Chapter 4

Feature extraction and classification of woven fabric using optimized Haralick parameters : A rough set based approach

4.1. Introduction

Fundamental features of the gray scale image of woven fabric sample are texture, tone and context. At present, out of these three fundamental features only tone and texture are evaluated automatically by computer based system [162,163,164]. Considering the varieties of textures of fabric and also various types of defects those may be present in those many varieties, the question of feature selection is open for further exploration. In this context, basic parameters of texture as defined and determined by Haralick and known as Haralick parameters [165] needs to be reopened. This Chapter presents a concept of selection of suitable Haralick parameters as features of woven fabric, in the light of theories of rough set as applicable for classification of woven fabric.

Haralick parameters are 14 statistical parameters which are necessary to classify any texture images. As the determination of Haralick parameters consumes appreciable time, therefore to reduce the time complexity many methods are proposed to group Haralick parameters [166]. A reduced set of Haralick parameters is thus evolved depending on particular application [167]. Such elimination of redundant features enhances the classification rate. Redundancy has also been observed when a set of Haralick parameters are used to classify a fabric sample of a given fabric class. As a result a reduced set of Haralick parameters is required for the classification of the woven fabric sample with enhanced classification accuracy along with the reduction of computational cost. This set of minimal Haralick parameters giving maximum classification accuracy of a given fabric samples is termed as optimized Haralick parameters for the determination of fabric class. However, this set of optimized Haralick parameters is not universal or unique and depends on a particular type fabric class.

Selection of optimized Haralick parameters may be considered as the process of finding an optimal subset from the original set of non optimized Haralick parameters according to some specified criterion. Therefore, the problem may be tackled by using rough set theory [168,169]. In the rough set theory, the notation of reduct [170] is defined as the minimal subset of condition attributes which preserves degree of dependency between decision and condition attributes. In other words a reduct is a minimal subset of attributes that discerns all objects which are discernible by the whole set of attributes or features. Therefore, the idea of selection of optimized Haralick parameters can be explored by using the concept of reduct.

In this context, it may be mentioned that many classification algorithms [171] are now available for use in fabric classification. Algorithm of support vector machine (SVM) [172,173,174,175] and K-nearest neighbor (KNN) [176,177,178,179,180] are two prominent classifiers which have been extensively used. In this chapter the results are also obtained for fabric classification using these two algorithms for comparison of performance with the proposed technique of using rough set. The performance of clustering of the fabric samples represented with optimized and non optimized Haralick parameters are compared in terms of the separability index (SI), which measures the degree at which inputs associated with the same output tends to cluster together. The class separability is finally tested using Fisher linear discriminant analysis [181].

4.2. Haralick parameters of the woven fabric images and their determination

Haralick parameters are based on gray level co-occurrence matrix (GLCM), which focuses on the distribution and relationships among the gray levels of an image [182,183]. The general idea of GLCM is to represent the texture characteristics by counting pixel intensity pairs, using a matrix that keeps track of all pixel-pair counts. The (i, j) th element of GLCM is obtained by counting the numbers of occasion a pixel with value i is adjacent to the pixel with value j. This adjacency is judged by the displacement vectors corresponding to a radius and an angle of orientation. It has been reported that for best realization of the textural properties of fabric image the value of r should be 1 or 2 and only four angles $0^0, 45^0, 90^0, 135^0$ are enough to determine GLCM. Finally by taking the average of GLCMs corresponding to the above mentioned angles of orientation the average GLCM is computed for each image.

The fabric images used for the selection of optimized Haralick parameters and training the classifiers are considered as the training fabric images. Let the average GLCM of p th gray scale training fabric sample belonging to q th fabric class be, $CM_{av_p}^{q} = [cm_{av_p}^{q}|_{ij}]$, where $cm_{av_p}^{q}|_{ij}$ is the (i, j) th entry of $CM_{av_p}^{q}$, and $1 \le p \le P$, $1 \le q \le Q$, the number of fabric class is Q, while number of training fabric images in each fabric class is P.

Considering N_G as gray levels of an image, from the elements of $CM_{av_p}^{q}$, the following statistical parameters (or features) for the fabric image are evaluated as,

$$C_{x\,p}^{q}(i) = \sum_{i=1}^{N_G} cm_{av\,p}^{\;q}|_{ij} \qquad 4.1(a)$$

$$C_{y\,p}^{q}(j) = \sum_{j=1}^{N_G} cm_{av\,p}^{\;q}|_{ij} \qquad 4.1(b)$$

$$C_{x+y\,p}^{q}(k) = \sum_{i,j:i+j=k} cm_{av\,p}^{\;q}|_{ij} \quad for(i+j) = 2,3,...,2N_G \qquad 4.1(c)$$

$$C_{x-y\,p}^{q}(k) = \sum_{i,j:|i-j|=k} cm_{av\,p}^{\;q}|_{ij} \quad for\,|i-j| = 0,1,...,N_G - 1 \qquad 4.1(d)$$

$$me_{p}^{q} = \text{ mean of } CM_{avp}^{q} \qquad 4.1(e)$$

$$me_{x\,p}^{q}, me_{y\,p}^{q} = \text{ mean of } C_{x\,p}^{q}, C_{y\,p}^{q} \text{ respectively} \qquad 4.1(f)$$

$$me_{x-y\,p}^{q} = \sum i.C_{x-y\,p}^{q} \qquad 4.1(g)$$

$$sd_{x\,p}^{q}, sd_{y\,p}^{q} = \text{ standard deviation of } C_{x\,p}^{q}, C_{y\,p}^{q} \text{ respectively} \qquad 4.1(h)$$

$$E_{x\,p}^{q}, E_{y\,p}^{q} = \text{ entropies of } C_{x\,p}^{q}, C_{y\,p}^{q} \text{ respectively} \qquad 4.1(i)$$

$$EXY1_{p}^{q} = -\sum_{i=1}^{N_G}\sum_{j=1}^{N_G} cm_{avp}^{q}|_{ij}\,.\log(C_{x\,p}^{q}(i).C_{y\,p}^{q}(j)) \qquad 4.1(j)$$

$$EXY2_{p}^{q} = -\sum_{i=1}^{N_G}\sum_{j=1}^{N_G} C_{x\,p}^{q}(i).C_{y\,p}^{q}(j).\log(C_{x\,p}^{q}(i).C_{y\,p}^{q}(j)) \qquad 4.1(k)$$

From the statistical parameters representing features, 14 Haralick parameters for each fabric image are determined. As these Haralick parameters are derived from the average GLCM, these are termed as the average Haralick parameters. The average Haralick parameters of the p th fabric image belonging to q th fabric class are found out in terms of $cm_{av\,p}^{\;q}|_{ij}$ as,

1. Energy $H1_p^q$ is given by $$H1_p^q = \sum_i \sum_j cm_{avp}^q |_{ij}^2 \quad 4.2(a)$$

Energy is a measure of textural uniformity i.e., the repetitions of pixel pairs in a woven fabric image and has maximum value of 1. For uniform textured woven fabric image, the value of this parameter is close to 1. This is also known as uniformity or angular second moment.

2. Entropy is $H2_p^q$ given by $$H2_p^q = -\sum_i \sum_j cm_{avp}^q |_{ij} .\log(cm_{avp}^q |_{ij}) \quad 4.2(b)$$

Entropy measures the disorder or complexity of a woven fabric image. It has large value for non uniform woven fabric image. Energy and entropy are inversely related to each other. So knowing the value of one, the randomness of the woven fabric image can be predicted without evaluating the other. As energy has smaller normalized value, it is preferred over the entropy.

3. Contrast $H3_p^q$ is given by, $$H3_p^q = \sum_{n=1}^{N_G-1} n^2 .C_{x-y_p}^q (n) \quad 4.2(c)$$

Contrast measures the spatial frequency of a woven fabric image. It is the difference between the highest and lowest values of a contiguous set of pixels. It measures the amount of local variations in the woven fabric image.

4. Correlation $H4_p^q$ is given by, $$H4_p^q = \frac{\sum_i \sum_j ((i.j) cm_{avp}^q |_{ij}) - \mu_{x_p}^q .\mu_{y_p}^q}{\sigma_{x_p}^q .\sigma_{y_p}^q} \quad 4.2(d)$$

Correlation measures linear dependence of gray level values in the average GLCM of the woven fabric image.

5. Variance ${H_5}_p^q$ is given by, $${H_5}_p^q = \sum_i \sum_j (i - \mu_p^q)^2 \qquad 4.2(e)$$

Variance measures the homogeneity of the woven fabric image and the value increases as the elements of average GLCM differ from the mean.

6. Local homogeneity ${H_6}_p^q$ is given by, $${H_6}_p^q = \sum \sum \frac{1}{1+(i-j)^2} cm_{avp}^q |_{ij} \qquad 4.2(f)$$

It measures the homogeneity of the woven fabric image and assumes more value if the gray tone differences between pair elements of average GLCM is less. Homogeneity and contrast are inversely related to each other but nowhere related to the energy.

The above mentioned parameters are referred to as the primary Haralick parameters. From these parameters, the remaining 8 Haralick parameters, termed as the secondary Haralick parameters are derived.

7. Sum Average $${H_7}_p^q = \sum_{i=2}^{2.N_G} i.{C_{x+y}}_p^q(i) \qquad 4.2(g)$$

8. Sum Variance $${H_8}_p^q = \sum_{i=2}^{2.N_G} (i - {H_6}_p^q)^2.{C_{x+y}}_p^q(i) \qquad 4.2(h)$$

9. Sum Entropy $${H_9}_p^q = -\sum_{i=2}^{2.N_G} {C_{x+y}}_p^q(i).\log({C_{x+y}}_p^q(i) \qquad 4.2(i)$$

10. Difference Variance $${H_{10}}_p^q = \sum_{i=0}^{N_G-1} (i - {\mu_{x-y}}_p^q)^2.{C_{x-y}}_p^q(i) \qquad 4.2(j)$$

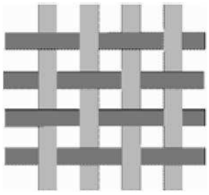
11. Difference Entropy $${H_{11}}_p^q = \sum_{i=0}^{N_G-1} {C_{x-y}}_p^q(i).\log({C_{x-y}}_p^q(i) \qquad 4.2(k)$$

12.	Information Measure of Correlation 1	$H_{12}{}_p^q = \dfrac{H_3{}_p^q - EXY1_p^q}{\max(E_{x}{}_p^q, E_{y}{}_p^q)}$	4.2(l)
13.	Information Measure of Correlation 2	$H_{13}{}_p^q = 1 - e^{-(0.2(EXY2_p^q - H_3{}_p^q))^{0.5}}$	4.2(m)
14.	Maximal Correlation Coefficient	$H_{14}{}_p^q$ = second largest eigen value of the square root of, $H_{14}{}_p^q = \sum_{i=0}^{N_G} \dfrac{cm_p^q(i,I).cm_p^q(j,I)}{C_{x_\sigma}^q(i).C_{y_\sigma}^q(j)}$	4.2(n)

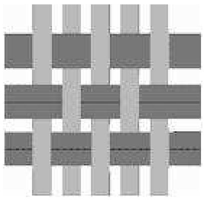
The primary Haralick parameters of the synthetic fabric samples shown in Figure- 4.1(a)-(l) are plotted in Figures 4.1 (m)- (r). From the plot of average energy in Figure 4.1 (m) it is seen that fabric images 7 to 11 cannot be classified from the average energy, as their values are very close.

In the same way, the average entropy cannot classify the fabric image groups 4,5 and 3,9; the average contrast cannot classify fabric image groups 4,5; 3,8 and 7,10; average variance cannot classify fabric image groups 5,6; 9,11 and 7,10; the average homogeneity cannot classify the fabric image groups 1,4; 5,6 and 7,11 and average correlation cannot classify the fabric image groups 4,5,6 and 9,10.

Thus, it is required to find out the minimal subset of Haralick parameters which is capable of classifying the given woven fabric samples into classes with the maximum accuracy.



(a)



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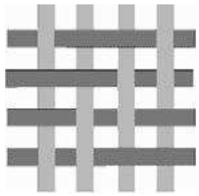

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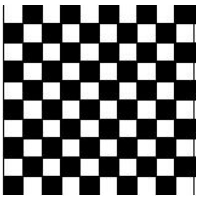

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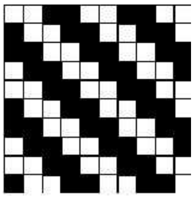

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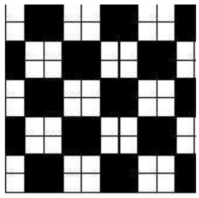

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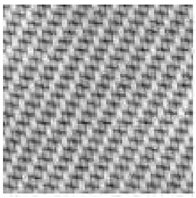
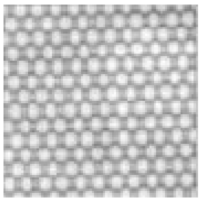
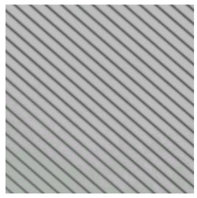


(g)

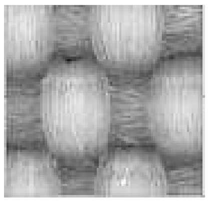


(h)

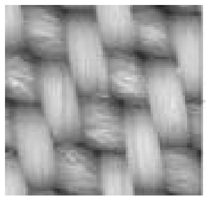


(i)

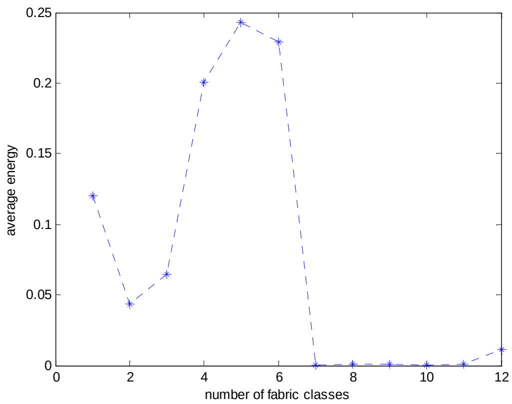
(j)



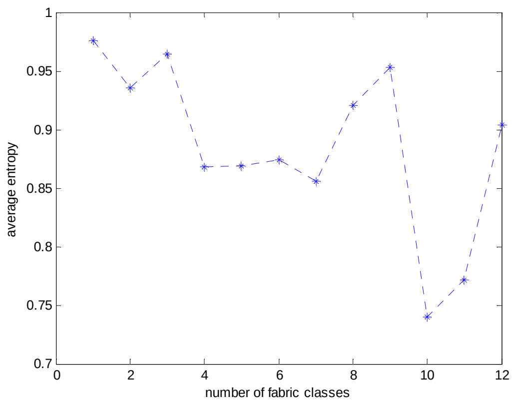
(k)



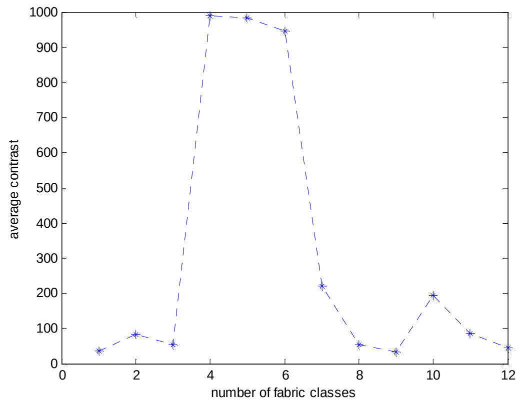
(l)



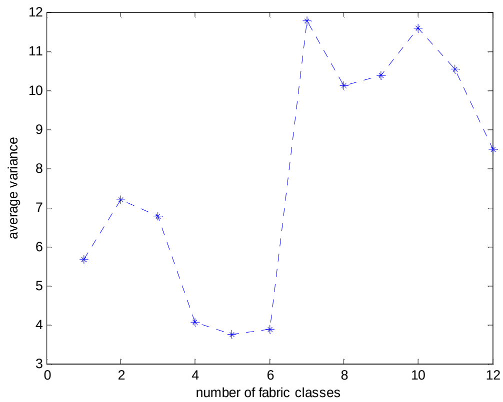
(m)



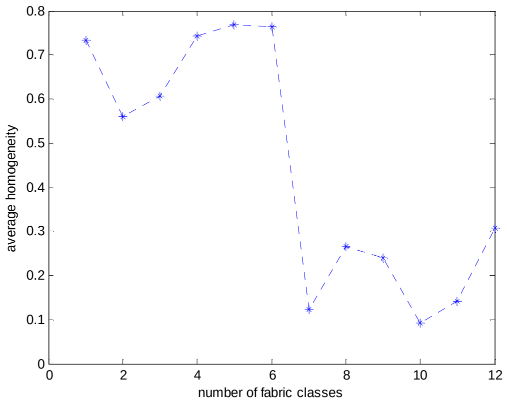
(n)



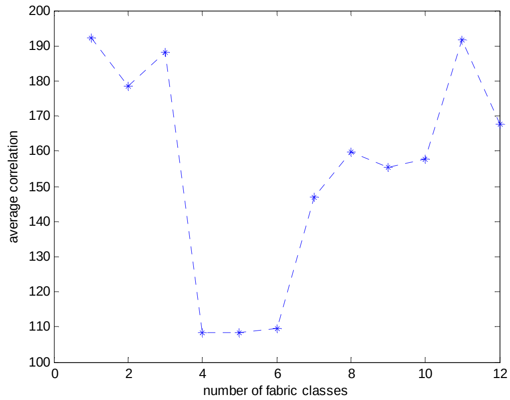
(o)



(p)



(q)



(r)

Figure- 4.1: (a)- (l) synthetically generated fabric image, (m) plot of average energy, (n) plot of average entropy, (o) plot of average contrast, (p) plot of average variance, (q) plot of average homogeneity, (r) plot of average correlation.

4.3. Selection of optimum Haralick parameters for classification of woven fabric by using rough set theory

The p th training fabric sample belonging to q th fabric class can be viewed as the projection to 14 dimensional fabric space and the projection vector is given by,

$$G_p^q = [H_{f_p^q}] \in \Re^{(1\times 14)} \tag{4.3}$$

where, $H_{f_p}^{q}$ is the f th Haralick parameter of p th training fabric image belonging to q th fabric class and f varies from 1 to 14.

Finally, the non-optimized Haralick space contains all training woven fabric samples and hence is denoted as,

$$G_{HS}^{NO} = [G_p^q] \in \Re^{(P.Q \times 14)} \tag{4.4}$$

It has been shown that all Haralick parameters are not required for the classification of pattern. In fact, there are no universal Haralick parameters, which are capable of classifying all types of woven fabric samples.

The performance of classification depends largely on the feature set and hence it is necessary to find out those attributes which give best classification [184]. The appropriate attributes i.e., the optimized Haralick parameters required for the classification of woven fabric samples from Q fabric classes are determined by using the rough set theory.

4.3.1. Storage of information of training fabric images in the form of information system (IS)

The information of the training fabric samples is stored in the form of information system (IS), which in fact is a decision table and defined by,

$$IS = (U, H \cup \{q\}, V, F) \tag{4.5}$$

where, U is a non-empty finite set of training fabric images i.e., objects, denoted as universe, H is a non-empty finite set of attributes, i.e., the non optimized Haralick parameters, such that, $H = [H_f]$, where f varies from 1 to 14. V is the union of attribute domains i.e., $V = \bigcup_{H_f \in H} H_{f_p}^{q}$, where $H_{f_p}^{q}$ denotes the domain of attribute H_f for p th training fabric sample belonging to q th fabric class in the non optimized Haralick space, F is a function, such that for any $u \in U$ and $H_f \in H$, $F(u, H_f) \in H_{f\,p}^{\,q}$ and q is the decision attribute i.e., the assigned fabric class of the training fabric images.

Information system (IS) is arranged in such a way, so that its rows correspond to the objects and the columns correspond to features i.e., attributes. The last column of IS contains the decision attribute.

4.3.2. Indiscernibility relation between the training fabric samples with respect to the reduced set of Haralick parameters

Let us consider H^c as the reduced set of Haralick parameters i.e., sub set of attributes such that, $H^c \subseteq H$. A decision table containing an equivalence relation of indiscernibility, denoted as, $IND(H^c)$ can now be generated in such a way so that two objects $(u_a, u_b \in U)$ are members of same equivalence class, if and only if, they cannot be discerned from each other based on the set of attributes H^c. The equivalence classes of H^c-indiscernibility relation are denoted as $[u]_{H^c}$. The indiscernibility relation $IND(H^c)$ can be defined as,

$$IND(H^c) = \{(u_a, u_b) : \forall H^c \in H_f, F(u_a, H^c) = F(u_b, H^c)\} \quad (4.6)$$

$IND(H^c)$ induces a partitioning of the universe U according to the attribute set H^c . The discernibility knowledge of the information system is commonly recorded in a symmetric discernibility matrix. A set of training fabric images, denoted as X_R, such that $X_R \subseteq U$ can be approximated solely based on information in $H^c \subseteq H$ by constructing H^c lower approximation and H^c upper approximation matrices of X_R.

4.3.3. H^c -lower approximations and H^c-upper approximations of X_R

For a given set, $X_R \subseteq U$, H^c -lower approximation of X_R is defined as ,

$$\underline{H^c} X_R = \bigcup_{u \in U} \{[u]_{H^c} : [u]_{H^c} \subseteq X_R\} \tag{4.7}$$

and H^c -upper approximation of X_R is defined as,

$$\overline{H^c} X_R = \bigcup_{u \in U} \{[u]_{H^c} : [u]_{H^c} \cap X_R \neq null\} \tag{4.8}$$

The lower approximation consists of objects those definitely belong to X_R and $IND(H^c)$,while the upper approximation contains the objects those possibly belong to X_R but surely belong to $IND(H^c)$. H^c - boundary region of X_R is defined as,

$$BN_{H^c}(X_R) = \overline{H^c} X_R - \underline{H^c} X_R \tag{4.9}$$

Consequently, X_R is classified as a rough set, if its H^c -boundary region is non-empty. This means that the region is uncertain with respect to the set membership. If X_R is not rough, it is a crisp set.

4.3.4. Determination of reduct set of Haralick parameters

The reduct set of Haralick parameters is the minimal subset of Haralick parameters those enable the same or even better classification of fabric images, under consideration as the whole set of non optimized Haralick parameters. Thus the reduct set of Haralick parameters is the opimized Haralick parameters [185]. In other words, the Haralick parameters those do not belong to a reduct set are superfluous, redundant or inconsistent with regard to classification of training fabric images.

Before determining the reduct set of Haralick parameters, it is required to have a concept of H^c positive region of decision attribute q, denoted as $POS_{H^c}(q)$ and defined as,

$$POS_{H^C}(q) = \bigcup_{X_R \cup U|q} \underline{H^c} X_R \qquad (4.10)$$

Thus, $POS_{H^c}(q)$ is the union of all H^c lower approximation of X_R, such that $X_R \subseteq U$ and X_R is constructed by considering $IND(q)$. A set of attributes $H^R \in H^c$ i.e., $H^R \subseteq H$ is a q reduct of H^c, if $POS_{H^c}(q) = POS_{H^R}(q)$.

4.3.5. Discretization of training fabric data set

The rough set method deals with discrete attributes. In order to select the optimized Haralick parameters from the real valued non optimized set of Haralick parameters of the training fabric samples, V, defined in all attributes domain by eq 4.5 needs to be discretized. There are several reported methods of discretization [186,187]. Here the discretization has been done by the method based on rough set and binary discernibility matrix required for discretization B_d. The algorithm used for discretization is given in appendix-4.1.

4.3.6. Generation of reduct set

To generate the reduct set from the set of non optimized Haralick parameters for the classification of fabric samples, the reduct finding algorithm is proposed. At first the binary discernibility matrix B is formed from the discretized information system, dIS, obtained by the discretization process. The binary discernibility matrix B represents the discernibility between pairs of objects i.e., training fabric images. The columns of this matrix are single condition attributes and rows are example pairs belonging to different concepts of decision attribute $\{q\}$. The algorithm used for reduct set generation is given in appendix-4.2.

In fact, the algorithm used for the selection of optimum Haralick parameters and discretization, are identical only with the exception that in the later case, the cut points i.e., the middle points of values of each attribute sorted in ascending or descending order are considered as the attributes. Further, in place of binary discernibility matrix B the binary discernibility matrix required for discretization B_d is considered.

Finally, the reduct set consisting of the most significant R attributes i.e., the optimum set of R Haralick parameters $(H^R \subseteq H)$ are obtained. These R attributes construct the sub set of minimum Haralick parameters which give the best classification result of Q fabric classes under consideration and hence these are termed as the optimized Haralick parameters. Thus, 14 dimensional non optimized Haralick space is reduced to the R dimensional optimized Haralick space, containing all the training fabric samples and is denoted as,

$$G_{HS}^{O} = [G_p^q \,|_{RED}] \in \Re^{(P.Q \times R)} \tag{4.11}$$

For classification, p th training fabric image belonging to q th fabric class may be considered to be projected on a fabric space having $R(<14)$ dimensions through the reduct projection vector given by,

$$G_p^q \,|_{RED} = [H_{t\,p}^{\,q}] \in \Re^{(1 \times R)} \tag{4.12}$$

where, $H_{t\,p}^{\,q}$ is the t th optimized Haralick parameter of p th training fabric sample belonging to q th fabric class and t varies from 1 to R, such that $R < 14$.

4.4. Projection of test fabric samples on non optimized and optimized Haralick spaces

For each test fabric sample Haralick parameters are determined. The test fabric sample is projected on the non optimized Haralick space through the following projection vector,

$$G_{test} = [H_{f_{test}}] \in \Re^{(1\times 14)} \tag{4.13}$$

where, $H_{f_{test}}$ is the f th Haralick parameter of the test fabric sample. f varies from 1 to 14.

In the same way the test fabric sample is projected on the optimized Haralick space through the following reduct projection vector,

$$G_{test}|_{RED} = [H_{t_{test}}] \in \Re^{(1\times R)} \tag{4.14}$$

where $H_{t_{test}}$ is the t th optimized Haralick parameter of the test fabric sample. t varies from 1 to R such that, $R < 14$.

4.5. Classification of test fabric samples in the optimized and non optimized Haralick spaces

As the fabric samples of a fabric class must be related to the identical Haralick parameters, so the points representing the test fabric samples of same class in the optimized and non optimized Haralick spaces, should be close to each other with respect to the points representing the fabric samples of some other classes.

The fabric class associated with the test fabric samples are determined by the multi class support vector machine (SVM) classifier [188,189] and K- nearest neighbor (KNN) classifier.

In general, SVM is a two class classifier, whose basic guideline is to find an optimal separating hyperplane, so as to separate two classes of patterns with maximal margin, such that the expected errors for the unknown test data is minimized. The samples closest to the decision hyperplane are the support vectors. The support vector machine (SVM) is a binary classifier and for the multi class classification problem, the binary SVM method is applied for Q times, where Q is the numbers of fabric classes.

Nearest neighbor algorithm is one of the extensively used classification algorithms, which is further extended to the k-nearest neighbor (KNN) algorithm for the non-separable data set. As the KNN classification is non parametric, it does not make any assumptions on the underlying data distribution. This makes it suitable to classify data, as this does not obey the typical theoretical assumption of data distribution. In case of KNN, the training phase is not explicit and therefore the training is very fast. Thus considering all the properties of KNN, it is selected as a classification method in fabric classification. During the training process of the KNN, corresponding to each projection vector of the training fabric sample, the class at which it belongs is known. The Euclidian distance between each training fabric sample represented by its projection vector with other training fabric samples is measured to arrive at a correct decision.

4.6. Test results on TILDA database

In general, depending upon the yarn density, coarseness and texture of fabric, the woven fabric samples may be classified as fine, medium, coarse etc. For testing of the developed system, images from four different fabric classes, namely fine, medium, semi coarse and coarse are taken from TILDA database [118].

The proposed method is tested on 200 woven fabric images belonging to the above mentioned four different fabric classes. 200 additional fabric images, 50 from each of the above four fabric classes are taken for the training of the system. For each training fabric image 14 Haralick parameters are determined. By using the proposed technique, reduced set of optimized Haralick parameters are determined. For the above mentioned fabric classes only two Haralick parameters, namely energy and correlation are found as the optimized one, and thus $R = 2$ and $H^R = \{\text{energy, correlation}\}$. Obviously, the reduct set of Haralick parameters, obtained for the given fabric classes do not contain the secondary Haralick parameters.

For the multi class SVM classifier the polynomial function is used as kernel. For the KNN classifier a neighborhood size of 8 is chosen by using the 5 fold cross validation method. In the 5 fold cross validation method the entire training fabric data set are divided into 5 groups, such that each group contains 40 fabric images, 10 from each fabric class. In each fold of the cross validation method, 160 fabric images i.e., 4 groups are taken for training the KNN, while the remaining group is used for the testing purpose. This process is continued for 5 times by considering each group as the test group for once. The total training and test errors of the KNN classifier are evaluated for all the folds with the variation of size of neighbor from 1 to 30. Finally from the plot shown in Figure 4.2, the size of neighbor (= 8) is selected which corresponds to minimum overall error.

The results of classification of test fabric samples in optimized and non optimized Haralick spaces using multi class SVM classifier and KNN classifier with a neighborhood size of 8 is shown in Table 4.1.

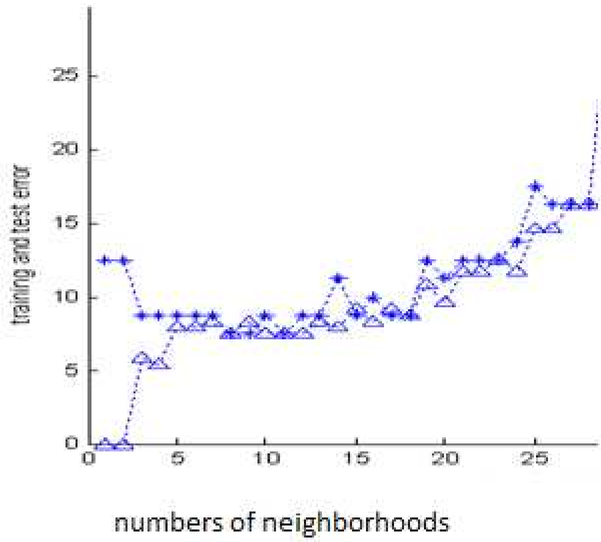


Figure- 4.2: plot of training and test errors for the 5- fold cross validation method, required for neighborhood selection of KNN. '^' symbol is for training data and '' symbol is for the test data.*

Table 4.1: Comparison of test results for multiclass SVM and KNN classifiers.

Type of woven fabric sample	Using kNN classifier				Using multi class SVM classifier			
	Optimized Haralick parameters		non- optimized Haralick parameters		Optimized Haralick parameters		non- optimized Haralick parameters	
	Number of woven fabric sample tested	Number of woven fabric samples correctly classified	Number of woven fabric sample tested	Number of woven fabric samples correctly classified	Number of woven fabric sample tested	Number of woven fabric samples correctly classified	Number of woven fabric sample tested	Number of woven fabric samples correctly classified
Fine	50	48	50	47	50	50	50	48
Medium	50	49	50	47	50	50	50	48
Semi coarse	50	44	50	39	50	48	50	46
Coarse	50	46	50	42	50	50	50	45
Total	**200**	**187**	**200**	**175**	**200**	**198**	**200**	**187**

From the results, it reveal that by using the multi class SVM classifier 99% success rate is obtained for optimized Haralick space which is better than the success rate of 93.5%, obtained for optimized Haralick space by using the KNN classifier. However, for both the classifiers used, the result is better in case of optimized Haralick space than the non optimized Haralick space.

4.6.1 Performance analysis of the proposed method in terms of separability index

The clustering capability of data set is observed with the help of separability index [190, 191]. More the index value more is the degree of separation. Therefore, separability index measures the degree to which inputs with same output tend to cluster together or it measures the degree of class overlap.

The separability index is measured as the ratio of trace of *between class scatter matrix* S_B to that of *within class scatter matrix* S_W. S_B and S_W of the training fabric images in case of the optimized Haralick space are defined as,

$$S_B = \sum_{q=1}^{Q} P.(me_q - me).(me_q - me)^T \in \Re^{(R\times R)} \qquad (4.15)$$

$$S_W = \sum_{q=1}^{Q} [\sum_{p=1}^{P} (G_p^q|_{RED} - me_q).(G_p^q|_{RED} - me_q)^T] \in \Re^{(R\times R)} \qquad (4.16)$$

where, $me_q \in \Re^{(1\times R)}$ is the mean of fabric images of qth fabric class in the optimized Haralick space, $me \in \Re^{(1\times R)}$ is the mean of all the fabric images in all the fabric classes in the optimized Haralick space and $G_p^q|_{RED}$ is defined in eq 4.12.

In case of non optimized Haralick space, S_B and S_W are defined in the same way with the only exception that in this case, $G_p^q|_{RED}$ is replaced by G_p^q and the means are evaluated in the non optimized Haralick space. In this case the dimensions of S_B and S_W are (14×14). The same process of determination of separability index can also be applied for test fabric image in both the Haralick spaces. The separability index of the test fabric classes in optimized and non optimized Haralick space are given in Table-4.2. The separability is judged for 200 test fabric images of 4 fabric classes.

Table- 4.2: Comparison of separability index for optimized and non optimized Haralick spaces.

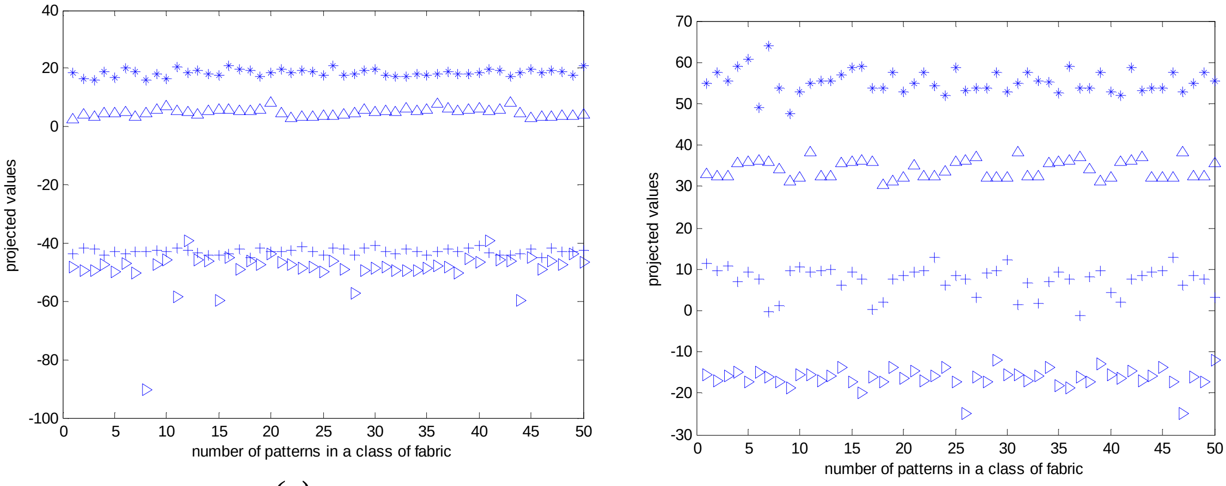
Space considered	Separability index
Optimized Haralick space	38.8768
Non optimized Haralick space	1.5699

4.6.2. Projection of test fabric images on the line of maximum class separability by using Fisher linear discriminant analysis (LDA)

According to Fisher's linear discriminant analysis (LDA), the optimum projection vector that projects the fabric samples in both the Haralick spaces on that line along which the projections of fabric samples give maximum class separability is determined by maximizing an objective function.

The line along which the fabric samples in both the Haralick spaces give maximum class separability is termed as the line of maximum class separability, which is obtained by solving the maximization problem. The test fabric samples in the optimized Haralick space are projected on the line of maximum class separability. In the same way the test fabric samples in the non optimized Haralick space are projected on the line of maximum class separability at the non optimized Haralick space. The projected values of test fabric samples on the line of maximum class separability is termed as the optimum projected values.

Figures 4.3(a) and (b) show the plot of optimum projected values of all the test fabric samples of all fabric classes in optimized and non optimized Haralick spaces respectively. It has been shown that all four fabric classes considered are properly classified when optimized Haralick parameters are used.



(a) *(b)*

Figure- 4.3: plot of optimum projected values of test fabric samples of all fabric classes (a) in non optimized Haralick space, (b) in optimized Haralick space. Different symbols indicate different fabric classes.

4.7. Conclusions

The proposed method of fabric classification is based on obtaining fabric features in terms of Haralick parameters. The optimum number of features required is obtained by using rough set theory. Though the gray scale fabric images has more computational complexity than the binary fabric images, yet during the determination of Haralick parameters the gray scale fabric images are taken as it carries more information than its binary counterpart. The optimized Haralick parameters are then used for classification of fabric using two well known classifier viz support vector machine and k-nearest neighbor classifier. From the test result, it has also been observed that multi class SVM classifier gives better classification than KNN classifier. The rough set based feature or attribute selection technique is better than the PCA-based technique, as the later does not guarantee the highest classification rate due to ignorance of the contribution of a feature on classification. Large number of data from TILDA database is used for testing, the result of which establish the feasibility of the proposed method. It may also been commented that the optimized Haralick parameters are not universal; rather it may change if the fabric classes under consideration are changed.

Appendix- 4.1: Algorithm steps for discretization

Input: The information system (IS), containing information of training fabric images along with the respective fabric classes.

Output: The optimal cut set (OCS) and discretized information system (dIS) .

- **Initialize:** $OCS = null\ matrix$.
- Sort continuous attributes i.e., Haralick parameters of the training fabric images in ascending or descending order.
- Get cut points, which are the mid points of all adjacent values of each Haralick parameter of all training fabric images and construct the cut set C_s by accumulating the cut points.
- Construct a new information system $IS^* = (U, C_s, V, F)$ comprising of all pairs of objects from IS with different decision values. The condition attributes of IS^* is equal to numbers of elements of cut-set C_s.
- Develop the binary discernibility matrix required for discretization B_d, the values of whose elements Ω_d are selected in the following way,

$\Omega_d((a;b), c_s) = 1$, if $\min[F(u_a, H_f), F(u_b, H_f)] < c_s < \max[F(u_a, H_f), F(u_b, H_f)]$
for $H_f \in H$ $, u \in U$ $, c_s \in C_s$, provided (u_a, u_b) have different q

Otherwise, $\Omega_d((a;b), c_s) = 0$, where, $\Omega_d((a;b), c_s)$ is the element of B_d, having row corresponding to (u_a, u_b) object pair and column c_s of IS^*. c_s is one of the elements of C_s.

- Delete the rows having all 0’s in IS^* . /* delete pairs of inconsistent objects*/
- While $(B_d \neq null\ matrix)$ {

i) Select a cut $c_s|_{sel}$ in IS^* i.e., significant cut point of a Haralick parameter of the training fabric samples with the highest sum value of column. [if several attributes have highest sum value of column, then the second attribute significance is computed as explained in reduct finding algorithm].

ii) $OCS \leftarrow OCS \cup \{c_s|_{sel}\}$

iii) Remove the rows which have "1" in the $c_s|_{sel}$ column from IS^*.

iv) Remove the $c_s|_{sel}$ column from IS^*.

} end while /* removal of redundant cut points from OCS */

• Put the unique integers for the elements of the partition defined by OCS corresponding to each attribute. For example, if OCS has n_c number of cut points corresponding to an attribute, then there are (n_c+1) number of discernable partitions for the attribute and the partitions are named like $1,2,....,n_c$. Thus each Haralick parameter of the training fabric samples is discretized with respect to its selected cut points.

• Assign the discretized IS as dIS

Appendix- 4.2: Algorithm steps for generation of reduct set

Input: The discretized information system dIS .

Output: The attribute reduct $H^R \subseteq H$.

- **Initialize** $H^R = null \;\; matrix$.
- Construct the binary discernibility matrix B from dIS . The elements of binary discernibility matrix Ω is selected in the following way,

$\Omega((a;b),H_f)=1$, for $F(u_a,H_f)\neq F(u_b,H_f)$, where $H_f \in H$, $F(u_a,q)\neq F(u_b,q)$

Otherwise, $\Omega((a;b),H_f)=0$, where, $\Omega((a;b),H_f)$ is the element of B , having row corresponding to (u_a,u_b) object pair and column H_f of IS .

- Delete the rows having all 0's in B . /* delete pairs of inconsistent objects*/
- While $(B \neq null \;\; matrix)$ {

i) Select an attribute H_f in B with highest sum value of column.

[if several attributes have highest sum value of column, then the second attribute significance is computed by using the equation given by,

$$S_2(H_f)=\sum_{a,b}\frac{\Omega((a;b),H_f)}{\sum_{H_f}\Omega((a;b),H_f)}$$

where, $\sum_{H_f}\Omega((a;b),H_f)$ denotes the row wise summation of B matrix]

ii) $H^R \leftarrow H^R \cup \{H_f\}$

iii) Remove the rows which have "1" in the selected H_f column from B .

iv) Remove the H_f column from B .

}end while /* removal of redundant attributes from H^R */