Middle-East Journal of Scientific Research 8 (6): 1008-1017, 2011
ISSN 1990-9233

Determining the Structural Parameters and Yarn Type Affecting Tensile Strength and Abrasion of Weft Knitted Fabrics Using Cluster Analysis

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Abstract: Weft knitted structures are grouped by cluster analysis of mechanical properties which consist of tensile and abrasion properties. The resulting classified groups show distinctive characteristics. By discriminative analysis the means of abrasion and tensile modulus are identified for each cluster. We intend to conduct a statistical investigation of the mechanical properties of weft knitted fabrics as a function of their structures. In this investigation, our approach is to determine the structural parameters and the type of the yarn affecting the tensile and abrasion properties of weft knitted fabrics.

Key words: Weft knitted . cluster analysis . tensile modulus . abrasion . discriminative analysis

INTRODUCTION

In the world of objects, we according to Rosch [1] apparently share basic knowledge. Objects maintain their attributes cross-situationally and over time. The cognitive process people use to categorize clothing items is based upon classification of structural features. This process may indeed, work when people categorize discrete items of fabric [1]; however, to facilitate an understanding of the nature of categorization of fabric, a more wholistic approach is desirable.

Previous researchers investigating relationships between fabric mechanical and physical properties and apparel manufacturing processes have concentrated primarily on developing objective measurement methods in order to instrumentally predict and improve fabric tailorability [2-4]. Objective measurement of fabric properties has recently been extended beyond the tailored clothing industry to other apparel fabrics. For example, Cheng, How and Yick [5] assessed the use of objective measurement to predict the performance of shirting materials. Chen *et al.* [6] introduced a statistical method of classifying apparel fabrics by end use from objective measurements. Fabrics were divided in to four clusters based on their end use and performance characteristics.

There are some other researches in the field of clustering method to classify fabrics based on their external and internal characteristics. Buckley [7] studied how dress is organized and stored by individuals at a basic category level. Respondents sorted 106 sketches of a variety of ensemble combinations according to their common features. Three main clusters at the basic level were obtained [7]. DeLong and Minshall [8] determined the extent to which a group of respondents agreed upon categories of dress beyond the basic level. Forms of dress within one basic category presented to a group of similar respondents allowed investigation of attributes which discriminates beyond the basic level. Orzada [9] tested effects of grain alignment on fabric mechanical properties by using nineteen samples. She determined that physical properties were significantly correlated with the mechanical properties. Yoon and Park [10] determined the structural parameters that effect overall properties of warp knitted fabrics using cluster analysis. Eighteen warp knitted structures were grouped by clustering method based on their both physical and mechanical properties. Results of classified groups, showed distinctive features.

The approach of sampling is based on dividing the society to limited distinctive units, called sampling units. The minimum unit that we can divide a society to, is called element. If we select sampling units so that each of them contains a number of elements, this type of sampling unit is called cluster [11].

A knitted structure consists of interlacing loops and properties of these fabrics depending on the relationships and production methods of these loops. In particular, a weft knitted structure differs from both woven and warp knitted fabrics. Therefore investigating the characteristics of weft knitted fabrics by structure is useful when designing fabrics for end use.

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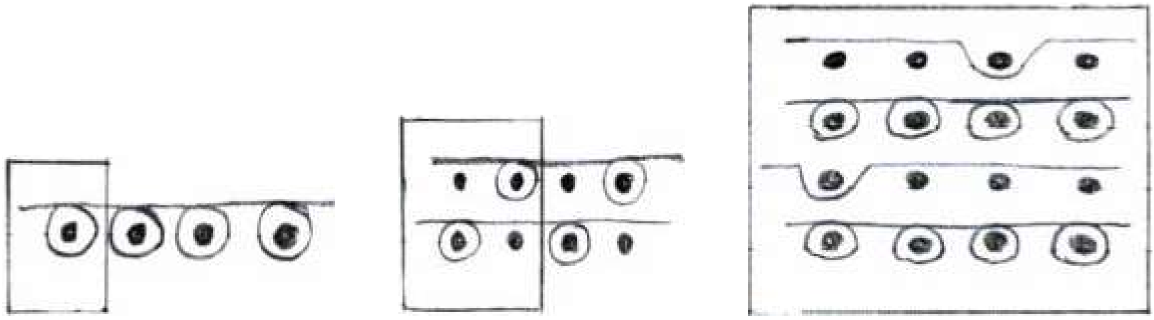

(1) (2) (3)

Fig. 1: Needle notation of fabric structures

In this investigation, our approach is to determine the structural parameters and the type of the yarn affecting the tensile and abrasion properties of weft knitted fabrics.

A few research have been done in the field of sampling and clustering analysis of textile materials and clothing. Businessmen can product desired fabrics with specified structure and yarn type by considering the four derived groups and tensile-abrasion features of them. In addition, when there is no possibility to produce one fabric of a cluster; they can replace another fabric of the same cluster. Because the similarity between fabrics in a cluster is maximum and the similarity between fabrics of different clusters is minimum.

In this investigation, we consider the effect of structural parameters of weft knitted fabrics and the type of the consumed yarns on the tensile strength and abrasion properties using cluster analysis.

MATERIALS AND METHODS

In this investigation, three different single weft knitted structures (1, 2 and 3), at three different loop length i.e, tight fabric with small loop length (S), medium loop length (M) and large loop length (L). These fabrics were produced on a circular knitting machine (gauge 18 and diameter 30") with 19.8 TEX polyester (65%) – cotton (35%) yarn (PC) and 11.4 TEX intermingle polyester yarn (P).

The needle notation diagram of the fabrics are shown in Fig. 1. The fabrics are coded as shown in Table 1, where; 1,2,3 = fabric structures, S,M,L= loop length, PC = polyester/cotton and P= polyester. These fabrics were dry relaxed before mechanical testing in lab conditioning at 25C and 36%RH for more than 24 hours.

MECHANICAL PROPERTIES

The tensile strength of eighteen different weft knitted specimens were measured in both course and wale directions with using tensile tester. Each knit structure were taken on five separate samples cut from the center of the specimen with: 30cm length, 5cm weight, 15cN pretension and 50cm/min cross/head speed and the average values of modulus were tabulated in Table 1.

The abrasion tests were performed on Martindale apparatus for each structure. Four circle samples with 4cm diameter were taken from each structure [12]. The ratio of weight losing is calculated as fabric abrasion with the following equation:

Fabric weight losing (abrasion value) = (fabric weight (before test) – fabric weight (after test)) / (fabric weight (before test))*100

Pilling property of the fabric was considered as another phenomenon from abrasion test using the standard coding system [12], as following:

Code 1 (between categories 1and 2)
Code 2 (between categories 2and 3)
Code 3 (between categories 3and 4)
Code 4 (between categories 4and 5)
Code 5 (category 5)

where, 1 and 5 numbers indicate the maximum and minimum pilling respectively.

One of these code number is attributed to each sample after abrasion test as the pilling value. The average values of fabric weight losing and pilling of each samples were calculated and shown in Table 1.

MATHEMATICAL PRINCIPLES

Mathematical principles have the advantage in objective sorting of fabric characteristics from mechanical properties because they can categorize fabrics according to a number of mechanical properties. In this paper, we use cluster analysis to solve the problem of classifying fabric properties objectively. The method is employed to discover the structure in the data set that is not readily apparent from visual inspection and it is introduced to divide fabrics in

Table 1: Tensile module and abrasion measures

Fabric code	Course tensile strength (cN/mm)	Wale tensile strength (cN/mm)	Weight losing (%)	Pilling (Number)
1SP	5	5	1.47	4.25
1MP	5	3	1.50	4.50
1LP	2	7	3.06	3.75
1SPC	12	9	0.66	1.50
1MPC	10	12	0.80	2.25
1LPC	9	11	1.51	1.00
2SP	14	6	0.24	4.00
2MP	11	5	0.54	3.00
2LP	16	5	0.38	2.75
2SPC	18	9	0.57	1.75
2MPC	11	12	1.74	1.75
2LPC	7	15	1.51	1.50
3SP	13	7	0.66	4.75
3MP	11	9	0.34	4.25
3LP	16	9	1.19	4.50
3SPC	15	18	0.24	1.75
3MPC	13	18	0.23	2.00
3LPC	12	18	0.59	1.75

1,2,3 = Fabric structures, S, M, L= Loop lengths, P = Polyester, PC = Polyester/Cotton

to groups, each representing a particular fabric performance and end-use characteristics. But different clustering methods can produce different results when applied to the same data, that is certain methods have inherent biases in them [13]. Therefore, to confirm the validation of the classification, we have examined the similarity of the results from five clustering methods when applied to the same data. We then classify the groups of fabrics using a hierarchical agglomerative cluster analysis and clusters are analyzed by discriminative analysis.

Clustering algorithms: A cluster problem can be described as follows: Let us call that

$$X = \{x_i, i = 1,\dots,N\}$$

is a set of l-dimensional vectors that are to be clustered. Also, call the definition of a clustering

$$\Re = \{C_j, j = 1,\dots,m\}$$

Where $C_j \subseteq X$

Agglomerative algorithms: Let $g(C_i,C_j)$ be a function defined for all possible pairs of clusters of X. This function measures the proximity between C_i and C_j. Let t denote the current level of hierarchy. Then, the general agglomerative scheme may be stated as follows:

Generalized Agglomerative Scheme (GAS)

1. Initialization:
   - 1.1. Choose $\Re_0 = \{C_i = \{x_i\}, i = 1,\dots,N\}$ as the initial clustering.
   - 1.2. $t = 0$.
2. Repeat:
   - 2.1. $t = t + 1$
   - 2.2. Among all possible pairs of clusters (C_r,C_s) in $\Re_{t-1}$ find the one, say (C_i,C_j), such that $g(C_i,C_j) = \{\min_{r,s} g(C_r,C_s)$, if g is a dissimilarity function $\{\max_{r,s} g(C_r,C_s)$, if g is a similarity function
   - 2.3. Define $C_q = C_i \cup C_j$ and produce the new clustering $\Re_t = (\Re_{t-1} - \{C_i, C_j\}) \cup \{C_q\}$.

Until all vectors lie in a single cluster.

In the sequel, we give an algorithmic scheme, the matrix updating algorithmic scheme (MUAS), that includes most of the algorithms of thus kind. Again, t denotes the current level of the hierarchy.

Matrix Updating Algorithmic Scheme (MUAS)

1. Initialization:
   - 1.1. $\Re_0 = \{C_i = \{x_i\}, i = 1,\dots,N\}$.
   - 1.2. $P_0 = P(X)$.
   - 1.3. $t = 0$
2. Repeat:

- 2.1. $t = t + 1$
- 2.2. Find C_i, C_j such that $d(C_i, C_j) = \min_{r,s=1,\ldots,N,\ r\neq s} d(C_r, C_s)$.
- 2.3. Merge C_i, C_j in to a single cluster C_q and form $\Re_t = (\Re_{t-1} - \{C_i, C_j\}) \cup \{C_q\}$.
- 2.4. Define the proximity matrix P_t from P_{t-1} by (a) deleting the two rows and columns that correspond to the merged clusters and (b) adding a new row and a new column that contain the distances between the newly formed cluster and the old(unaffected at this level) clusters.

Until $\Re_{N-1}$ clustering is formed, that is, all vectors lie in the same cluster.

Notice that this scheme is in the spirit of the GAS. A number of distance functions comply with the following update equation:

$$d(C_q, C_s) = a_i d(C_i, C_s) + a_j d(C_j, C_s) + b\, d(C_i, C_j) + c\left|d(C_i, C_s) - d(C_j, C_s)\right| \quad (1)$$

Different values of a_i, a_j, b and c correspond to different choices of the dissimilarity measure $d(C_i, C_j)$. The single link algorithm: This is obtained from Eq.(1) if we set $a_i = 1/2$, $a_j = 1/2$, $b = 0$ $c = -1/2$. In this case,

$$d(C_q, C_s) = \min\{d(C_i, C_s), d(C_j, C_s)\}$$

The complete link algorithm: This follows from Eq.(1) if we set $a_i = 1/2$, $a_j = 1/2$, $b = 0$ and $c = 1/2$. Then we may write,

$$d(C_q, C_s) = \max\{d(C_i, C_s), d(C_j, C_s)\}$$

The centroid link algorithm: Algorithm results on setting

$$a_i = \frac{n_i}{n_i + n_j}, a_j = \frac{n_j}{n_i + n_j}$$

$$b = -\frac{n_i n_j}{(n_i + n_j)^2}, \ c = 0, \text{ that is,}$$

$$d_{qs} = \frac{n_i}{n_i + n_j} d_{is} + \frac{n_j}{n_i + n_j} d_{js} - \frac{n_i n_j}{(n_i + n_j)^2} d_{ij}$$

The median link algorithm: This follows from Eq.(1) if we set $a_i = 1/2$, $a_j = 1/2$, $b = -1/2$ and $c = 0$. Then we may write,

$$d_{qs} = \frac{1}{2} d_{is} + \frac{1}{2} d_{js} - \frac{1}{2} d_{ij}$$

The Ward or minimum variance algorithm: Here, the distance between two clusters C_i and C_j, d'_{ij}, is defined as a weighted version of the squared Euclidean distance of their mean vectors, that is,

$$d'_{ij} = \frac{n_i n_j}{n_i + n_j} d_{ij}$$

where $d_{ij} = \|m_i - m_j\|^2$. Thus, in step 2.2 of MUAS we seek the pair of clusters C_i, C_j so that the quantity d'_{ij} is minimum. Furthermore, it can be shown that this distance belongs to the family of Eq.(1) and we can write

$$d'_{qs} = \frac{n_i + n_s}{n_i + n_j + n_s} d'_{is} + \frac{n_j + n_s}{n_i + n_j + n_s} d'_{js} - \frac{n_s}{n_i + n_j + n_s} d'_{ij}$$

Cluster analysis involves two fundamentals: the measure of similarities within observations and the clustering algorithms that are selected to produce a rule of classification.

Similarity Measure: The distance between two observation represents the closeness of this pair of observations and can be used as a measure of similarity or dissimilarity between observations.

The Euclidean distance is known as the major classification criterion for clustering sample points. So we use the squared Euclidean distance as the distance between members. We have normalized the original parameters of the samples before defining the distance between groups.

$$D^2 = \sum_{i=1}^{k} (x_{il} - x_{jl})^2 \quad (2)$$

Hierarchical Agglomerative Cluster Analysis: All members are gradually merged in accordance with their similarities in fabric characteristics. The whole procedure can be drawn in to a clustering tree, which may be viewed as a diagrammatic representation of the results of the clustering process.

Hierarchical cluster analysis is based on the theories of multivariate statistical analysis. We have adopted five of them using the SPSS statistical package for comparison because there are various definitions and therefore various algorithms: Single linkage, complete linkage, centroid linkage, median linkage and Ward's method.

RESULTS AND DISCUSSION

Hierarchical agglomerative cluster analysis: Through the SPSS statistical computer program and the

Fig. 2: Single linkage

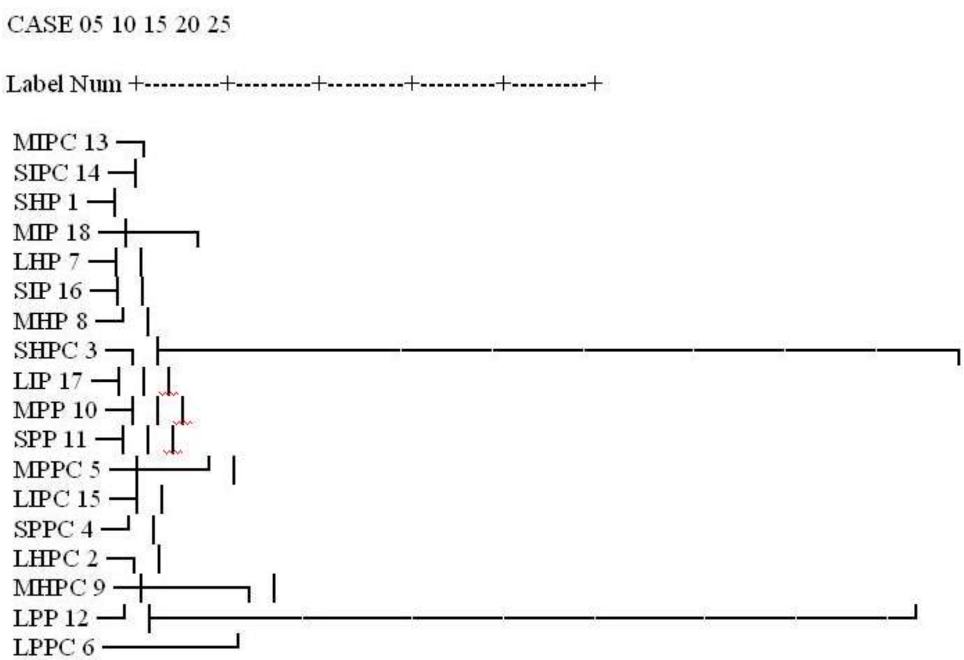

Fig. 3: Complete linkage

parameters of the sample set, we have obtained the results corresponding to these methods and we show them in Fig. 2-6.

From the similar results of the five methods of hierarchical clustering, we believe we have validated the classification of weft knitted fabrics in this investigation. The clustering trees of the various approaches only give a configuration for every number of clusters from one, the entire data set, up to the number of entities in which each cluster has only one member. Therefore, to determine the number of clusters present, real distance or scaled distance (from 1 to 25) are considered. If we determine the distance = 2, then draw a vertical line from there to diagram's lines, the number of lines cut while crossing this line will be equal to the number of clusters. So the number of clusters was determined four or five by using experimental method [14].

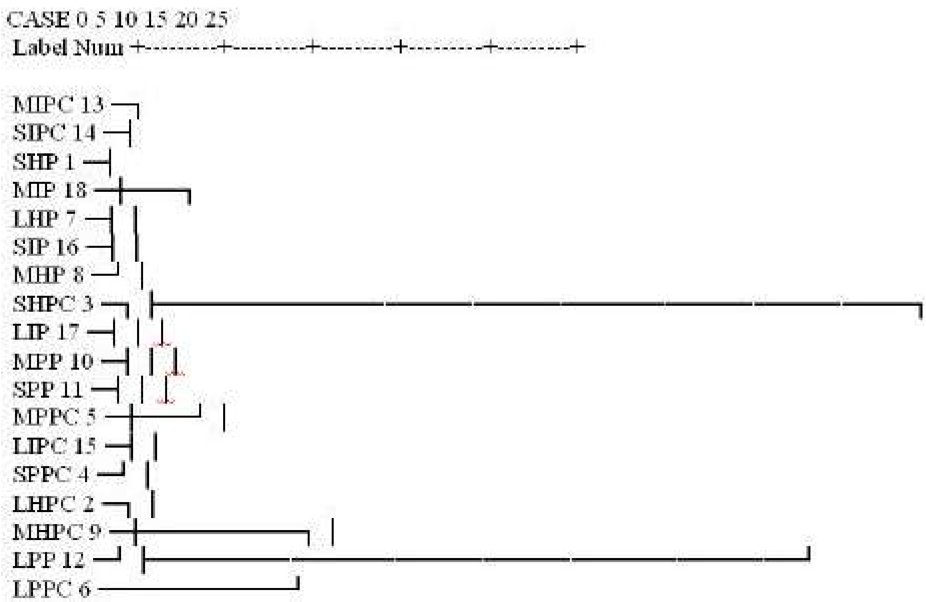

Fig. 4: Centroid linkage

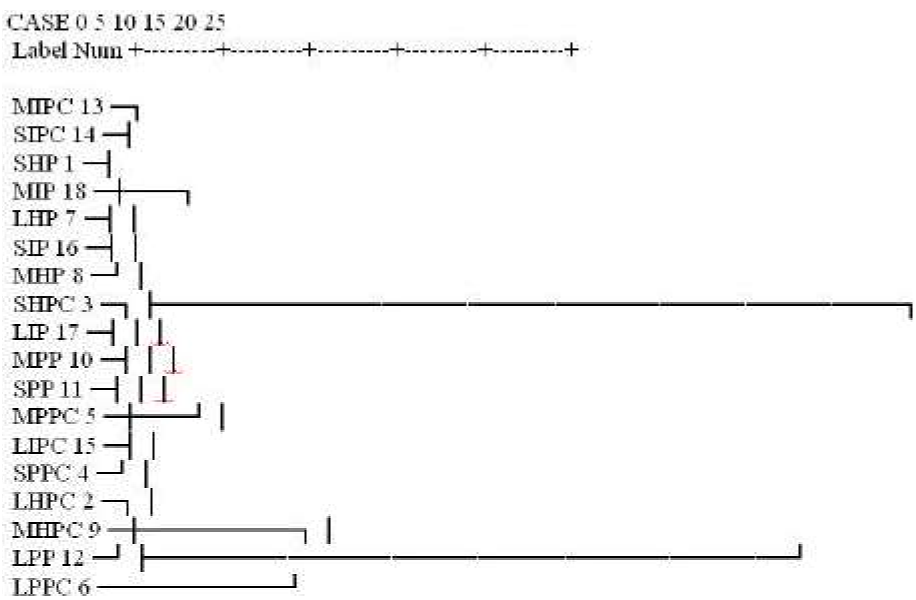

Fig. 5: Median linkage

From Fig. 2-6, all five hierarchical clustering trees can be divided in to two groups. The complete, the centroid, the median linkage and Ward's method, whose cluster number is four, compose the first group. The single linkage method, whose number is five, belong to the second group.

After taking the five hierarchical methods into consideration and investigation the relationship between fabrics, we can create an illustration representing the relationship of weft knitted fabrics based on Ward's method in Table 2.

This investigation suggests, however, that not only defining the number of clusters, but also exploring the general pattern of the relationships between entities as represented by a hierarchical tree, is of paramount importance.

Hierarchical Cluster Analysis

Dendrogram using Single Linkage

Rescaled Distance Cluster Combine

Table 2: Membership stages of fabrics in clusters

Agglomeration schedule

	Cluster combined			Stage cluster first appears		
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next stage
1	13	14	0.000	0	0	7
2	10	11	0.000	0	0	3
3	5	10	0.001	0	2	11
4	1	18	0.002	0	0	7
5	7	16	0.003	0	0	9
6	2	9	0.005	0	0	14
7	1	13	0.008	4	1	12
8	3	17	0.011	0	0	10
9	7	8	0.015	5	0	12
10	3	15	0.024	8	0	13
11	4	5	0.036	0	3	13
12	1	7	0.074	7	9	16
13	3	4	0.114	10	11	16
14	2	12	0.156	6	0	15
15	2	6	0.429	14	0	17
16	1	3	1.016	12	13	17
17	1	2	6.529	16	15	0

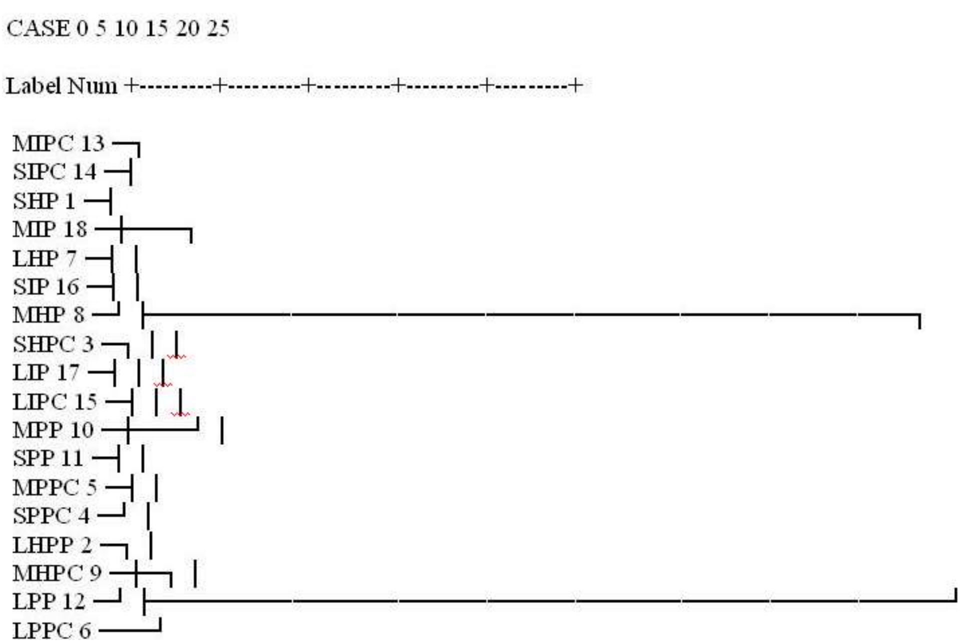

Fig. 6: WARD method

Hierarchical cluster analysis

Dendrogram using Complete Linkage
Rescaled Distance Cluster Combine

Hierarchical cluster analysis

Dendrogram using Centroid Method
Rescaled Distance Cluster Combine

Table 3: Clustering the fabrics

	Structure	Loop	Yarn
Cluster (1)	2	Small-Medium-Large	Polyester
	3	Small-Medium	Polyester-cotton, Polyester
Cluster (2)	2	Large	Polyester-cotton
	1	Small-Medium	Polyester-cotton, Polyester
	3	Large	Polyester-cotton, Polyester
Cluster (3)	2	Medium-large	Polyester-cotton
	1	Large	Polyester
Cluster (4)	1	Large	Polyester-cotton

Table 4: Effect of structural parameters and yarn type on clustering

Effect on clustering	Min	Medium	Max
Structure	Cluster (2)	Clusters (1, 3)	Cluster (4)
Loop	Cluster (1)	Cluster (2)	Clusters (3, 4)
Yarn	Cluster (3)	Clusters (1, 2)	Cluster (4)

Hierarchical cluster analysis

Dendrogram using Median Method
Rescaled Distance Cluster Combine

Hierarchical cluster analysis

Dendrogram using Ward Method
Rescaled Distance Cluster Combine

Classification weft knitted fabrics: Considering hierarchical cluster analysis, four clusters seem to be more appropriate to classification of weft knitted fabrics. We therefore provide four fabric groups representing specific characteristics, as shown in Table 3.

Fourteen fabrics are allotted in two main groups, A and B. The A group, includes seven fabrics (mostly contains polyester yarn, with mat-like and interlock structures) and the B group comprises seven fabrics (consists of both polyester and polyester-cotton yarns, with stiff plain structure.

But information about the characteristics possessed by each group can not be obtained from cluster analysis. What we do know is that only the groups of weft knitted fabrics are reported as having similar characteristics. Therefore, to support the results from cluster analysis and to identify the characteristics of the groups, we use discriminative analysis.

Discriminative analysis: Discriminative analysis is used for grouping observations into one of the number of certain groups, based on various characteristics [14]. In this paper, we use this analysis to identify the characteristics of the groups and so, compare clusters. The mean of tensile and abrasion characteristics for each cluster are shown in Table 5.

Within-group properties: First and second clusters have similar behavior in course and wale tensile: course tensile is more than wale tensile. The result of other clusters is reverse: wale tensile is more than course tensile.

Clusters1, 2 and 3 are similar in abrasion: pilling is more than the ratio of losing the weight. But the result of cluster 4 is reverse: the ratio of losing the weight is more than pilling.

Between-group properties: The course tensile is maximum for cluster 1 (0.1329), medium for clusters 2 (0.1114) and 4 (0.0900) and minimum for cluster 3 (0.0667).

The wale tensile is maximum for clusters 3 (0.1133), medium for cluster 1 (0.0971) and minimum for cluster 2 (0.0950).

The ratio of losing the weight is maximum for cluster 3 (2.1033), medium for clusters4 (1.5100) and 2 (0.9686) and minimum for cluster 1 (0.3757).

The pilling is maximum for cluster 1 (3.2143), medium for clusters 2 (2.6875) and 3 (2.3333) and minimum for cluster 4 (1.0000).

ANOVA Table 6 represents comparison of clusters' means for tensile and abrasion properties. Hypothesis tests can be appointed according to the P-Value measure identified by sig.

Hypothesis test: via H_1=inequality for at least one mean i = 1,2,3,4 $H_0 : \mu_{i1} = \mu_{i2} = \mu_{i3} = \mu_{i4}$

Where i represents character and j represents cluster.

If P-Value is less than reliability (α), equality of clusters' means for a specified property will be rejected. Reversely, If P-Value is more than reliability (α), equality of clusters' means for a specified property will be accepted.

Equality for course tensile

$$H_0 : \mu_{11} = \mu_{12} = \mu_{13} = \mu_{14}$$

Table 5: The mean of tensile and abrasion characteristics

Group statistics

CLUSTER		Mean	Std. Deviation	Valid N (list wise) Un weighted	Weighted
1	COURSETENSILE	0.1329	0.01890	7	7.000
	WALETENSILE	0.0971	0.05823	7	7.000
	ABRASION	0.3757	0.16692	7	7.000
	PILLING	3.2143	1.14953	7	7.000
2	COURSETENSILE	0.1114	0.04981	7	7.000
	WALETENSILE	0.0929	0.04855	7	7.000
	ABRASION	0.9686	0.41002	7	7.000
	PILLING	2.9286	1.41211	7	7.000
3	COURSETENSILE	0.0667	0.04509	3	3.000
	WALETENSILE	0.1133	0.04041	3	3.000
	ABRASION	2.1033	0.83644	3	3.000
	PILLING	2.3333	1.23322	3	3.000
4	COURSETENSILE	0.0900	0.[a]	1	1.000
	WALETENSILE	0.1100	0.[a]	1	1.000
	ABRASION	1.5100	0.[a]	1	1.000
	PILLING	1.0000	0.[a]	1	1.000
Total	COURSETENSILE	0.1111	0.04255	18	18.000
	WALETENSILE	0.0989	0.04776	18	18.000
	ABRASION	0.9572	0.73522	18	18.000
	PILLING	2.8333	1.28624	18	18.000

a. Insufficient data

Table 6: ANOVA of cluster's means

Tests of equality of group means

	Wilks' Lambda	F	df1	df2	Sig.
COURSETENSILE	0.685	2.142	3	14	0.141
WALETENSILE	0.974	0.127	3	14	0.943
ABRASION	0.280	11.986	3	14	0.000
PILLING	0.815	1.056	3	14	0.399

via H_1 = inequality for at least one mean

According to P-Value=0.141, if α = 0.05, equality of clusters' means for course tensile will be accepted, so we can replace every cluster with another one.

if α = 0.05, equality of clusters' means for course tensile will be rejected, so clusters will be different in course tensile completely.

Equality for wale tensile

$$H_0: \mu_{21} = \mu_{22} = \mu_{23} = \mu_{24}$$

via H_1=inequality for at least one mean

According to P-Value = 0.943, equality of clusters' means for wale tensile is accepted, so we can replace every cluster with another one.

Equality for the ratio of losing the weight

$$H_0: \mu_{31} = \mu_{32} = \mu_{33} = \mu_{34}$$

via H_1=inequality for at least one mean

According to P-Value=0.000, equality of clusters' means for the ratio of losing the weight is rejected, so clusters will be different in the ratio of losing the weight completely.

Equality for pilling

$$H_0: \mu_{41} = \mu_{42} = \mu_{43} = \mu_{44}$$

via H_1=inequality for at least one mean

According to P-Value=0.399, if α = 0.05, equality of clusters' means for pilling will be accepted, so we can replace every cluster with another one.

Table 7: Effect of mechanical properties on clustering

	Course tensile strength	Wale tensile strength	Weight losing (%)	Pilling
Effect on clustering	Medium	Min	Max	Medium

If α = 0.40, equality of dusters' means for pilling will be rejected, so clusters will be different in pilling completely.

CONCLUSIONS

The essence of cluster analysis is to sort the samples into groups and this method has the advantage of requiring little or no knowledge about the category structures in a sample set. All that is needed is a collection of measured parameters. From the resulting groups, the degree of "property association" is high between members of the same group and low between members of different groups.

In this investigation, we have found that weft knitted structures can be grouped by cluster analysis and the resulting classified groups show distinctive characteristics between groups. By analyzing the structures within and between groups, we can compare the characteristics of weft knitted fabrics.

Eighteen kind fabrics are grouped in four cluster by agglomerative hierarchical analysis.

- There is structure 2 in clusters (1,2,3), structure 1 in clusters(2,3,4) and structure 3 in clusters(1,2).
- There are small loop in clusters (1,2), medium loop in clusters(1,2,3) and large loop in clusters (2,3,4).
- Loop does not have any effect in clustering of polyester yarn, with structure 2.
- The type of the yarn has minimum effect in clustering, because in all clusters (except fourth cluster) there are both polyester and polyester-cotton yarns.
- In cluster 3 polyester-cotton fabrics are twice polyester fabrics, in cluster 3 polyester-cotton fabrics are equal to polyester fabrics and in cluster 1 polyester-cotton fabrics are half polyester fabrics.

Tensile and abrasion means of clusters are identified and compared with discriminative analysis.

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