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An Alternative Approach to the Objective Measurement of Fabrics

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ABSTRACT

Objective measurements of fabric mechanical properties have great potential for quality control of clothing materials. However, access to the requisite instruments still remains a problem for many potential users due to their high cost. Therefore, a scheme for measuring all the relevant property parameters on an Instron is proposed in this article. Also, in view of the lengthy measurement process typically required by the Kawabata KES-FB system, this work provides a theoretical approach for selecting the pertinent parameters from those of the KES-FB system, so that measurement time and complexity of further data analysis can be reduced. As to the overall evaluation of fabric performance or utilization of acquired results, a graphical technique using circular diagrams is proposed to "fingerprint" or characterize fabrics. Data obtained on selected fabrics of different fiber types, weave construction, and fabric thickness are presented to illustrate this method and its applications.

Traditionally, the testing of fabric mechanical properties has focused on various strengths such as tensile, tearing, and bursting in relation to fabric failure. As living standards have risen, however, it has become more common for garments to be selected or discarded not because of their strength but because of their overall performance (*i.e.*, the properties related to garment service and wearing functions). Traditional strength-oriented mechanical testing seems to be of little relevance in this respect. Consequently, a new concept of so-called objective measurement of fabric mechanical properties has been proposed [1, 4, 13]. This concept is based on a determination of the mechanical response of fabrics at a far lower stress than the actual breaking stress. The results are hypothesized to simulate the actual fabric loading situation during garment processing and wearing, which provides more meaningful information in guiding the manufacturing and designing processes. For example, these data can be used to predict tailorability and appearance of fabrics, and the tactile response of people to a specific fabric. In fact, the objective measurement of fabric properties will enable fabric manufacturers and garment makers to optimize and assure the consistency of the quality of their products, and as a result, to minimize the cost. Applications of this approach have been extended to fabric finishing control and to new products and finishes [13].

Logically, there are two fundamental issues involved in objective measurement—what to measure and how to interpret the measured results. The second issue will be discussed in a later section of this article. The first question, although it may be the easier one to answer, has not been fully resolved, while there have been several practical proposals resulting in the construction of instruments.

One solution to this problem is that, since almost every aspect of the mechanical properties of a fabric is related to its performance, all should be tested. For example, fullness and softness as well as finish stability are all related to fabric compressional properties. Bending properties determine the stiffness of a fabric, and low stiffness may cause problems in handling during garment manufacturing. Tensile tests provide indications of extensibility, a significant factor along with bending and shearing properties in determining fabric formability (tendency to buckle), which is essential for a smooth garment-making process. The unique shearing property of fabrics is the major characteristic that differentiates fabrics from other fibrous sheets such as paper. Proper shearing and bending properties allow fabrics to have excellent drape, an indispensable attribute in making an elegant garment. Accordingly, Kawabata [5] and Nasu [10] have suggested that instruments be built to measure as many aspects of fabric

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mechanical properties as possible. This strategy has been reflected in Kawabata's KES-FB system [5] in which six different kinds of properties are covered and at least sixteen parameters are measured or calculated, as shown in Table I.

In contrast, Kim and Vaughn [8] applied an alternative method to selecting properties to be measured: among all parameters measurable in a textile laboratory, they focused on those whose correlation coefficients with subjectively assessed sensory evaluations of fabric hand were higher than an arbitrary critical value. This method has the advantage of taking the human factor into consideration, but it is well established that subjective human judgments bring uncertainty and bias into the conclusions. Therefore such conclusions may not be universally rational and acceptable.

There is a common drawback in both these approaches—there may be high intercorrelations between selected parameters. In other words, the selected parameters may overlap and contain duplicate information. Unnecessary parameters will not only increase the complexity of the instruments and raise costs, but more importantly, they will increase the difficulty of interpreting of results.

Another concern with the KES-FB is its high price due to its sophisticated structure and functions. Tester and DeBoos [14] reported that "for routine measurements and application of those fabric objective properties particularly relevant to industry, only a fraction of the information obtained from previously available systems (such as KES-FB) was required." It is from this consideration that CSIRO in Australia developed its own routine fabric measurement system [14] named FAST (fabric assurance by simple testing). This is a much simpler system compared with the KES-FB and measures fewer parameters. Despite the fact that the FAST system is much less expensive than the KES-FB system, it is still not readily affordable for most textile laboratories. Since Instron testers are available in many textile labs, we propose an alternative approach in which all the tests can be completed on this instrument.

Objective Measurement with an Instron

All the property categories covered by the KES-FB system as shown in Table I can be run on an Instron tensile tester, provided proper attachments are available. This concept is not novel, but considering the different requirements of these tests and the diverse ways to measure the same property, a format to organize these tests into a complete frame and to standardize the testing procedures is desirable for establishing a comprehensive and consistent approach.

Below is a brief description of the procedure for each property to be determined on the Instron. The specific test procedures, the corresponding attachments, and the testing conditions, either collected from other existing sources as indicated below or our suggestions, are presented in Figures 1–5 and Table II. The key is to maintain an appropriate stress level far lower than the breaking stress. However, the stress level should be such that the nonlinear behavior of the fabric is detectable [5].

PROPERTY TESTS

Tensile test: Since the Instron is designed for tensile testing, there is no problem in performing this test; it is simply a case of selecting an appropriate load or extension range. In our example, all results are obtained

TABLE I. Kawabata's parameters, properties and apparatus.

Properties	Parameter	Description	Unit	Apparatus
Bending	B (X_1)	bending rigidity	gf·cm²/cm	KES-FB2
	2HB (X_2)	hysteresis of bending moment	gf·cm/cm	KES-FB2
Surface	MIU (X_3)	coefficient of friction	none	KES-FB4
	MMD (X_4)	mean deviation of MIU	none	KES-FB4
	SMD (X_5)	geometrical roughness	μm	KES-FB4
Tensile	LT (X_6)	linearity of tensile curve	none	KES-FB1
	WT (X_7)	tensile energy	gf·cm/cm²	KES-FB1
	RT (X_8)	tensile resilience	%	KES-FB1
Shearing	G (X_9)	shear stiffness	gf·cm·deg.	KES-FB1
	2HG (X_{10})	hysteresis at 0.5°	gf/cm	KES-FB1
	2HG5 (X_{11})	hysteresis at 5°	gf/cm	KES-FB1
Compression	LC (X_{12})	linearity of compression curve	none	KES-FB3
	WC (X_{13})	compressional energy	gf·cm/cm²	KES-FB3
	RC (X_{14})	compressional resilience	%	KES-FB3
Thickness	T (X_{15})	fabric thickness	mm	KES-FB3
Weight	W (X_{16})	fabric weight	mg/cm²	a balance

TABLE II. Testing parameters on the Instron tensile tester.

Testing conditions	Tensile	Bending	Shearing	Compression[a]	Friction
Sample length, cm	15[b]	6.35	15[b]	6.35	20
Sample width, cm	1.27	3.81	1.27	6.35	10
Cross head speed, mm/min	1	10	1	0.5	10
Chart speed, mm/min	50	50	50	50	50
Displacement, mm	2	2[b]	2	given load 2.5 g/cm^2	40

[a] Initial distance between upper and lower compression plates = 6 cm. [b] actual testing gauge length = 7.62 cm.

at a given jaw displacement or extension (Table II), as shown in Figure 1.

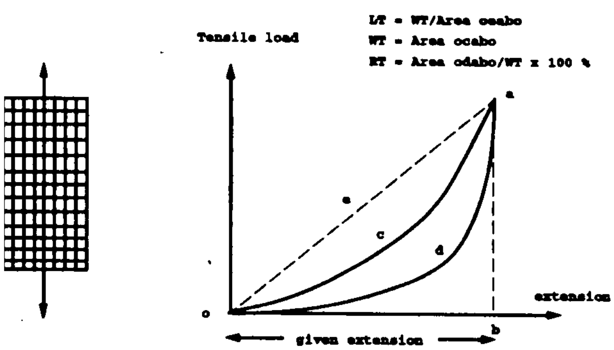

FIGURE 1. Tensile test and a typical curve with derived parameters.

Bending test: We used a compression cell to test bending on the Instron. By seaming two sides of a rectangular shaped sample of the fabric we obtained a tubular specimen. We tested a pure bending of this fabric by compressing the tube to a given displacement (Table II), as shown in Figure 2.

Shearing test: Fabric shear is essentially a test of yarn mobility within a fabric. Since it is not easy to establish a classic pure shearing test on the Instron, we adopted a bias tensile test similar to that applied in the FAST system. Although Grosberg [3] has indicated that there are some differences between fabric shearing tests and bias tensile tests, under low stress levels both tests convey the same information on yarn mobility. So we replaced the shearing test by a 45° bias tensile test at a given jaw displacement (Table II), as illustrated in Figure 3.

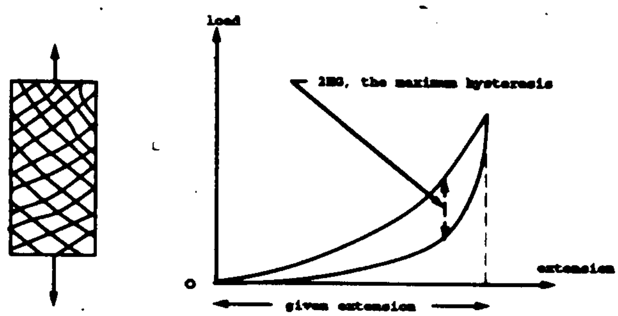

FIGURE 3. Shear (bias tensile) test and a typical curve with derived parameters.

Compression and fabric thickness: A compression cell is available for the Instron. The tester must pay attention to maintaining an appropriate optimum compression load (Table II) for all samples (see Figure 4).

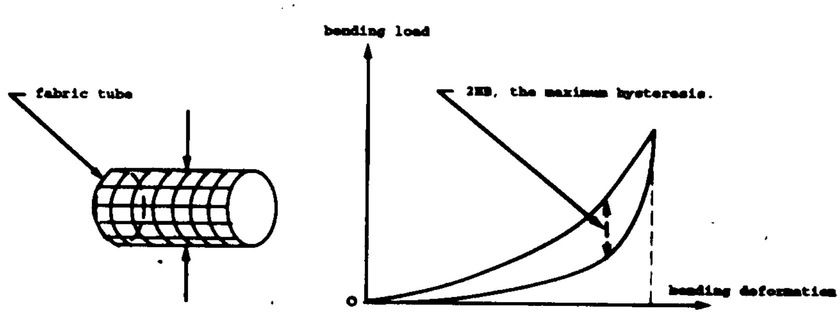

FIGURE 2. Bending test and a typical curve with derived parameters.

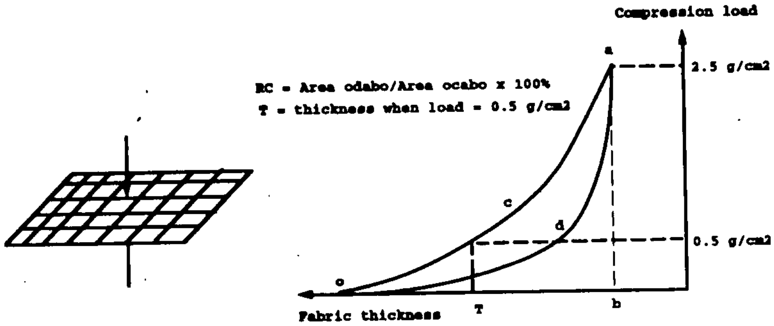

FIGURE 4. Compression test and a typical curve with derived parameters.

Frictional test: As reported in the literature [2], a frictional test on the Instron needs a device like that shown in Figure 5. The test conditions again are given in Table II and the results of the test in Figure 5.

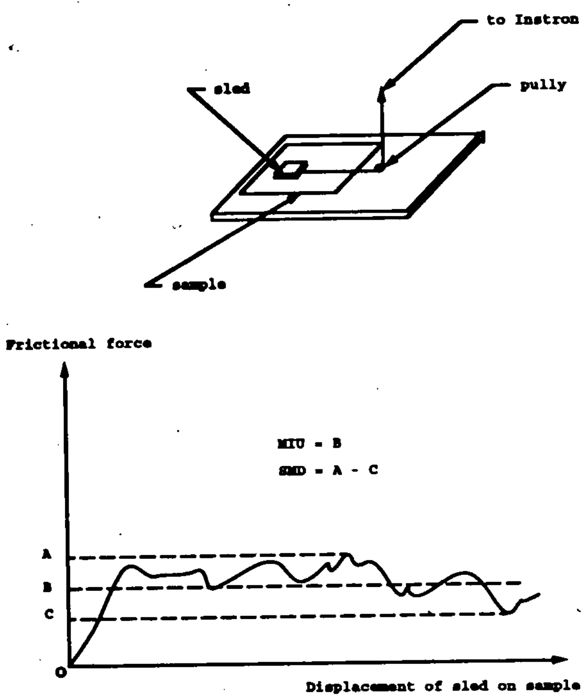

FIGURE 5. Frictional test [3] and typical results.

Parameter Determination

We have obtained various curves with these tests, as is the case with the KES-FB system. Because of the differences between the Instron tensile tester and the KES-FB system, and because of differences in sample size and shape and measurement procedures, the values of the parameters we derived from the curves may not have the same magnitudes as those from KES-FB. Moreover, some of the curves, especially those for shearing and bending, may not be the same as those using KES-FB system. Nevertheless, these parameters in general reveal the same information or have the same intrinsic physical meanings as data from the KES-FB system.

Another question is the number of parameters required. Even if we assume that the sixteen parameters of the KES-FB system listed in Table I have completely extracted all the information contained in these curves, there is still a question of the possibility of information overlap or superfluous elements existing in the KES-FB parameters. In other words, we have to determine whether all sixteen parameters are required to fully specify a fabric. If not, we then need to identify and discard unnecessary variables. A selection procedure is desirable so that measurements and further data processing as well as the fabric evaluation procedure can be greatly simplified. Some of our previous theoretical analyses [12] given below show the importance or contribution of each of the KES-FB parameters. In order to further refine the method proposed in this article, we believe that a brief introduction of the analyses is necessary, and we provide that in the next section.

VARIABLE SELECTION FROM THE KAWABATA PARAMETERS

In our previous study on fabric performance [12], we chose and tested fifty samples using the KES-FB system, each having sixteen Kawabata parameters. The observation matrix (the random vector) is thus formed as

$$\mathbf{X} = \begin{bmatrix} X_{11} & X_{12} & - & X_{1N} \\ X_{21} & X_{22} & - & X_{2N} \\ - & - & - & - \\ X_{M1} & X_{M2} & - & X_{MN} \end{bmatrix} , \qquad (1)$$

where $N = 16$ represents the sixteen Kawabata parameters (Table I), and $M = 50$, the number of the samples.

All samples were medium thickness suiting fabrics. Some major characteristics of the samples are shown in Table III.

TABLE III. The major characteristics of the fabric samples [12].

	Max.	Min.	Mean	Variance
Weight, mg/cm²	30.50	18.59	26.08	2.67
Thickness, mm	0.930	0.475	0.770	0.092

Since the following analysis is based on the assumption that the random vector **X** obeys a multinormal distribution, a statistical test is required here to test this hypothesis. None of multinormality tests is effective when $N > 2$ [9], where N, as defined above, is the dimension of vector **X**. Thus, based on the recommendation in the literature [9], we used the W test to check the marginal distributions of sixteen parameters instead. Even though the marginal normality of the components does not always lead to multinormality of the vector itself, the exception is very rare [9]. Our test results showed that all parameters possessed the normal marginal distribution, except three surface property variables MIU, MMD, SMD, where slight deviations existed. This conclusion was consistent with that indicated by Kawabata [5]. Therefore, in general, the hypothesis of multinormality of vector **X** is considered acceptable.

Test of the Collinearity of Kawabata Parameters

This test is intended to establish if there are any surplus elements, known as the collinearity in multivariate analysis, existing among the sixteen Kawabata parameters. According to theory [7], the determinant value $|\mathbf{V}|$ of the covariance matrix **V** of the random vector **X** is an indicator of the extent of the collinearity in **X**. A value of $|\mathbf{V}|$ close to 0 will definitely prove the existence of superfluous elements. Our calculation shows that

$$|\mathbf{V}| = 2.24 \times 10^{-7} \rightarrow 0 \quad , \qquad (2)$$

indicating that the matrix **V** is nearly singular, and therefore there are certainly some superfluous parameters existing in **X** or among the sixteen KES-FB parameters, contributing little to the results.

Results of Principal Component Analysis (PCA)

In order to identify and eliminate unnecessary parameters, the contribution or importance of each parameter has to be examined. According to Kendall [7], principal component analysis can be used for this purpose. Using this analysis, some new variables, known as the principal components, fewer in number than the original parameters but still fully representing the original data, can be derived by condensing the original parameters. This is a relatively common analysis, and its theoretical details can be found elsewhere [7]. The results of our observation matrix have been provided in other publications [11, 12]. The effective dimension of the matrix can be determined by extracting the first eight principal components ranked according to their eigenvalues = 25.3226, 18.4603, 12.9936, 10.9099, 8.09512, 6.0766, 5.0298, and 4.2404%, totally accounting for 91.9844% of the variance. Accounting for 85% of the variance is considered satisfactory [7]. In other words, the first eight components represent nearly all the information. We thus reduce the effective dimension of the variables from sixteen to eight by discarding the other eight principal components with smaller eigenvalues. Then, in light of the method proposed by Kendall [7], the parameters having the largest correlation coefficients with respect to these discarded components are considered unimportant and therefore can be dropped. In other words, the importance of all sixteen parameters can be determined by their correlation with the ranked principle components, and the results, combined with other results, are provided in Table V.

Variable Clustering Analysis and Results

Variable clustering analysis shows the relationships between all parameters so that the closeness or similarities among them will be revealed. This is helpful in clarifying the interrelationships between all the variables before selection. The theory and calculation procedures are reported by Kendall [7]. If we choose a group number of eight, the results of variable clustering are as shown in Table IV. All the variables in one group

TABLE IV. Results of variable clustering analysis.

Group	Parameter in the group	Correlations between the parameters
1	X_9, X_{10}, X_{11}	$r(9, 10) = 0.637$, $r(9, 11) = 0.846$, $r(10, 11) = 0.843$
2	X_7, X_{13}, X_{15}	$r(7, 13) = -0.579$, $r(7, 15) = -0.425$, $r(13, 15) = 0.748$
3	X_1, X_2, X_6	$r(1, 2) = 0.630$, $r(1, 6) = 0.473$, $r(2, 6) = 0.566$
4	X_4, X_5	$r(4, 5) = 0.658$
5	X_8, X_{16}	$r(8, 16) = 0.523$
6	X_{12}	
7	X_{14}	
8	X_3	

prove to be highly correlated or, in other words, overlap with each other in terms of carried information. As a result, some of them indeed can be discarded.

D-Optimal Method and Results

To test or verify the conclusions obtained from these two methods, we used another statistical analysis, the so-called D-Optimal method [6]. The principle of this method is to determine the significance or sensitivity of a parameter by its value of generalized conditional variance (the GCV values as abbreviated in the following analyses).

Since this method is not commonly applied, we provide a simple outline here.

Suppose there are two random vectors,

$$\mathbf{X} = (X_1, X_2, \ldots X_i, \ldots, X_N) \tag{3}$$

and

$$\mathbf{X_i} = (X_1, X_2, \ldots X_{i-1}, X_{i+1}, \ldots, X_N) \quad . \tag{4}$$

That is, the matrix $\mathbf{X_i}$ or $\mathbf{X_i} | X_i$ is the matrix $\mathbf{X}$ without the parameter X_i. Let $\mathbf{V}(\mathbf{X_i} | X_i)$ represent the conditional covariance matrix of $\mathbf{X}$ to parameter X_i. The GCV value of X_i is defined as $|\mathbf{V}(\mathbf{X_i} | X_i)|$, the determinant of matrix $\mathbf{V}(\mathbf{X_i} | X_i)$. The D-Optimal method claims that the importance or the significance of a parameter can be judged by its GCV value; a more important parameter results in a smaller GCV value. This is called the D-Optimal criterion. In other words, the most important parameter X_i gives

$$|\mathbf{V}(\mathbf{X} | X_i)| = \min_{1 \le j \le N} |\mathbf{V}(\mathbf{X}_j | X_j)| \quad . \tag{5}$$

Because of its proved multinormality, $\mathbf{X}$ can be divided into two parts [9], *i.e.*,

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}^1 \\ \mathbf{X}^2 \end{bmatrix} \quad , \tag{6}$$

where $\mathbf{X}^1$ and $\mathbf{X}^2$ are matrices themselves.

Correspondingly, the covariance matrix $\mathbf{V}$ of $\mathbf{X}$ can be expressed as

$$\mathbf{V} = \begin{bmatrix} \mathbf{V}_{11} & \mathbf{V}_{12} \\ \mathbf{V}_{21} & \mathbf{V}_{22} \end{bmatrix} \quad , \tag{7}$$

where $\mathbf{V}_{11}$, $\mathbf{V}_{12}$, $\mathbf{V}_{21}$, and $\mathbf{V}_{22}$ are the covariance matrices corresponding to the submatrices $\mathbf{X}^1$ and $\mathbf{X}^2$. The conditional covariance matrix $\mathbf{V}(\mathbf{X}^1 | \mathbf{X}^2)$ of $\mathbf{X}^1$ to $\mathbf{X}^2$ is defined [9] as

$$\mathbf{V}(\mathbf{X}^1 | \mathbf{X}^2) = \mathbf{V}_{11} - \mathbf{V}_{12}\mathbf{V}_{22}^{-1}\mathbf{V}_{21} \quad , \tag{8}$$

where $\mathbf{V}_{22}^{-1}$ is the inverse matrix of $\mathbf{V}_{22}$.

Based on matrix theory and Equation 8, if $\mathbf{V}_{22}^{-1}$ exists, the determinant of matrix $\mathbf{V}$ can then be written as

$$\begin{aligned} |\mathbf{V}| &= |\mathbf{V}_{22}|\,|\mathbf{V}_{11} - \mathbf{V}_{12}\mathbf{V}_{22}^{-1}\mathbf{V}_{21}| \\ &= |\mathbf{V}_{22}|\,|\mathbf{V}(\mathbf{X}^1 | \mathbf{X}^2)| \quad . \end{aligned} \tag{9}$$

Let $\mathbf{X}^1 = \mathbf{X_i}$ and $\mathbf{X}^2 = X_i$; then Equation 7 becomes

$$\mathbf{V} = \begin{bmatrix} \mathbf{V}_{11} & \mathbf{V}_{12} \\ \mathbf{V}_{21} & \mathbf{V}_{22} \end{bmatrix} = \begin{bmatrix} \mathbf{V}_{11} & \mathbf{V}_{12} \\ \mathbf{V}_{21} & \sigma_{ii} \end{bmatrix} \quad , \tag{10}$$

where σ_{ii} is the variance of X_i.

From Equation 8 we get

$$\mathbf{V}(\mathbf{X}^1 | \mathbf{X}^2) = \mathbf{V}_{11} - \frac{1}{\sigma_{ii}} \mathbf{V}_{12}\mathbf{V}_{21} \quad . \tag{11}$$

Considering $\sigma_{ii} > 0$, we then have from Equation 9

$$\begin{aligned} |\mathbf{V}| &= |\sigma_{ii}|\,|\mathbf{V}_{11} - \frac{1}{\sigma_{ii}} \mathbf{V}_{12}\mathbf{V}_{21}| \\ &= \sigma_{ii} |\mathbf{V}(\mathbf{X_i} | X_i)| \quad . \end{aligned} \tag{12}$$

Since for a given observation matrix $\mathbf{X}$, the value of $|\mathbf{V}|$ is a constant, we can then infer from Equation 12 that minimizing the GCV value $|\mathbf{V}(\mathbf{X_i} | X_i)|$ is equivalent to maximizing σ_{ii}, and that the sensitivity or importance of a parameter is represented by its σ_{ii} value. In other words, selecting the most important parameters by finding those with minimum GCV values, based on the D-Optimal method, is identical with selecting those having maximum σ_{ii} values. Note that after each selection step, we have to update the covariance matrix $\mathbf{V}$ by recalculating all the variances of remaining parameters. The specific calculation procedure and the results for all sixteen Kawabata parameters can be found elsewhere [12]. Table V provides the ranking of the importance of these parameters judged by the PCA and D-Optimal methods.

FINAL SELECTION

By combining the results in Tables IV and V, the selection of necessary parameters can proceed using the following expedient criteria: First, there should be at least one parameter from each property category listed in Table I selected in the final results. Second, selection of parameters should be done according to their importance, which is revealed in Table V.

Based on the D-Optimal method, nine parameters will be selected, whereas based on the PCA method, the same conclusion will be reached without parameter X_7, the tensile energy per unit area (WT). Our final selection is shown in Table VI. For the convenience

TABLE V. Ranking of the importance of parameters.

Rank of importance	PCA method	D-Optimal method
1	X_{10}	X_{10}
2	X_5	X_6
3	X_2	X_{14}
4	X_{14}	X_7
5	X_6	X_5
6	X_8	X_3
7	X_3	X_{15}
8	X_{15}	X_8
9	X_{12}	X_2
10	X_7	X_{12}
11	X_{16}	X_9
12	X_9	X_1
13	X_4	X_4
14	X_{11}	X_{16}
15	X_{13}	X_{11}
16	X_1	X_{13}

TABLE VI. Selected parameters.

Selected	Recode of the selected	Discarded
2HB (X_2)	Y_1	B (X_1)
MIU (X_3)	Y_2	MMD (X_4)
SMD (X_5)	Y_3	G (X_9)
LT (X_6)	Y_4	2HG5 (X_{11})
WT (X_7)	Y_5	LC (X_{12})
RT (X_8)	Y_6	WC (X_{13})
2HG (X_{10})	Y_7	W (X_{16})
RC (X_{14})	Y_8	
T (X_{15})	Y_9	

of further data manipulation, all the selected parameters are recoded.

Re-test of Collinearity of Selected KES-FB Parameters

After discarding the less sensitive or less important parameters, we have theoretically reduced the collinearity in the original data. To test this, we need once again to calculate the determinant value of the covariance matrix $\mathbf{V}_s$ of the new observation matrix formed by the selected parameters. It turns out that

$$|\mathbf{V}_s| = 7.06162 \times 10^{-2} \gg |\mathbf{V}| = 2.24 \times 10^{-7} \quad . \tag{13}$$

As we can see, the value of $|\mathbf{V}_s|$ is much greater (about 3×10^5 times) than the previous one before selection, indicating that the collinearity problem has been largely improved.

In conclusion, by using all the preceding analyses, we have successfully determined the relative importance of all sixteen KES-FB parameters, eliminated the unnecessary ones, and selected a sufficient number to characterize a fabric. The nine parameters selected can be evaluated by tests on the Instron, based on the KES-FB definitions, using the methods illustrated in Figures 1-5.

Data Presentation and Interpretation

We will now consider the second question raised in the introduction, namely data interpretation. Measurements will make sense only when test results can be correlated with fabric performance. Thus, further analysis is needed to derive a comprehensive conclusion based on the results.

Using multivariate analysis, data interpretation can be done in several ways. For example, as long as the measured variables and the resulting fabric performance are available, multivariate regression analysis can be used to establish an expression for performance prediction similar to the development of Kawabata's handle value equations. Also, discriminant analysis can be used to grade the samples based on their overall performance. However, since fabric performance in most practical cases is not readily obtainable or well defined, all these well-documented methods may not always be applicable, and a new approach has to be explored. Several alternatives [8, 10] have been considered, including the one we have suggested [11]. For industrial applications however, a simpler and more expressive approach is preferable.

Another way of handling multivariables is to use multidimensional graphic methods like the Kawabata and the FAST systems, where a multi-axial system has been adopted and each of the data is expressed on one of these axes. All the axes are in the form of parallel lines. A fabric is therefore represented by the locus connecting its parameters located on the axes. This is the so-called snake chart. In our study, we use a more visually concise circular chart instead (Figure 6). The chart consists of a circle and nine radii evenly distributed over the whole circumference, each representing one parameter; these are the parameter radii of the chart. Then each fabric tested can be represented by its locus formed on the chart by connecting all its data points on all the parameter radii. This chart can therefore be treated as the fingerprint of the fabric and can be used to represent it.

There are actually two different ways to scale each parameter on a radius: (a) Parameters without data normalization process: The raw data of each parameter will be adjusted and the scale on each radius determined so that the maximum and the minimum values of the parameter can all be accommodated on the whole range of its radius. (b) Parameters after normalization: An-

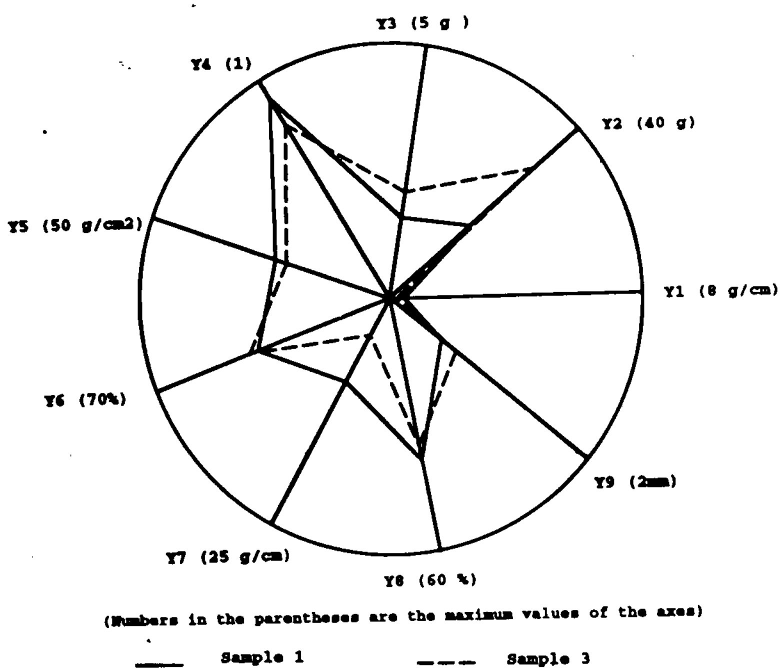

FIGURE 6. Circular chart for a cotton print cloth (sample 1) and a cotton twill (sample 3).

other way with more generality is to normalize all the raw data as

$$X_j' = \frac{X_{jmax} - X_j}{X_{jmax} - X_{jmin}} , \qquad (14)$$

where X_j, X_j' are the values of jth parameter before and after normalization, and X_{jmax} and X_{jmin} are the maximum and minimum values of this parameter. By normalizing the data, all parameters will range from 1 to 0, so the circle becomes a unit radius. The chart will look more concise and become more comparable for various situations. In this article, only the first method is illustrated.

A Practical Example

We selected nineteen fabric samples ranging diversely in terms of weave structure and fiber type (Table VII). For each fabric, based on the variation of the trials, we tested four to six specimens and obtained the mean value of the data. For the tensile and bending tests, where results may change in the warp and weft directions, we used the average value of the warp and weft data. The final results are shown in Table VIII.

Results and Discussion

Some judgements can be made by simply looking at the data of individual properties in Table VIII. For instance, the cotton denim (sample 19) possesses the greatest bending hysteresis (Y_1) and shear hysteresis (Y_7), indicating a high yarn bending stiffness, a very tight structure, and high interyarn friction or low yarn mobility. On the other hand, sample 12 is a very loose, light twill weave of rayon blended with polyester and has the lowest bending and shear hysteresis values. The three taffeta fabrics (samples 14, 15, and 16), the satin fabric (sample 17), and the sheer fabric (sample 9) are all made from filament yarns with smooth surfaces. As a result, they show remarkably low surface frictional coefficients (Y_2). It is also worth noting that although the surface frictional coefficient of sample 9 is low, it has the highest geometrical roughness (Y_3), a reflection of its excessively undulating surface due to the weave. This provides a very good example of the different physical meanings of parameters Y_2 and Y_3.

With respect to the three tensile parameters, we can compare the polyester gabardine (sample 10) and the acetate satin (sample 17). Both fabrics retain similar values of tensile linearity (Y_4) and tensile resilience (Y_6), yet their tensile energy (Y_5) values represent two extremes, which can be attributed to their weave structures. Acetate satin with a tighter structure is much less extensible than polyester gabardine, so when the fabrics are extended the same amount, the acetate satin has a much higher tensile loading and hysteresis. By definition, Y_4 and Y_6 are the ratios of areas related to tensile loading and hysteresis, so different loading magnitudes can yield similar results (see Figure 1). Differences in tensile behavior are revealed only by the tensile energy values (Y_5).

TABLE VII. Specifications of the 19 selected fabrics.

No.	Fabric name	Fiber content	Weave	Fabric count warp × weft (no/2.5 cm)	Fabric weight g/m²
1	Prints	100% cotton	plain	71 × 71	106.24
2	Prints	50% polyester/50% cotton	plain	102 × 55	116.72
3	Prints	100% cotton	twill	71 × 71	110.27
4	Denim	100% cotton	twill	63 × 43	298.91
5	Canvas	100% cotton	plain	71 × 43	307.88
6	Flannel	100% cotton	plain	47 × 43	131.81
7	Flannel	100% cotton	twill	47 × 31	289.17
8		100% wool	twill	31 × 31	256.69
9	Sheer (F*)[a]	100% nylon	plain	134 × 102	32.44
10	Gabardine	100% polyester	twill	67 × 47	221.17
11		25% wool/65% polyester	plain	43 × 39	195.55
12		50% polyester/50% rayon	twill	83 × 63	137.67
13		100% rayon	plain	106 × 79	115.72
14	Taffeta (F*)	100% silk	plain	122 × 102	49.94
15	Taffeta (F*)	100% polyester	plain	98 × 94	81.44
16	Taffeta (F*)	100% acetate	plain	91 × 51	122.21
17	Satin (F*)	100% acetate	satin	142 × 67	175.13
18	Denim	100% cotton	twill	64 × 41	279.45
19	Denim	100% cotton	twill	74 × 42	334.86

[a] F* = filament yarns.

TABLE VIII. Test results for 19 selected fabrics[a].

Fabric	Y_1[b] 2HB[c], g/cm	Y_2 MIU, g	Y_3 SMD, g	Y_4 LT	Y_5 WT, g/cm²	Y_6 RT, %	Y_7 2HG, g/cm	Y_8 RC, %	Y_9 T, mm
1	0.44	17.08	1.59	0.92	23.37	39.74	9.42	38.33	0.51
2	0.35	23.95	4.04	0.83	14.69	59.20	4.57	36.62	0.59
3	0.23	30.46	2.09	0.80	21.01	42.06	4.27	34.96	0.66
4	2.68	23.98	2.27	0.91	1.93	41.95	7.39	36.42	0.99
5	4.74	21.53	1.90	0.96	2.15	43.86	16.92	41.06	1.02
6	0.86	35.93	2.35	0.72	13.94	51.40	8.94	40.44	0.91
7	4.96	29.53	1.75	0.95	1.65	45.03	4.80	41.47	1.58
8	1.12	34.38	2.72	0.78	2.17	51.39	4.98	39.48	1.21
9	0.19	10.66	4.42	1.00	8.04	64.97	3.45	56.00	0.32
10	0.78	12.96	1.64	0.91	0.36	68.37	1.19	40.94	0.87
11	0.52	39.26	2.34	0.88	1.12	56.94	2.15	41.41	1.37
12	0.18	30.76	1.20	0.73	4.22	57.95	0.69	39.24	0.79
13	0.18	22.79	1.06	0.86	2.38	62.51	6.93	36.00	0.56
14	2.13	7.64	1.15	0.77	18.37	59.85	5.99	43.28	0.27
15	0.45	5.72	1.23	0.88	37.53	58.61	8.18	55.60	0.27
16	1.68	6.34	2.32	0.95	41.66	66.85	6.58	55.55	0.35
17	2.52	4.89	1.47	0.90	48.71	68.57	6.96	49.67	0.43
18	4.20	18.34	1.25	0.88	5.99	45.96	10.94	34.01	0.98
19	7.90	28.77	1.82	0.90	15.12	40.39	23.77	32.73	1.11

[a] Fabric code given in Table VII. [b] Parameter code used in this paper (Table VI). [c] Kawabata parameter code (Table I).

The circular charts representing the fabrics can be drawn using these data, the so-called fabric "finger printing" process. Each chart can then serve for as a fabric performance evaluation. For example, samples 1 and 3 are cotton fabrics of similar weight, and their data can be plotted on the same chart (Figure 6) to show the property differences due to their different weave structures, plain and twill. On the other hand, samples 7 and 8 have the same twill weave and similar fabric count and weight, and their chart reveals property differences due mainly to the different fiber types, cotton and wool, respectively (Figure 7). Also, samples 4, 18, and 19 are all cotton denim fabrics and can be compared on a chart (Figure 8) to examine the effects of count and weight on their properties. All taffeta fabrics (samples 14, 15, and 16) are plotted on one chart as well (Figure 9) and can be used to study fiber influences (silk, polyester, and acetate, respectively).

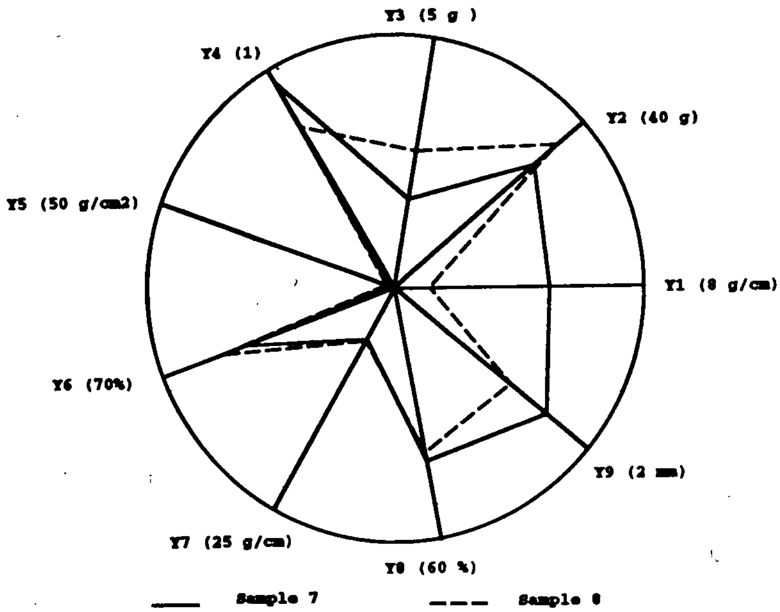

FIGURE 7. Circular chart for a cotton twill fabric (sample 7) and a wool twill fabric (sample 8).

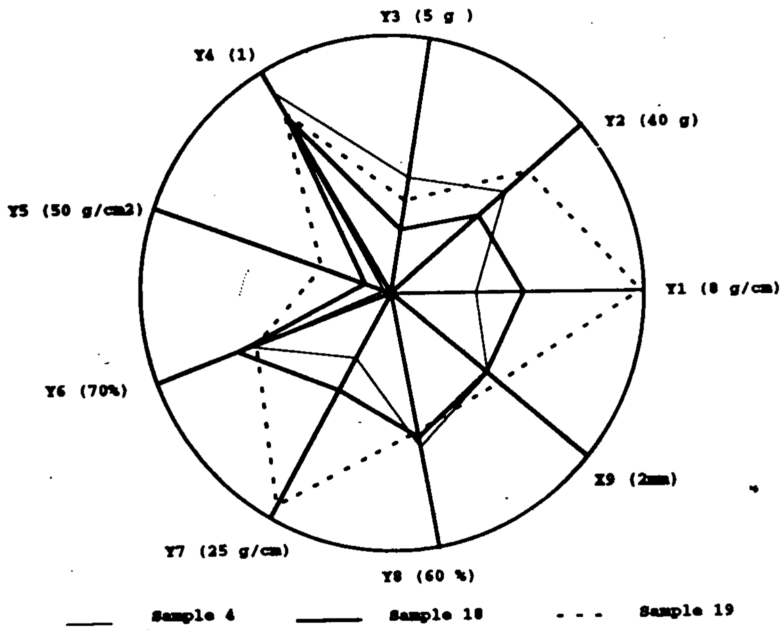

FIGURE 8. Circular chart for three denim fabrics (samples 4, 18, and 19).

In addition, the charts can serve as a reference for fabric quality control. For instance, if a fabric with properties similar to a reference sample is requested, the resulting product can be plotted against the reference sample on the same chart. By examining the differences between the individual parameters of the two fabrics, their performance similarities can be ascertained. These differences also serve as a clear indication for further improvement. The same approach can be applied for fabric handle or other relevant performance evaluations, if the reference sample is available as a standard.

Satisfactory fabric performance results from the appropriate level of all related properties; excessively high or low parameter values will usually lead to poor performance. Obviously, on the circular chart there will be a range of values for the parameters where fabrics with satisfactory performance will normally fall. The properties in areas outside this range will then be considered unacceptable. Of course, the specific range depends on the fabric type and the quality required, and should therefore be determined experimentally or based on previous experience.

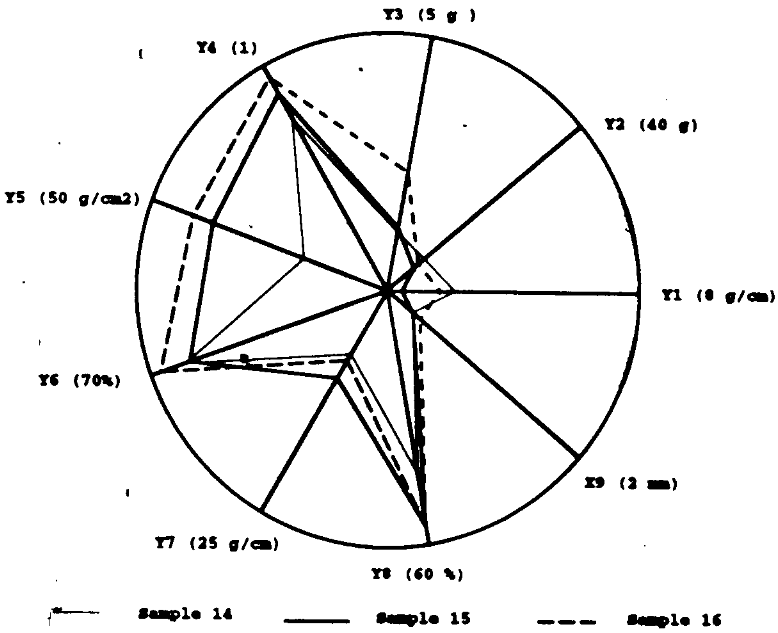

FIGURE 9. Circular chart for three denim fabrics (samples 14, 15, and 16).

Conclusions

The theoretical analysis shown above indicates that some overlapping elements exist in Kawabata's sixteen parameters. To save measurement time and reduce the complexity of further data processing, only nine of these parameters are required, based on their sensitivities and contributions to the final result. These nine parameters can be determined using the Instron testing instrument rather than the KES-FB and FAST systems. Furthermore a chart can be conveniently used as the representation or finger print of the properties of a fabric for various practical applications.

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