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Technique Based on Fuzzy Logic for Cotton Bale Lay-down Management

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Abstract
In this paper a new technique has been proposed for cotton bale management using fuzzy logic. The fuzzy c-means clustering algorithm has been applied for clustering cotton bales into 5 categories from 1200 randomly chosen bales of the J-34 variety. In order to cluster bales of different categories, eight fibre properties, viz., the strength, elongation, upper half mean length, length uniformity, short fibre content, micronaire, reflectance and yellowness of each bale have been considered. The fuzzy c-means clustering method is able to handle the haziness that may be present in the boundaries between adjacent classes of cotton bales as compared to the K-means clustering method. This method may be used as a convenient tool for the consistent picking of different bale mixes from any number of bales in a warehouse.

Key words: *cotton bale, cluster analysis, fibre property, fuzzy logic, fuzzy c-means algorithm.*

Introduction

The world textile industry has under-Cotton fibres have very high variability in their characteristics, and therefore it is a challenging issue for every spinning industry to convert cotton fibres into yarns with consistent quality throughout the year. Only a sound bale management system can enable to tackle the issue of consistent yarn quality. The bale management technique for a consistent end product demands the grading of each and every bale in the population on the basis of fibre properties. If the cotton bales are grouped on the basis of individual fibre properties, the number of category combinations will be enormously high. As a consequence, it becomes an impossible task to select a consistent bale mix for consecutive laydowns from such a huge population of bale groups. In order to simplify the bale management system, some overall quality indices of cotton fibre based on the multivariate regression model viz., Fiber Quality Index (FQI), Spinning Consistency Index (SCI) and Premium Discount Index (PDI) have been developed for grouping bales into only a few categories [1-5]. These indices were formulated based on certain types of cotton fibres which are seldom generalised to all cotton varieties.

Only a few works have been reported on the categorization of cotton using clustering techniques [6-7]. Ghosh et. al. [8] proposed the *K*-means square clustering technique of cotton bale management, in which a set of cotton bales were clustered into a few groups by minimising the within-group Euclidean distance of each member in a cluster to its cluster centre and maximising the Euclidean distance between the cluster centres. Eight HVI fibre properties of each cotton bale were considered in the study. Basically the *K*-means square clustering method is used to classify cotton bales in a crisp sense, i.e. each bale will be assigned to one and only one class, and each class has a hard boundary. Nevertheless adjacent classes of cotton bales may have hazy and overlapping boundaries, which thus make crisp-boundary methods ineffective for cotton bale classification. Fuzzy logic is specialised to deal with such a kind of ambiguity in cotton bale classification. Considering the above-mentioned drawbacks of the *K*-means square clustering algorithm, in this work a fuzzy *c*-means (FCM) algorithm has been used for cotton bale clustering which is a more reliable way of grouping cotton bales by eliminating the hard boundary problems associated with cotton bale clustering.

Concept of fuzzy logic

The concept of fuzzy logic was fathered by Lotfi A. Zadeh [9] at the University of California at Berkeley, USA. A classical crisp set is a container that wholly includes or wholly excludes any given element. Suppose that we have a crisp set *A* which contains individual elements *x*. Mathematically,

$$\mu_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases} \qquad (1)$$

where $\mu_A(x)$ indicates the unambiguous membership of element x in set A. Obviously $\mu_A(x)$ is either 0 or 1. On the contrary, the fuzzy set contains elements with only a partial degree of membership, i.e., membership of an element in the fuzzy set is not a matter of affirmation or rejection, but solely its degree of belongingness. A remarkable difference between crisp and fuzzy sets lies in the nature of their membership functions. For a fuzzy set, a membership function maps its elements onto a space in the interval between 0 and 1. Symbolically,

$$\mu_{\tilde{A}}(x) \in [0,1] \qquad (2)$$

where $\mu_{\tilde{A}}(x)$ is the degree of membership of element x in fuzzy set $\tilde{A}$. Commonly the fuzzy set $\tilde{A}$ is expressed in terms of ordered pairs as:

$$\tilde{A} = \{x, \mu_{\tilde{A}}(x) | \, x \in X\} \qquad (3)$$

Concept of cluster analysis

Cluster analysis involves categorization: dividing a large group of observations into smaller groups so that those within each group are relatively similar and they possess largely the same characteristics. The observations in different groups are relatively dissimilar. In other words, cluster analysis aims at grouping data objects of a similar kind into respective categories or clusters in such a way that the degree of association between two objects is maximum if they belong to the same group and minimum otherwise [10].

The *K*-means square clustering algorithm is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem [11-12]. The procedure follows a simple and easy way to classify a given set of data. The first step is to select a *K* number of clusters, define *K* centroids, one for each cluster, and then find the Euclidian distance of each data from the *K* centroids. In the next step each data point associate it to the nearest centroid and include it in that cluster. The process continues until there is no change in the cluster.

Fuzzy C-means algorithm

Bezdek [13] developed an extremely powerful classification method to accommodate fuzzy data. In this algorithm an individual can have partial membership in more than one class, which is not possible in the *K*-means square algorithm. A family of fuzzy sets $\{A_i, i = 1, 2, ...c\}$ is a fuzzy c-partition on a universe of data points *X*. Then the membership value of the k^{th} data point in the i^{th} fuzzy cluster is $\mu_{ik} = \mu_{A_i}(x_k) \in [0,1]$ with the constraint that the sum of all membership values is unity i.e. $\sum_{i=1}^{c} \mu_{ik} = 1$ for all *k = 1, 2, ..., n*.

The steps of the algorithm are as follows [9]:

Step 1: Fix c $(2 \le c < n)$ and select a value for parameter m'. Initialise the partition matrix, $U^{(0)'}$. Each step in this algorithm will be labelled r, where $r = 0, 1, 2, ……..$

Step 2: Calculate c centers $v_i^{(r)}$ for each step using

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}^{m'} . x_{kj}}{\sum_{k=1}^{n} \mu_{ik}^{m'}} \text{ ; where } j = 1, 2, \ldots m \tag{4}$$

Step 3: Update the partition matrix for the r^th^ step, $U^{(r)'}$ as follows:

$$\mu_{ik}{}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}{}^{(r)}}{d_{jk}{}^{(r)}} \right)^{\frac{2}{(m'-1)}} \right]^{-1}$$

$$\text{for} = I_k = \emptyset \tag{5}$$

or, $\mu_{ik}{}^{(r+1)} = 0$ for all classes i where i $\epsilon I_k'$ (6)

where $I_k = \{ i \mid 2 \le c < n;\ d_{ik}{}^{(r)} = 0 \}$ (7)

and $\quad I_k' = \{ 1,2,…..,c \} - I_k$ (8)

and $\quad \sum_{i \in I_k} \mu_{ik}{}^{(r+1)} = 1$ (9)

Step 4: If $\left\| U^{(r+1)'} - U^{(r)'} \right\| \le \epsilon_L$, stop; otherwise set r = r +1 and return to step 2.

In step 4, a matrix norm $\| \ \|$ of two successive fuzzy partitions is compared to a prescribed level of accuracy, ϵ_L, to determine whether the solution is good enough. Parameters I_k and $\tilde{I}_k$ comprise a bookkeeping system to handle situations when some of the distance measures, d_{ij}, are zero, or extremely small in a computational sense.

Calculation of the fuzzy matrix and centroids are demonstrated with a 1 x 7 data matrix i.e. {2; 3; 4; 7; 9; 10; 11}. Suppose the initial centroid of two clusters (when $c = 2$) is 3 and 11. ***Equation (5)*** was used to calculate the fuzzy membership of 1^st^ data (i.e. 2) to 1^st^ cluster (U_{11}) and 2^nd^ cluster (U_{12}) as shown below ***Equations (10)*** and ***(11)***.

Similarly the fuzzy membership of 2^nd^ data (i.e. 3) to 1^st^ cluster (U_{21}) and 2^nd^ cluster (U_{22}) was 1 and 0, respectively. The fuzzy membership of 3^rd^ data (i.e. 4) to 1^st^ cluster (U_{31}) and 2^nd^ cluster (U_{32}) was 0.98 and 0.02, respectively, as shown ***Equations (13)*** and ***(14)***.

Equations (14) and ***(15)*** determined the fuzzy membership of 4^th^ data (i.e. 7) to 1^st^ cluster (U_{41}) and 2^nd^ cluster (U_{42}), respectively.

Equation (16) exemplifies the calculation of the first centroid (c_1).

$$U_{11} = \frac{1}{\left(\frac{2-3}{2-3}\right)^{\frac{2}{2-1}} + \left(\frac{2-3}{2-11}\right)^{\frac{2}{2-1}}} = \frac{1}{1+\frac{1}{81}} = \frac{81}{82} = 0.99 \tag{10}$$

$$U_{12} = \frac{1}{\left(\frac{2-11}{2-3}\right)^{\frac{2}{2-1}} + \left(\frac{2-11}{2-11}\right)^{\frac{2}{2-1}}} = \frac{1}{81+1} = \frac{1}{82} = 0.01 \tag{11}$$

$$U_{31} = \frac{1}{\left(\frac{4-3}{4-3}\right)^{\frac{2}{2-1}} + \left(\frac{4-3}{4-11}\right)^{\frac{2}{2-1}}} = \frac{1}{1+\frac{1}{49}} = \frac{1}{\frac{50}{49}} = 0.98 \tag{12}$$

$$U_{32} = \frac{1}{\left(\frac{4-11}{4-3}\right)^{\frac{2}{2-1}} + \left(\frac{4-11}{4-11}\right)^{\frac{2}{2-1}}} = \frac{1}{49+1} = \frac{1}{50} = 0.02 \tag{13}$$

$$U_{41} = \frac{1}{\left(\frac{7-3}{7-3}\right)^{\frac{2}{2-1}} + \left(\frac{7-3}{7-11}\right)^{\frac{2}{2-1}}} = \frac{1}{1+1} = \frac{1}{2} = 0.50 \tag{14}$$

$$U_{42} = \frac{1}{\left(\frac{7-11}{7-3}\right)^{\frac{2}{2-1}} + \left(\frac{7-11}{7-11}\right)^{\frac{2}{2-1}}} = \frac{1}{1+1} = \frac{1}{2} = 0.50 \tag{15}$$

$$c_1 = \frac{(0.99)^2 * 2 + (1)^2 * 3 + (0.98)^2 * 4 + (0.50)^2 * 7 + ...}{(0.99)^2 + (1)^2 + (0.98)^2 + (0.50)^2 + ...} \tag{16}$$

Equations (10), (11), (12), (13), (14), (15) *and* **(*16*).**

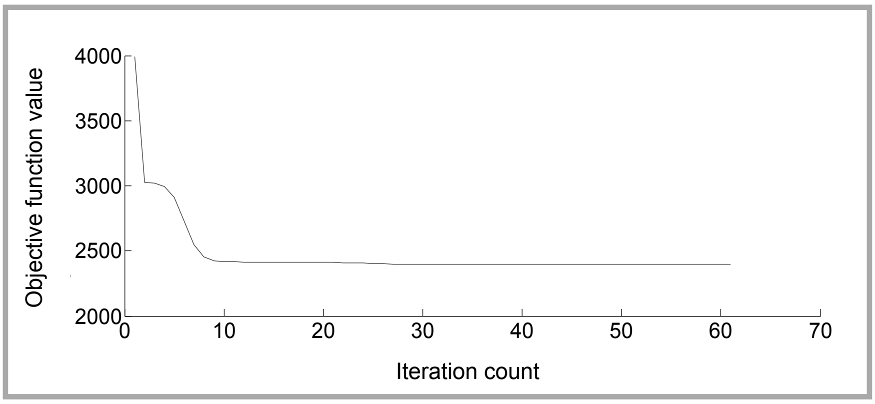

Figure 1. Objective function minimisation with iterations.

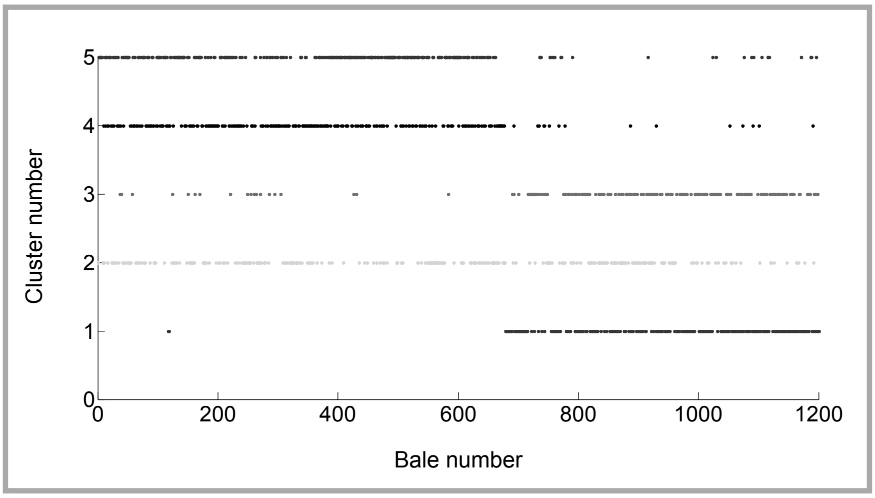

Figure 2. *Clustering of 1200 bales in 5 clusters.*

Table 1. *Summary statistics of cotton fibre properties.*

Fibre properties	Minimum	Maximum	Mean	Standard deviation
FS, cN/tex	24.5	30.2	27.6	0.950
FE, %	3.81	7.75	5.95	0.794
UHML, mm	23.56	28.90	26.20	0.751
UI, %	78.46	84.22	81.18	0.747
SFI, %	4.3	15.1	8.9	1.915
FF, µg/in	3.21	5.50	4.28	0.373
Rd	58.44	78.61	71.31	2.393
+b	5.97	10.80	8.16	0.670

Table 2. *Proportion of bales in 5 different clusters.*

Cluster No.	No. of bales	Proportion of bales, %
1	234	19.50
2	254	21.17
3	175	14.58
4	245	20.42
5	292	24.33

Application of FCM

1200 randomly chosen cotton bales of the J-34 variety (suitable for 20's Ne mixing) were tested in a Indian spinning mill using Uster HVI-900 instrument (Switzerland) to measure different fibre properties, viz., fibre strength (FS), fibre elongation (FE), upper half mean length (UHML), length uniformity index (UI), micronaire (Mic), reflectance (Rd), and yellowness (+b) for each and individual bale. The short fibre index (SFI) of each bale was tested by a Uster AFIS instrument. ***Table 1*** represents a summary of statistics of the fibre properties of 1200 cotton bales. If there are 5 groups, each of which belonging to fibre strength and UHML and 4 groups to fibre elongation, UI, SFI, Mic., *Rd* and *+b*, the cotton bale population can be assumed to comprise $5^2 \times 4^6$, i.e., 102400 varieties of bales. It is an unrealistic task to make a consistent selection of a 40-bale mix from such a huge population of cotton bales. This apparently impossible task can be handled by employing the FCM cluster algorithm for grouping cotton bales into respective groups. The FCM can also handle the the imprecision that may be present in cotton bale clustering. Hence a single cotton bale may have partial membership in more than one class. MATLAB 7.11 coding was used to execute the problem on a 2.6 GHz. PC.

Figure 1 demonstrates the optimisation function values and iteration count. It can be inferred from the curve that the fuzzy partition matrix (U) changes rapidly at the beginning, which gives a sudden fall of the curve at first few iterations and then gradually settles down as the model converges towards the optimum values. The later part of the curve indicates that there were very few changes in the clusters from the 10^{th} iterations. The optimization model meets the stopping criteria at the 63^{rd} iteration, which ends the program. ***Figure 2*** illustrates the belonging of the individual bales into 5 different clusters. The proportion of bales in 5 different clusters is given in ***Table 2***. The number of bales belonging to clusters 1 to 5 are 234, 254, 175, 245 and 292 respectively. Now the frequency relative picking method may be employed for the consistent selection of a 40-bale mix for 30 consecutive lay-downs, which constitutes a ratio of 8 : 8 : 6 : 8 : 10 after rounding off.

Conclusion

The fuzzy *c*-means based cotton bale management technique gives a consistent selection of cotton bales. The present study was conducted on 1200 randomly chosen cotton bales of the J-34 variety to partition into 5 categories. Hence it is possible to prepare a consistent 40-bale mix for 30 consecutive lay-downs using the frequency relative picking method. This method is also suitable for consistent picking of different bale mixes from any number of bales in a warehouse. The method of bale management proposed is more realistic and capable of handling the imprecision that may be present in the boundaries between adjacent classes of cotton bales.

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