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Female Body Shape Classifications and Their Significant Impact on Fabric Utilization

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Abstract: In apparel manufacturing, more than 50 % cost is consumed by the textile fabric. Therefore companies have significant apprehensions in the fabric utilization. It can result in more efficient and cost-effective in fabric utilization if they are related to different body shapes. The purpose of this study is to classify female body shapes and evaluate fabric utilization efficiency for each category of the body shape. To this end, three dimensional (3D) body scans are collected from 124 young female subjects. For the body shape analysis, 3D body scans are processed by using Moore neighbor algorithm and region prop function to perceive the outermost shell. Moreover, both front and side view of the scans is processed for data reduction using Principle Component Analysis (PCA) and clustering using K-Means ++. It has been observed through our analysis of a dataset that female bodies can be categorized into four body shapes, that is, oval shape, circle shape, triangle shape, and rectangle shape. It has also been observed that all four body shape categories exhibit dissimilar anthropometric size measures. The result implies that these body shapes have devoured different fabric utilization for the garments (fitted trouser and fitted shirt). It has been noted that in fitted trouser and fitted shirt the most effective is the rectangle shape (cluster 4) and the least is the circle shape (cluster 2) in the fabric consumption. Similarly, the fitted trousers utilize less fabric while the fitted shirts consume more fabric in all body shapes. These findings provide a better reference of fabric utilization and cost-effectiveness to the apparel manufacturers while producing garments for different categories of the body shape.

Keywords: Body shape clustering, Moore neighbor algorithm, Region prop function, PCA, Fabric utilization

Introduction

In apparel manufacturing, fabric efficiency is the percentage of the total fabric actually utilized in the attire component parts [1]. Since the fabric utilization constitutes 50-60 % of the total cost of the apparel [2]. Therefore the saving of fabric through new approaches and effectual resource utilization results into cost-effectiveness [3]. For instance, a saving of two million dollars per year was achieved through a 0.1 % improvement in fabric consumption [4]. Henceforth apparel companies, in the conventional run-through of producing garments, have substantial anxieties in fabric consumption reduction [5,6]. To control the fabric efficiencies, female body shapes are particularly imperious, since minute variations in pattern, which are constructed on body shapes and their anthropometric size, leads to the enormous consumption of fabric [7]. The efficient fabric consumption and controlling its cost has remained an unresolved issue in the apparel industries.

With the dissimilarity in body dimensions and morphological appearances in the people, many studies [8-11] have discriminated them into different figure types e.g. triangle, inverted triangle, square, rectangle, circle, and oval etc. The body shape classification plays a deceive role in pattern making ultimately fabric consumption [12]. They contribute to the issue of cost in apparel manufacturing irrespective to the conventional approach which was limited to a single standard body shape and size [13]. Thus due to dissimilar body structure designs, the similar clothing styles have different fabric consumptions in the garment [14].

In the 1940s, W.H. Sheldon firstly categorized the human body into three discrepancies (endomorph, mesomorph, and ectomorph) by using photographic technique and developed the sizing system for the manufacturing of garments [12]. Laterally, Jo Connell, found that similar size costume cannot be anticipated to the same somatotypes due to the shape differences [14]. Also, the existing sizing standards either based on the differences between bust and hip (ISO, ASTM) or the differences between bust and waist (Chinese) do not conform to the diversity of human body shapes [15]. Thus the effectiveness of fabric utilization can be improved significantly through if it's related to human body shapes [16]. However, due to the complexities involved in the female body shapes and postures, their analysis always

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remains a challenge [17]. Recently, the new technology developments as three-dimensional body scanning technique, many studies articulated in a more comprehensive way to the learners for depth analysis of surface point cloud data for human body shape identification and complete elimination of the time consuming traditional anthropometric methods and measures [18-20]. For example, "My Virtual Model Tour 2000" by Lands' End was the very first scanner used for scanning the models virtually for gathering the anthropometry data [21].

In the literature and learning resources, one study showed nine classifications of female body shapes (spoon 17.1 %, diamond, hourglass 21.6 %, bottom hourglass 40 %, top hourglass, rectangle 15.8 %, oval 3.6 %, triangle 1.8 %, inverted triangle) [22-24]. Another study evaluated eight classes [25]. The results were limited to a one-dimensional measure. Accordingly, it was noticed that all the models in the population data set belong to only five female figure types. Additionally, the ratio of representation to an ideal body (triangle shape in fashion backdrop) was the least. This means the standard body shape is not standard at all for the whole population. Thus the garments represented an ideal shape body unable to communicate appropriately to the other shapes (more percentage ratio) in the data set.

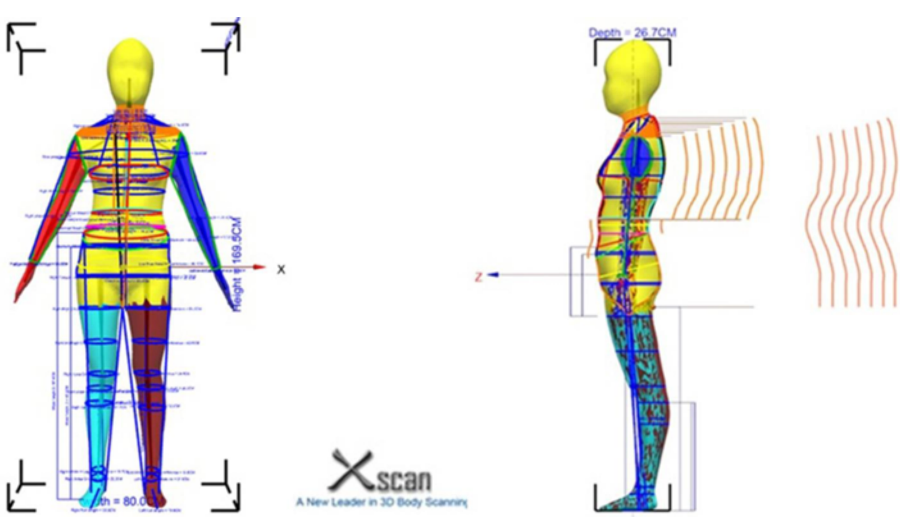
The fact and figures from the literature review show that most of the researchers have focused either mainly on human body shape identification, their categorization [26-29] or sizing [30-32] but none with attire relationship by means of fabric utilizations in garment manufacturing companies. For instance, Chung *et al.* nine body shape classifications since the students at the age of 18 are grown up into different well proportional body shapes whereas the children under the age of 12 years mostly would have no or little shape or belong to a single shape because there drop value (chest girth minus hip girth) is not obvious [32]. Similarly Choi and Nam studied body shape analysis but that study limited to only upper lateral body shapes [17]. Too many classifications enhance difficulties for apparel producing companies to accommodate all body types for the bulk productions. The work of Xia *et al.* has improved the information of body shapes analysis based on longitudinal section silhouette into four classifications however her approach does not consider basic body anthropometric measurements and correlation between them for fabric utilization [33].

As the body structure (shape) is recognized as vital to clothing provision and fabric consumption business [34]. Therefore, this paper aims to investigate female body shapes and the influence of body type classifications on fabric consumption efficiencies. In this scope, 3D body scans have been processed by using Moore neighbor algorithm and region prop function for the body shape analysis. Moreover, both front and side view of the scans has been processed for data reduction using Principle Component Analysis (PCA) and clustering using K-Means ++. Further, the fabric consumption efficiencies for garment style (fitted trouser and fitted shirt) have been examined on different categorized body shapes.

Experimental

Research Design

In this quasi-experimental design, only unmarried young female subjects were selected. For the reason that pregnancy (the period of fetal development from conception until baby birth) affects the anthropometric measures and shape of the female bodies [35,36]. Moreover, during pregnancy hormones in the females cause them to increase in size and gain in



(a) Front view (b) Side view

Figure 1. Female scanned postures with the coordinate system.

weight as the uterus grows to accommodate the growing fetus.

The age of these adult female subjects was between 18 to 25 years old, since, at this age, female bodies have been grown into different well proportional shapes. All these female subjects wearing tight underwear were scanned through the multi-motor-scanner machine using 12 RGB-Depth cameras in a standard given posture as shown in Figure 1. The 3D body scanner machine (TC2-19B) takes 9-10 s to scan a complete human body. While scanning, the room temperature was kept 23 ^{o}C to 25 ^{o}C, without wind [37].

The scanning was specially conducted in the early hours of the day (morning between 10 AM to 11 AM) in order to avoid the pressure on the spine of an individual. Since the pressure causes loss of liquid content in the intervertebral discs during the day that affects the height (shortening) of humans [20]. It is statistically verified from the research that individuals are taller in the dawn and shorter at the time of sunset [38].

Data Acquisition

Data collection of scanned three-dimensional female body images were collected and exported in OBJ format after de-noised and reduction process. Through Geomagic Studio software (reverse engineering software 2013), we accessed the body shapes, the lines and the orientation of the female body, i.e. body height (vertical landmarks) is associated laterally to Y-axis, body width (horizontal landmarks) aligned through X-direction and body thickness (front and back direction) line up with Z-axis, is harmonized with the coordinate axis of the system (Figure 1). Female torso area (body minus arms, legs, and neck) as shown in Figure 2 was chosen for body shape analysis as this area has 80 % emotional impact of all clothing problems. Torso area comprehends key dimensions (bust, waist, hips) and also dictates cut and sewing lines fit different body shapes [39].

The three-dimensional images consist of a lot of pixels. From the data set, all the images of female bodies were converted and saved into PNG files through 3D MAYA software (2010) with their front view and side postures. The reason was to reduce the pixels through 2D image for further processing. Therefore, images were transformed into "binary" form i.e. 0 or 1, where zero represented black or background and one represented white or foreground/body image. The Figure 2(a) and Figure 2(b) explained the binary form of a 2D image. The frontal face and side posture images were converted into binary images which were accessible into the programming code for features extractions through MATLAB (R2015) to store into a variable programming code. The program loaded each body part individually and then converted the image to black and white. This was primarily because the convex hull of the shape was associated with the two-dimensional projection of the body. After converting to monochrome, we identified the convex hull and centroid of each image and used this reduced dataset as our base data. The outer boundaries of all body images of female subjects were collected.

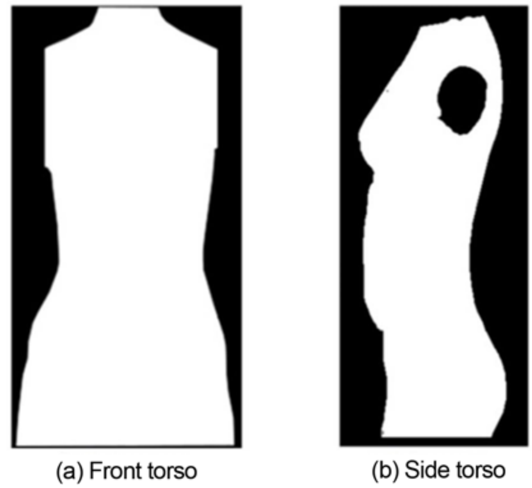


Figure 2. The binary form of 2D images in the frontal and side (torso) posture of the female body.

Moore Neighbor Algorithm and Region Props Function

The Moore neighbor Algorithm was used to perceive the outermost shell of the female subjects as displayed in Figure 3. Figure 3(a) indicated the torso portion with the surrounding outer shell curve. Figure 3(b) specified only the curve without torso body. The values of these outer body shells were detected in the XY coordinate axis system which consisted of a number of discrete points originally resembled and also depicted the body shape. Figure 3(c) showed the central point of the body. The central point of the torso (centroid of the region) was calculated thorough region props function which worked well for ellipsoid-shaped features like human bodies. It measured the geometric properties of the image (shape) area. Through all over the body, at least 452 points were selected that were not adjacent to the central point but also supported in defining the structure of the body completely using Moore neighbor algorithm. Figure 3(d) showed the points on the outermost shell curve which are located at a distance from the centroid.

Distance Formula

The distance between the central point of the female subject and those points (on the outer shell of the female subject) were measured through the "distance formula" ($d^2=x^2+y^2$) and made a column vector. This process was accomplished on all female torso subjects and data matrix was developed in which every column denoted a female subject. Laterally, principal component analysis (PCA) was applied that required N dimensional features space as its input.

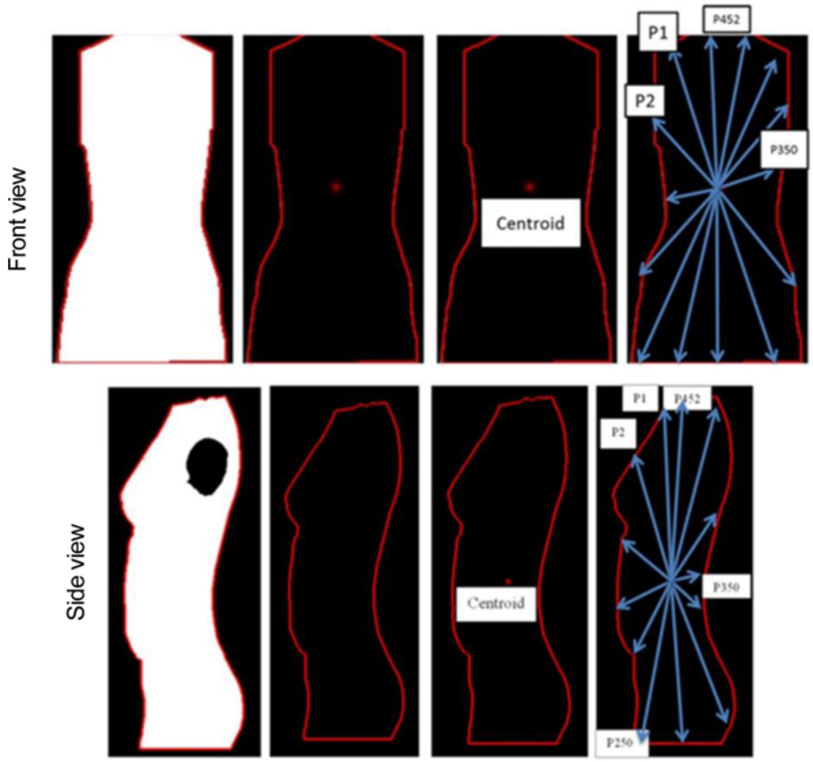


Figure 3. The steps lead to get the outer shell (boundary) and the central point in the body; (a) torso portion with outer shell, (b) the outer boundary without torso, (c) central point of the outer boundary, and (d) 452 point on the outer shell curve.

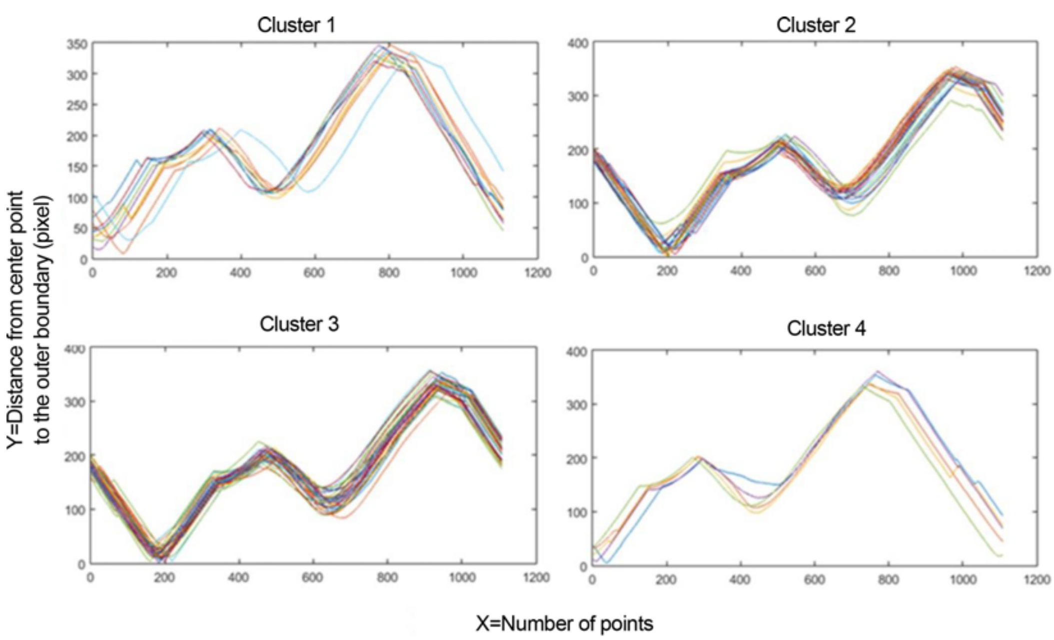


Figure 4. Cluster distance graph.

Principal Component Analysis (PCA) to Determine the Characteristics of Indicators

To reduce the number of data-points we applied principal component analysis (PCA) to extract the most pertinent features from the data. The original dimensions were in the order of hundreds depending upon the shape of the individual. PCA finds the linear combination of data-points, pixels in this case, and orders them according to their

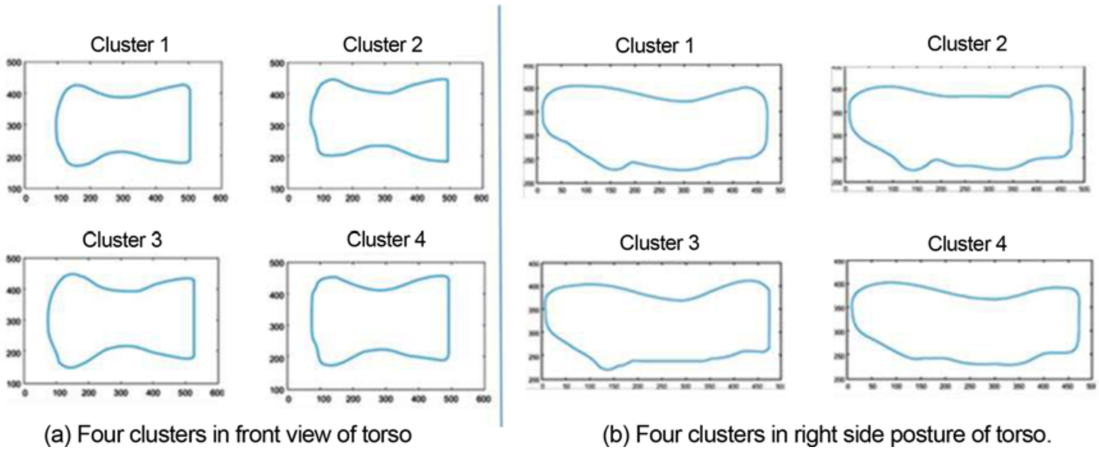


Figure 5. Four clusters with both front view and side view torso.

variation in the dataset. The eigenvectors thus ordered by PCA ranked the level of relevance of each data-point in the dataset. From these features, we selected the four highest-ranking eigenvectors for our clustering computation. PCA converts 124×124 feature matrices into 1×124 latent column vectors. It converted column vector as its output.

Cluster Distance Graph

Figure 4 has shown the cluster distances graph of different bodies which have been consistently categorized into four groups. The X-axis is designated with a number of points while the Y-axis has been represented by the distance from a center point to the outer boundary (pixel) of the bodies. The starting point of the boundary begins from the most top right to the most top left (in a counterclockwise direction) and then touches to the initial started point. In the figure, each curve is the representation of each female individual model. Therefore the curves have explained the distances between the outer boundaries of the bodies from there centroids (middle point). The trends (overlapping) of the individual curves were steady in each cluster with differences in a number of peaks and nodules that illustrated similarities and differences among female individuals. The different patterns in the trend of the curves have described the obvious variations from one another in the data set.

K-Means Cluster Analysis for Shape Classification

The female subjects were divided into unknown K groups through K-means++ clustering algorithm (advanced). This distinctive unsupervised clustering was performed for centroid initialization and squared Euclidean Distance to find similarities and dissimilarities in the sample space respectively. Every sample was consigned to a class according to the minimum spaces or distances. K-means++ spontaneously classify the clustering into K groups. Therefore, 124 female subjects were optimally partitioned into four groups or shapes. The curves (shapes) of these four types were selected from human body database for classification. Figure 5 has shown the difference between four categories of torso curves.

Results and Discussion

Result of PCA

The female body subjects were subjected to PCA analysis. Table 1 has described the feature matrix through PCA in which every column represented a unique feature (F1, F2, F3… F123, F124) and every row represented a sample or a class. Variance of feature matrix as shown in Table 2, was evaluated through the cumulative sum of latent i.e. {Variance= cumsum(latent)./sum(latent)}. It explained the varied data information and conveyed the space distance between two points. Furthermore, it was analyzed that the first two components were responsible for 99 % variance values.

Figure 6 has explained the variance percentage of the first two components of 124 samples. The variance contributions of these PCs were 81.94 % and 17.027 %. This implied that these two components i.e. PC1 and PC2 could be used to represent original features without the loss of generality. Therefore, only these two components have been used for clustering.

Results of Clustering

Figure 7 has shown the number of subjects distributed in four clusters from the data set. The blue color bar has represented the data of subjects (group) selected in front view whereas the red color bar indicated the data of subjects chosen in the side view of the same clusters. The first cluster has included a selection of 24 models in the front view and made a selection of 22 models in the side view. Similarly, the other clusters have (38, 41), (43, 46) and (19, 14) subjects in the front view and the side view respectively.

Table 1. Feature matrix through PCA

Class	F1	F2	F3	F4	…………	F124
Sample 1	-0.0084	0.2374	-0.2405	-0.0848	…………	-4.2106
Sample 2	0.1216	-0.0081	-0.0393	-0.0303	…………	-0.0680
Sample 3	0.0866	0.2193	0.2482	0.0998	…………	-0.0466
Sample 4	0.1234	0.0183	0.0960	-0.2279	…………	-0.0793
…………	…………	…………	…………	…………	…………	…………
Sample 124	0.1233	-0.0378	-0.0480	0.1147	…………	-0.1290

Table 2. Variances of the feature matrix

Feature	Eigenvalues	Variance explained (%)	Cumulative variance explained (%)
F1	65.552	81.94	0.8239
F2	13.622	17.027	0.9900
F3	0.435	0.544	0.9952
………..	……….	……..	…….

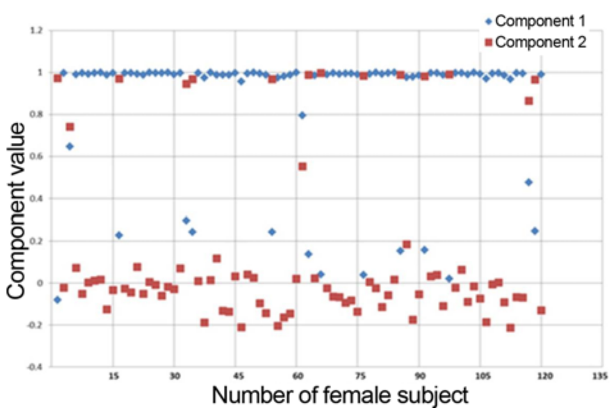


Figure 6. PCA components of 124 female subjects.

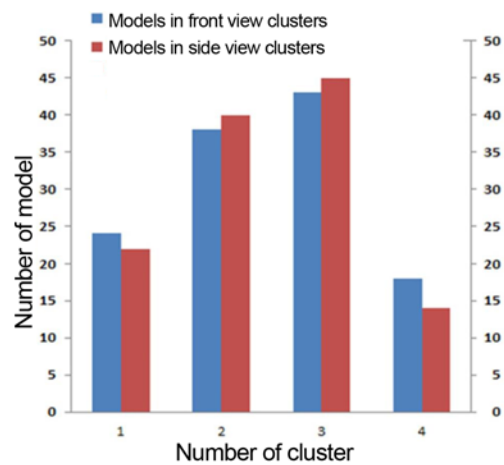


Figure 7. Female subjects categorized into four classes (front and side view) with PCA.

From the data set of each cluster only matched models (17.74 %, 30.64 %, 34.67 % and 11.29 %) were selected and the miss fit models (1.62 %, 2.5 %, 1.62 % and 4 %) were dropped for an appropriate body shape categorization and anthropometric analysis. It was done to equalize weight (both front view and side view) of models in each particular cluster. For example, in the first cluster, the front view contained 24 models and the side view enclosed 22 subjects. Therefore, only 22 subjects were selected and the miss matched two subjects were excluded. The similar approach was applied to the other clusters for their data set. Generally, the front view of the human body has always been considered with higher weight than the other views (right side view, left side view, back view, a top view and bottom view) of the body [39].

Figure 7 has also demonstrated that the apparel companies which produce garments for the subjects of cluster 4 and cluster 1 are at the major risks as their products do not overcome the satisfaction level of the large quantity of dataset. While the companies which produce garments for the cluster 3 and cluster 2 would overcome more inhabitants. The figure also revealed that the production of apparels for any single cluster (shape) would experience fit issues from the subjects belong to other clusters. Therefore, this research work has provided a consciousness reference to the apparel manufacturers in creating the right clothing for four different female body types.

Curve Fitting

The fitting curve of female models of four clusters was found different. Figure 8 has demonstrated the variations of the fitting curve (mean) of four different clustering categorizations. The front view (first row) and the side view (third row) has represented to the cluster curves, accomplished in the previous section (Figure 5). The second row and the fourth row have described the mean torso bodies (blue color) of the classified models in the left while to their right, the representative curves (outer shell of the torso bodies in red color). The curves double arrow connector (dark blue color) represented to cluster curve and the curve double arrow connector (orange color) pointed to the curve of torso bodies

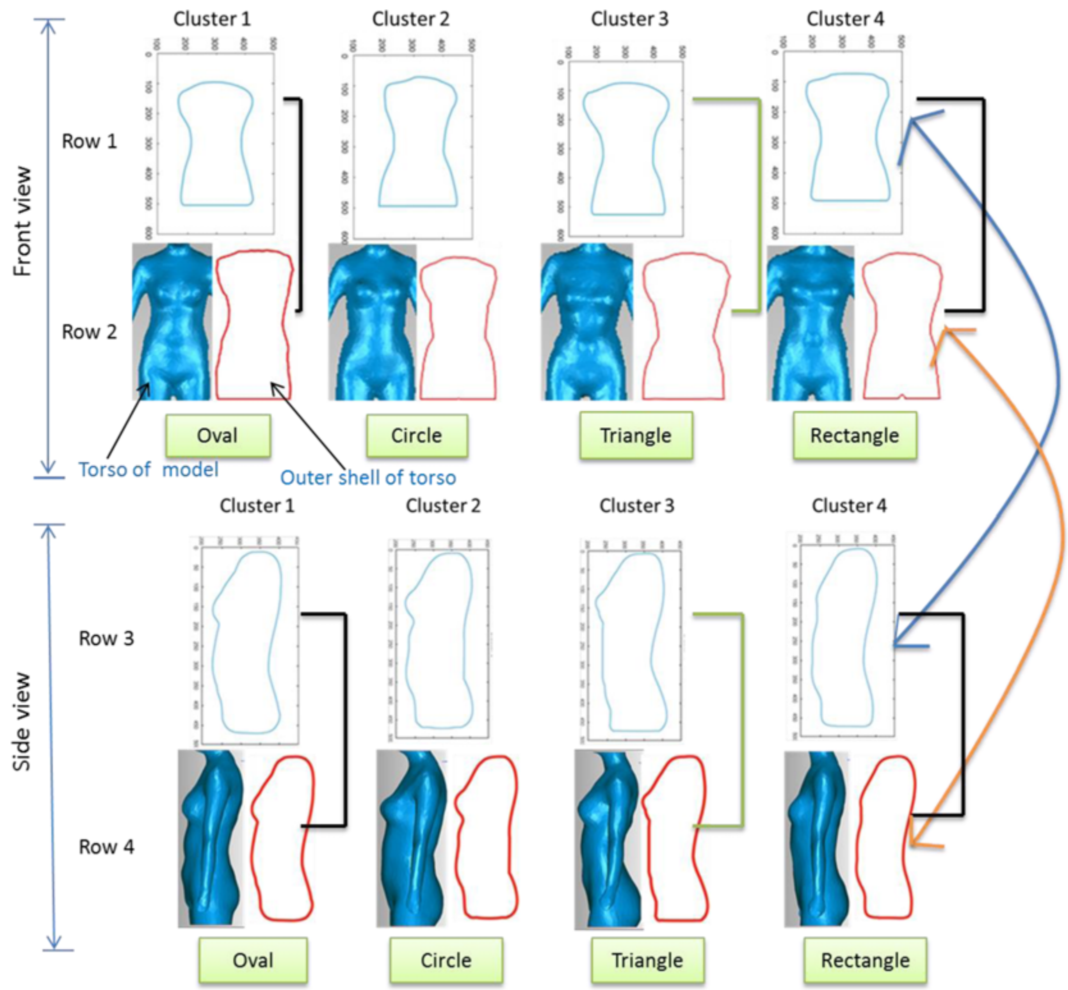


Figure 8. The fitting curve of torso bodies of four different clusters in front view and side view.

Table 3. Comparison analysis of key body landmarks of four clusters

Sr. No	Description	Cluster 1	Cluster 2	Cluster 3	Cluster 4
1	Body shape	Oval	Circle	Triangle	Rectangle
2	Bust girth (fullest)	Medium breast	Full breast	Fuller breast	Less full breast
3	Waist girth (narrowest)	Medium	Small	Smallest	Large
4	Hips girth (fullest)	Elliptical bumps	Round bumps	Voluptuous bumps	Flat bumps
5	Thigh girth (below crotch)	Medium thighs	Smaller thighs	Fuller thighs	Medium thighs

of four classified female body shapes.

The curves of the torso bodies have a close resemblance to the clustering group (indicated through black and green color bracket in both front and side views). The outer shell of the torso body of cluster 1 was an oval shape and cluster 2 was roundish/circle shape. The bust and hip areas of cluster 2 were more roundish comparative to other shapes of the clusters. The cluster 3 torso curve was the angular/triangle shape while the torso curve of cluster 4 was the straight/rectangle. The waistline was very much defined in cluster 3 whereas the waistline has not defined obviously in cluster 4. The bust, waist, and hip areas were nearly flat in comparison with other clusters. Moreover, the key factors of the torso portion like bust, waist, and hips which identify the body shapes have been summarized in Table 3.

Figure 9 has been equipped with visual analysis of different portions (bust, hips, waist and lateral) of the torso curve of four clusters. The curves relative to each shape at different proportions of the body has verified the differences. These curves were taken only from the side view (as shown

Description	Body Shape	Geometric shape	Bust Curve	Hip Curve	Waist curve	Lateral curve
Cluster 1	Oval Curvaceous (curvy)		Oval breast contour with natural bulge Concave chest makes cleavage more ostensible	Derriere are elliptical and elongated but not fully roundish, hip bone is set lower than waist line	Curvy abdomen with medium waist line	Bend, back is more ovoid and not flat
Cluster 2	Circle More curvaceous (curvier)		Well rounded breast contour with natural bulge Concave chest has most cleavage	Wight indent in hips, hip bone set below waist line	Curvilinear abdomen with small waist line	Flat and than circular, Back or hip is more roundish
Cluster 3	Triangle Most curvaceous (highly curviest)		Pyramid breast contour with obvious bulge Flatter straight chest has less cleavage	Stunning and well-endowed curve, angular hip bone which is set higher at waist line	Thin abdomen with smallest waist line	Obvious bend, back has more vent
Cluster 4	Square Less curvaceous (less curvy) (rectangle)		Flatter or wider contour breast Concave chest area has less cleavage	Smooth and flat curve with less waist indentations, no roundish bumps, hip bone set high at waist line	Flat abdomen with large waist line	Flat with little bend, back is little straighter

Figure 9. Visual analysis of different parts of torso curves of four clusters.

in Figure 8) of the classified four groups. This indicated that these four different body structure designs have a different sense of pattern designs and clothing efficiencies.

The classification of female subjects (Figure 15 in the appendix) into four types i.e. clusters 1 (oval shape), cluster 2 (circle shape), cluster 3 (triangle shape) and cluster 4 (rectangle), was based on the torso part of the body. However, for the study of clothing efficiencies of shirt and trouser, the representative models of each cluster were taken with their complete anthropometric measurements. The anthropometric measurements and differences amongst four classified body types have been shown in Table 4.

The anthropometric measurements of scanned female subjects were taken through XScan (a new leader in 3D body scanning) software [40]. The average landmark values of each cluster were obtained by an aggregate sum of all values in each cluster. The anthropometric measurements of each cluster were utilized for the pattern making drawings

Table 4. Anthropometric analysis of four clusters and the average body

Sr. no	Description	Cluster 1 (C1) (cm)	Cluster 2 (C2) (cm)	Cluster 3 (C3) (cm)	Cluster 4 (C4) (cm)	Average body (cm)	Weightage
1	Body shape	Oval	Circle	Triangle	Rectangle	Triangle	C3
2	Neck girth (narrowest)	31.5	33	28.6	31.6	31.175	C1
3	Bust girth (fullest)	93.3	99.8	94.8	92	94.9	C3
4	Waist girth (narrowest)	70.5	78.9	74.4	72.1	73.975	C3
5	Hips girth (fullest)	89.6	101.7	96.6	88	93.975	C3
6	Thigh girth (below crotch)	51	56.2	53.5	50	52.675	C3
7	Knee girth	34.9	40	37.5	34.4	36.7	C3
8	Calf girth (fullest)	32.5	37.2	34.6	32	34.07	C3
9	Ankle girth (narrowest)	20	19.3	19.9	19.6	19.7	C4
10	Inseam linear (crotch to ankle)	65.8	60.9	64.7	63.4	63.7	C4
11	Shoulder girth	86.3	89.6	89.0	91.5	89.1	C3
12	Shoulder span linear	38.4	38.2	38.7	39.7	38.75	C3
13	Shoulder span curve	39.6	40.3	40.9	43.9	41.175	C3
14	Armscye (perpendicular to armpit)	26	30.6	26.1	26.3	27.25	C4
15	Arm length (low point shoulder to wrist)	52.5	48.2	50.8	49.6	50.275	C4
16	Wrist	12.5	15.8	14.9	12.7	13.975	C3
17	Shoulder slope	28	29.5	27	26	27.75	C1
18	Body height	169.5	165.4	168.3	167.6	167.7	C4
19	Bust to waist ratio	1.323	1.265	1.274	1.276	1.284	C3
20	Bust to hip ratio	1.041	0.981	0.981	1.045	1.012	C1/C4
21	Waist to hip ratio	0.786	0.776	0.77	0.82	0.788	C1/C2

through AccuMark pattern design, grading, marker making, and production planning software (Garment Gerber Technology). This was intended for the manufacturing of shirts and trousers.

The average body shape was evaluated through four steps:

(i) Match the landmark value of the average body to the closest value of any four clusters.

(ii) Weightage each landmark of an average body.

(iii) Add the weight of a landmark, similar in clusters, of an average body.

(iv) The resultant average body acquires the label in accordance with maximum resemblance from four clusters.

For example, from 21 anthropometric body landmark measurements, the average body responded to each cluster in weight as {C1: 2 (9.5 %), C2: 1 (4.7 %), C3: 12 (57.1 %), C4: 6 (28.57 %)}. Therefore, based on maximum percentage weight (57.1 %), the average body resembled a triangle body shape (cluster 3).

Pattern Making by Flat Pattern Method

Figure 10 (also Figure 16-18 in the appendix) has shown the patterns of the fitted shirt and fitted trousers, drawn by flat pattern method through Garment Gerber Technology (GGT, V10.351) software, in accordance with identified four body shapes and an average body shape. The patterns were drawn with the optimal relationship between the body measurements (following the body curves, outlining the figure) and the garment design measurements of a close fitted dress shirt and fitted trouser styles. This means that measurements for bust, waist, hip and so on, and ease allowances for movements (constant for all shapes), are marked. Ease allowances were added to make the garment comfortable to wear. Thus the constructed patterns (Figure 10) include the body measurements and the additions (garment design allowances). The additions were kept equal and constant for all the constructed patterns of different clusters. The body measurements of all models were recorded. For example, the Figure 1 (in the previous section) has demonstrated the detailed body measurements of the model, which belong to the cluster 1. Further ease allowances were added for the construction of patterns of trouser and shirt. The same procedure was applied to the models of other clusters. The design parameters for the shirt pattern were bust girth, waist girth, shoulder span, neck girth, sleeve length and wrist girth while for the trousers were waist girth, hip girth, knee girth, ankle girth, inseam length (inside leg from ankle to the crotch point) and outseam length.

The double arrow line in the pattern blocks have indicated the lengthwise or warp direction of the fabric. The patterns of four body shape and the average body shape are

Figure 10. Patterns of fitted trousers and a fitted shirt.

represented by different colored lines i.e. C1 (dark blue), C2 (red), C3 (orange), C4 (yellow) and the average body (turquoise color). The average body pattern has lied in between the other body patterns. The key anthropometric measures (bust, waist, and hip) and armscye depth of circle body (cluster 2) in red color have greater design measures than all other bodies. Therefore in Figure 10, the circle shape body has a wider area and sleeve width (armscye) in patterns comparative to other shapes.

100 % cotton woven fabric {white shirt with fabric construction (warp count × weft count/ends per inch × picks per inch=fabric width; 100 × 80/40 × 40=58, black trouser with fabric construction: 66 × 36/10 × 10 = 58)} was taken with shrinkage 2 % in warp and weft. The width of both the fabrics was 58 inches (147 cm). Five garment pieces were drawn relative to each cluster. Moreover, they were cut in a total number of five markers (lays), i.e. each marker relative to each shape and an average body for the shirt and similarly for trouser separately. The fabric consumption efficiencies for garment styles (fitted trouser and fitted shirt) corresponding to each cluster have been evaluated using GGT software respectively.

Fabric Consumption Efficiencies

To explore the effect of four shapes on fabric consumption efficiencies, the preparations of pattern markers of the fitted shirt and fitted trouser have been accomplished through GGT software for each cluster. Figure 11 has shown the pattern marker of the fitted shirt and fitted trouser of one cluster and average body as an example. Each pattern marker was kept constant (consist of five garment pieces) for all body shapes.

It was observed that every cluster has different fabric utilization ratios as shown in Figure 12. Oval shape female body has utilized (79.908 cm, 93.454 cm) of the fabric in trouser and shirt. The other shapes has utilized (85.018 cm, 108.974 cm), (81.852 cm, 96.136 cm) and (76.804 cm, 92.62 cm) fabric respectively. The average body shape has consumed (83.936 cm, 95.488 cm) fabric. The figure explained that the rectangle shape body, representation to Cluster 4, in comparison to other body shapes has consumed less fabric (cost effective), both in fitted trouser and fitted

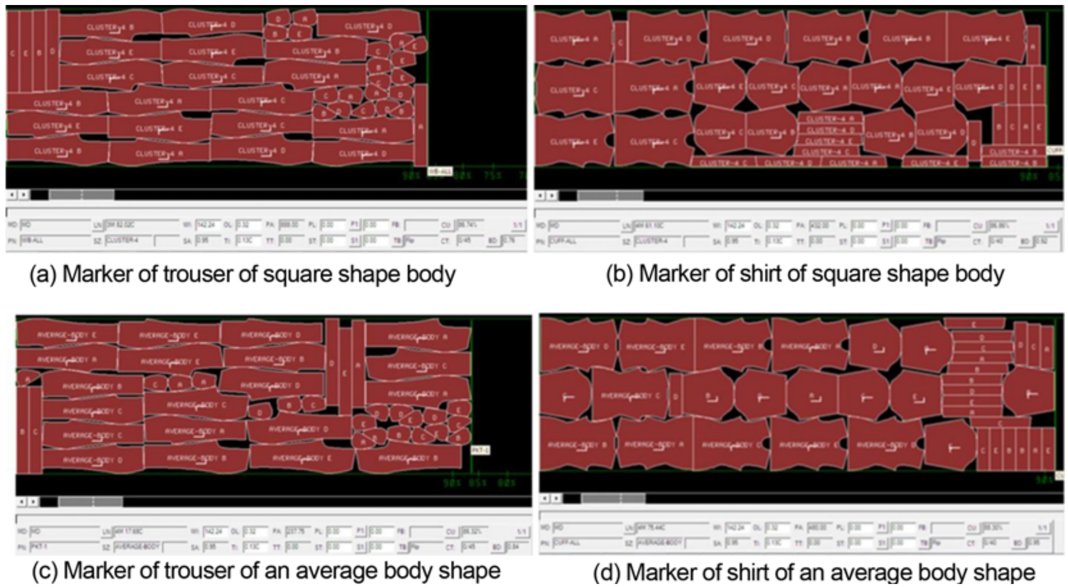


Figure 11. Pattern markers of trousers and shirts in different women body shapes.

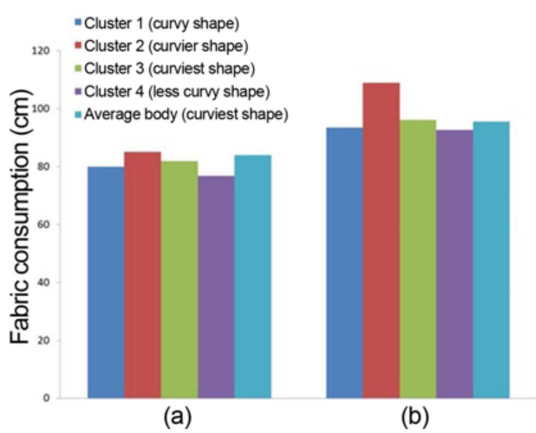


Figure 12. Fabric consumption of fitted trousers and shirt in four women body shapes.

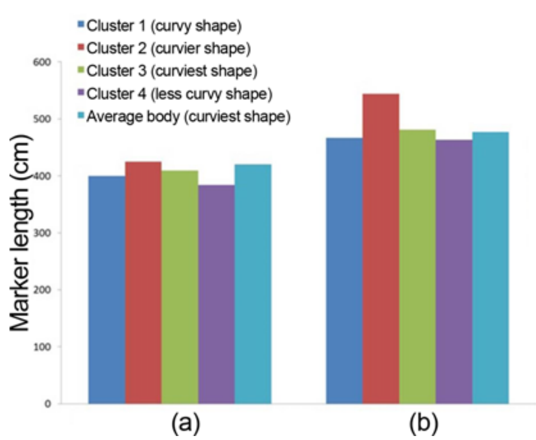


Figure 13. Fabric consumption of fitted trousers and shirt in four women body shapes.

shirt while the circle shape body has devoured more fabric (less profitable) from the other body shapes. The reason is due to the flat contour with the non-obvious bulge. Triangle body was a succeeding shape that consumed more fabric. Henceforth, the circle shape body has required more fabric and consequently more cost for the trouser and shirt in comparison to the square shape body.

Likewise, Figure 13 has shown the results of generated marker lengths in all body shapes. The pattern trend was similar to fabric consumption, which illustrated that it depends on marker length. The longer the marker length, the more is the fabric consumption and vice versa. Furthermore, the Figure 12 and Figure 13 also depicted that women body structures devoured more fabrics (hence more cost) in upper wear garments relative to bottom wear garments in all body shapes. This is due to the more voluptuous of breast and the number of fabric cut panels involved in the cutting and sewing. However, the females with pregnancy and age would have more voluptuous (fats) at hips as compared to the bust. The reason might be both or any, while comparison with the consumption of fabric in shirt and trouser manufacturing, the results revealed that shirt consumed more fabrics (i.e. less the fabric consumed, more is the cost-effectiveness) than the trouser in all body shapes.

Figure 14 has described the marker efficiency results of four body shapes. The increase in marker efficiency (independent variable) leads to a decrease in fabric loss (dependent variable). It was observed that shirt markers were less (maximum average value: 85.1 %) efficient while the trouser markers were more (maximum average value: 86.5 %) efficient. Therefore, working on trouser (bottom wear) was more efficient in material utilization than the shirt (top wear). In the nutshell, the apparel company would have

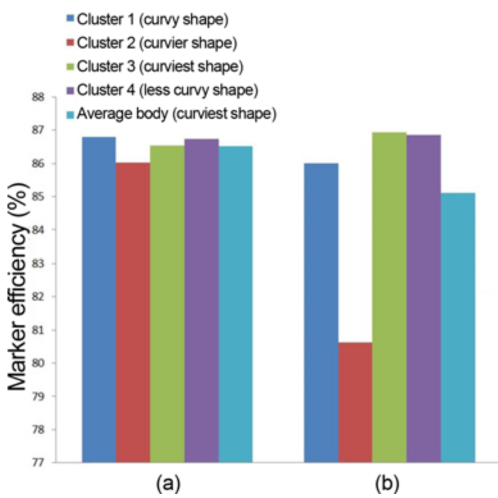


Figure 14. Pattern marker efficiency of fitted trouser and fitted shirt in four shapes of women (%).

more profitability and efficient fabric utilization for the production of trouser manufacturing specifically for the square shape body.

The research was processed with a small sample size of data set and complied with only two styles (trouser and shirt). For more strengthening the knowledge, there is a need to increase the sample size and to explore more garment styles which would be highly expensive study. It might be a guideline for an apparel manufacturing to quantify and qualify the products in relevance to different body shapes. To set exact efficiencies of clothing parameters relative to different curvier body shapes for their products. Otherwise, the exaggeration in clothing which appears temporarily good, affects not only the production cost but also the contentment level of patrons in actual wearings for longer runs. Thus, instead of transforming the surface and shape of the human body through clothing's which change the body silhouette, the apparel designers and professionals make the costumes in accordance with body shapes and upgrade the material consumption efficiencies and profitability ratios respectively.

Conclusion

In this paper, three dimensional (3D) body scans were collected from 124 young female subjects and classified into four body shapes i.e. oval, circle, triangle and rectangle, using Moore neighbor algorithm and region prop function through MATLAB. In addition, fabric consumption efficiencies were evaluated relative to each classified body shapes. It has been observed through our analysis that all body shape categories exhibit different anthropometric dimensions and morphological appearances. Likewise, the fabric utilization has been found dissimilar in the garments (fitted trouser and fitted shirt) manufactured for all body shapes. This study reveals that rectangle shape consumes the fabric most efficiently and thus results in cost-effectiveness. While the circle shape body utilizes the fabric least effectually. It has been noted that the rectangle shape body has the optimum fabric consumption and profit, both in fitted trouser and fitted shirt garments. However, the fitted trousers use less fabric (cost-effective) while the fitted shirts consume more fabric (less cost-effective) in all body shapes. These findings provide a better reference to fabric utilization and cost-effectiveness to the apparel manufacturers while producing garments relative to different body shapes.

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References

1. R. E. Glock and G. I. Kunz, "Apparel Manufacturing: Sewn Product Analysis", 4th ed., pp.173-183, Upper Saddle River, NJ, Prentice Hall, 2005.
2. W. K. Wong and S. Y. S. Leung, *Int. J. Prod. Econ.*, **114**, 376 (2008).
3. D. M. Rose and D. R. Shier, *Comput. Oper. Res.*, **34**, 3209 (2007).
4. Z. Li and V. Milenkovic, *Eur. J. Oper. Res.*, **84**, 539 (1995).
5. T. Naveed, A. Hussain, and Y. Zhong, *Text. Res. J.*, **88**, 1571 (2017).
6. E. Ko and S. Kim, *Fiber. Polym.*, **14**, 860 (2013).
7. E. K. Burke, R. S. R. Hellier, G. Kendall, and G. Whitwell, *Eur. J. Oper. Res.*, **179**, 27 (2007).
8. D. A. Agbo and V. Igoli, *IJSRISE*, **1**, 29 (2015).
9. D. A. Agbo, *Nigeria Journal of Education, Health and Technology Research*, **4**, 1 (2013).
10. V. Chattaraman, K. P. Simmons, and P. V. Ulrich, *Cloth. Text. Res. J.*, **31**, 291 (2013).
11. C. H. Hsu, *Expert Syst. Appl.*, **36**, 4185 (2009).
12. B. Allen, B. Curless, and Z. Popović, 03 ACM SIGGRAPH, **22**, 587 (2003).
13. K. Okabe, N. Yamana, and K. Yamamoto, *Journal of the Japan Research Association for Textile End-uses*, **36**, 42 (1995).
14. R. Otieno, G. Pisut, and L. Jo Connell, *J. Fashion Marketing and Management*, **11**, 366 (2007).
15. L. H. Bai and W. B. Zhang, *J. Text. Res., China Text. Eng. Soc.*, **27**, 113 (2006).
16. D. B. Nascimento, J. Neiva de Figueiredo, S. F. Mayerle, P. R. Nascimento, and R. M. Casali, *Int. J. Prod. Econ.*, **128**, 379 (2010).
17. Y. L. Choi and Y. J. Nam, *Hum. Factor Ergon. Man.*, **20**,

378 (2010).
18. X. Jing, *Int. J. Cloth. Sci. Tech.*, **27**, 358 (2015).
19. A. Petrova and S. P. Ashdown, *Cloth. Text. Res. J.*, **26**, 227 (2008).
20. G. Mori and J. Malik, *IEEE Transactions on Pattern Analysis & Machine Intelligence*, **28**, 1052 (2006).
21. J. Nantel, *J. Interact. Mark*., **18**, 73 (2004).
22. K. P. Simmons, Ph. D. Dissertation, NCSU, North Carolina, 2003.
23. K. Simmons, C. Istook, and P. Devarajan, *J. Text. Apparel, Technol. Manag.*, **4**, 1 (2004).
24. K. Simmons and C. L. Istook, *J. Text. Apparel, Technol. Manag.*, **4**, 16 (2004).
25. V. Arzu and B. Ender, *Int. J. Cloth. Sci. Tech.*, **23**, 46 (2011).
26. A. Knox, L. J. Connell, P. Ulrich, and G. Hutton, "Research Report for External Body", NTU, Nottingham, 2015.
27. J. Yim Lee, C. L. Istook, Y. Ja Nam, and S. M. Park, *Int. J. Cloth. Sci. Tech.*, **19**, 374 (2007).
28. W. Lee and H. Imaoka, *Int. J. Cloth. Sci. Tech.*, **22**, 297 (2010).
29. N. Kim, H. K. Song, S. Kim, and W. Do, *Fiber. Polym*., **19**, 1781 (2018).
30. S. Goel and R. Tashakkori, *Collaborative Mathematics and Statistics Research*, **109**, 161 (2015).
31. L. Yin, L. Xia, and C. Xu, *J. Text. Res., China Text. Eng. Soc.,* **35**, 113 (2014).
32. M. J. Chung, H. F. Lin, and M. J. J. Wang, *Int. J. Ind. Ergon.*, **37**, 707 (2007).
33. F. Xia, H. Xie, D. Li, G. Wu, and Y. Zhong, *Journal of Textile Research, China Textile Engineering Society*, **38**, 86 (2017).
34. Y. A. Nada and H. Meshref, *Int. J. Comput.*, **105**, 15 (2014).
35. ASTM D5586/D5586M-10, Standard Tables of Body Measurements for Women Aged 55 and Older (All Figure Types), ASTM International, West Conshohocken, PA, 2010.
36. P. Komarkova and V. Glombikova, *Tekst Konfeksiyon*, **23**, 409 (2013).
37. M. H. Sohn and E. Bye, *Cloth. Text. Res. J.*, **33**, 64 (2015).
38. Hutton, C. William, Malko, A. John, Fajman, and A. william, *Aviat. Space Environ. Med.*, **74**, 73 (2003).
39. I. Riter, "The Science of Personal Dress Complete Study: Body Shapes", 2nd ed., pp.151-157, Pleasanton, California, USA, 2015.
40. Y. Zhong, *China Patent*, ZL 200910194538.X (2009).

Appendix

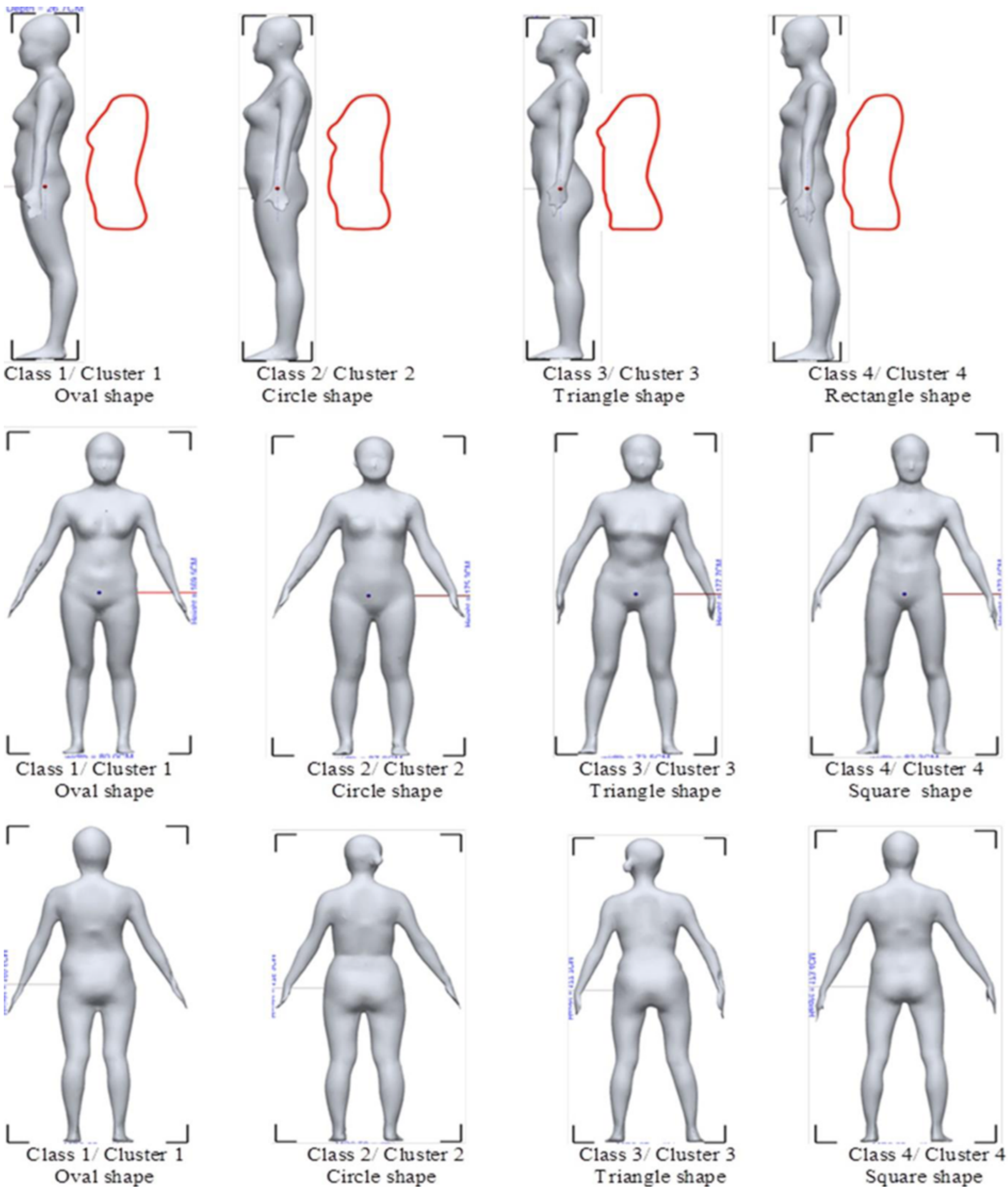

Figure 15. Representative female models in side view, front view and back view of four clusters.

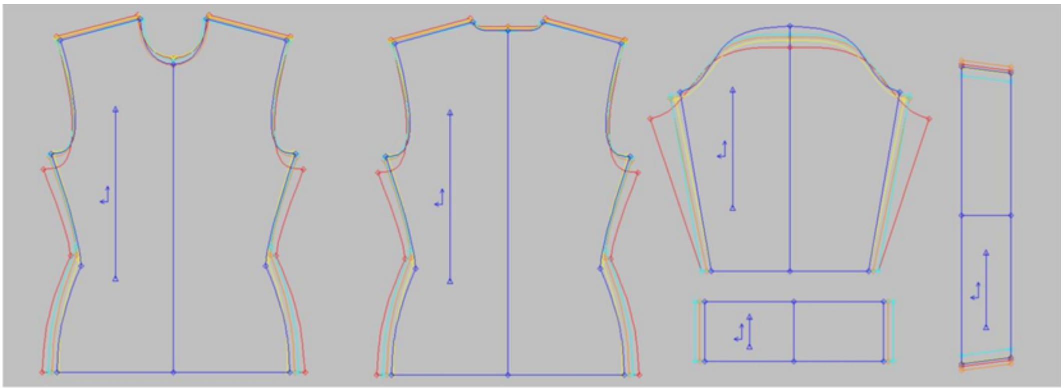

Figure 16. Shirt patterns.

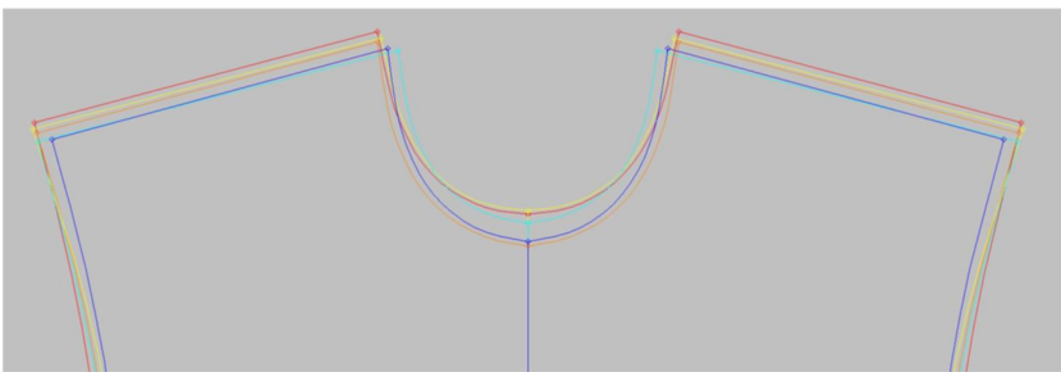

Figure 17. Shirt front panel shoulder area.

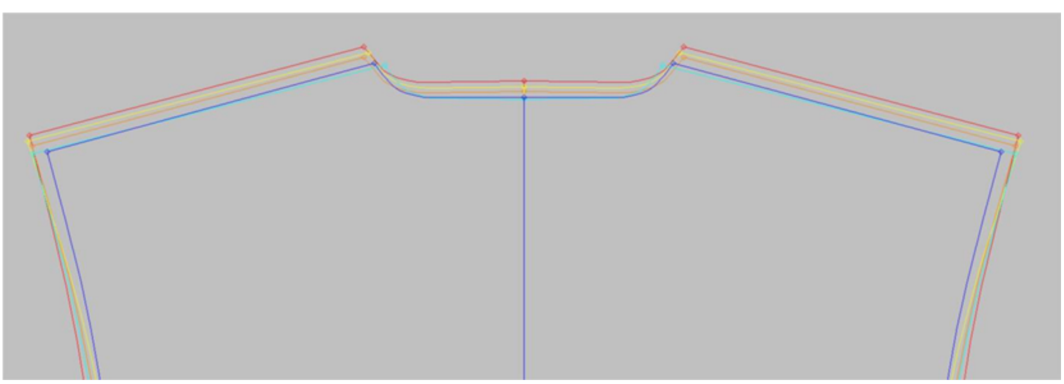

Figure 18. Shirt back panel shoulder area.