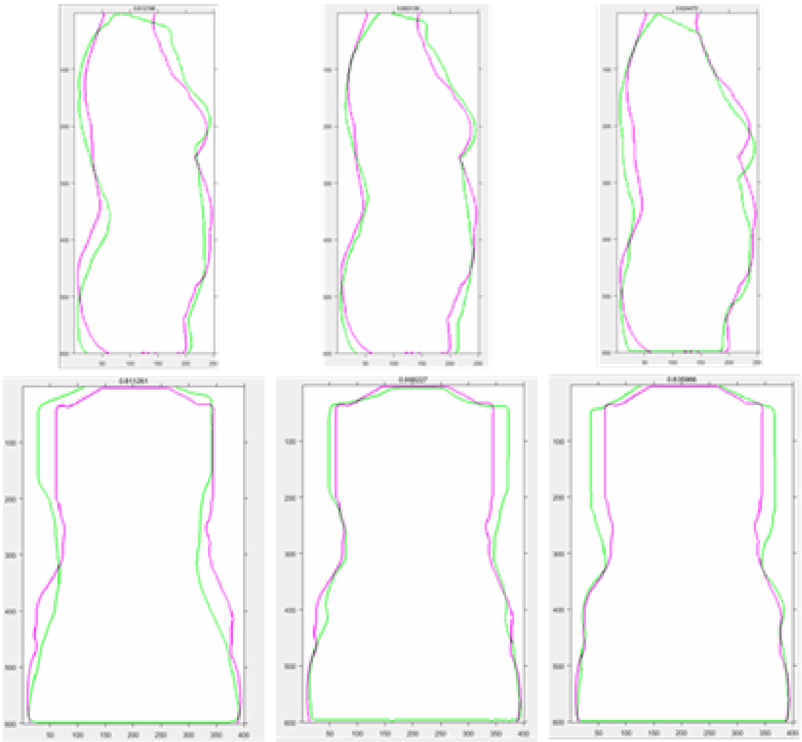


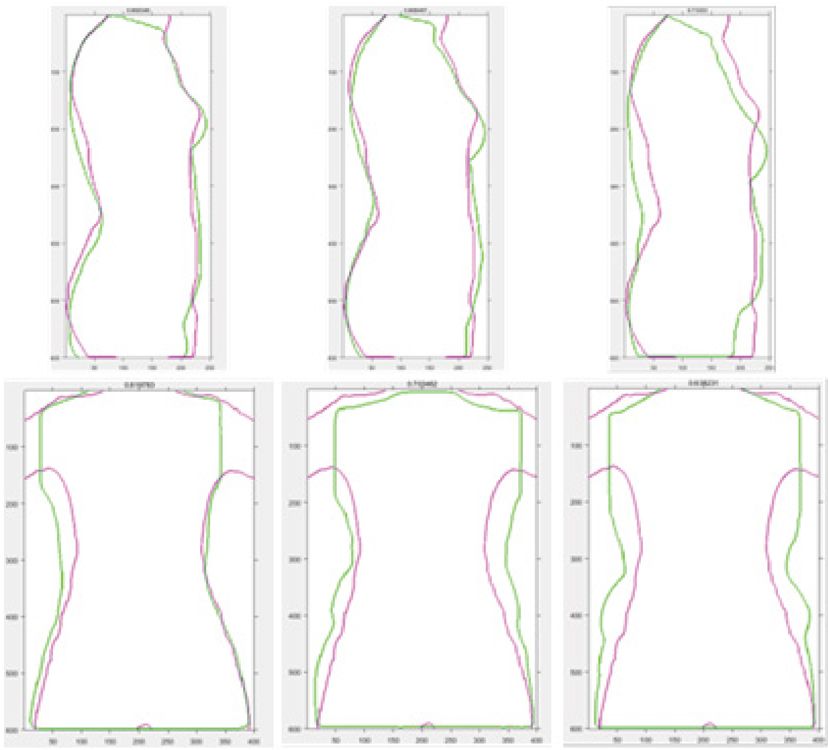
Figure 7: 2D shape descriptors of the 3D morphotypes for the cluster 1: (a), 2: (b), 3: (c).

Nevertheless, for an e-commerce, there is an existing need for the pattern recognition of client's body. The knowledge of the clients' measurements can be globally obtained by the clustering of a morphology database on which we can define the measurement charts. Additionally, by using the 3D database the Clint's shape can be identified. Our method makes possible to recognize the client's shape and in next step to create the avatar, which is a demand in the tailor-made sector.



(a) (b) (c)

Figure 8: Comparison between morphology in the anterior and lateral view with the morphotypes for the cluster 1: (a), 2: (b), 3: (c).



(a) (b) (c)

Figure 9: Comparison between new client in the anterior and lateral view with the morphotypes for the cluster 1: (a), 2: (b), 3: (c).

Without recognition of an individual client to a particular target population represented by size or morphotype, the fashion industry would not be able to fit the garment on the client. To obtain the perfect match of the garment to the body is essential in consideration of the client's 3D posture and the stature. Matching the characteristic client morphology to the morphology cluster of a target population is a crucial step for effectiveness and profitability of fashion industry. A designing garment for the correct morphology improves the percentage of the well-fitted garment and decreases the number of returns.

Conclusion

We argue in this paper that today's methodology of 2D pattern making, which associates the measurements with one standard morphology without taking into account 3D morphology variations, which is a crucial factor in the sector of made-to-measure garments, is not sufficient to obtain the right fit of the garment.

While most of the research focuses on an automatic process of 3D garment creation, it is not considered in the validation of their method the adequacy of the garment to existing body morphotypes [47]. Therefore, the objective was to suppress this gap on the client's morphology by implementing a process of morphological recognition from an existing database. For that, we have used a 3D measurements database resulting from the measurement campaign with a wide territorial range and having a vast multiplicity and diversity of measurements that enable a statistical inference.

A 2D shape descriptor applied on images taken in different point of view has led to define a specific signature of these shapes. This descriptor has been used for both the client and the morphotypes of the database after his clustering. The DSC has been mean to classify this customer from these 2D shape descriptors. The method has been validated with a sample of fifteen women' subjects of the same database and tested with a new client. Finally, the client has been assigned to one of the morphotypes of the different cluster. The next step of this work is to adjust the 3D adaptive morphotype by the stature of this new client to create his 3D avatar, which will be presented in next paper.

Other works show the possibility of creating directly basic garment on the 3D adaptive morphotype [48]. The merge of this approaches leads to the tailor-made garment. We see the need for further research in this area because it is essential to obtain an Internet-based platform with the ability to handle a broad range of body diversity over a large area.

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