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Identification of handloom and powerloom fabrics using proximal support vector machines

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This study endeavors to recognize handloom and powerloom products by means of proximal support vector machine (PSVM) using the features extracted from gray level images of both fabrics. A *k*-fold cross validation technique has been applied to assess the accuracy. The robustness, speed of execution, proven accuracy coupled with simplicity in algorithm hold the PSVM as a foremost classifier to recognize handloom and powerloom fabrics.

Keywords: Handloom fabrics, Image processing, Pattern classification, Proximal support vector machine, Powerloom fabrics

1 Introduction

A loom is a well-known textile machine that mechanizes the pattern of interlacements between two sets of threads, viz. warps and wefts resulting in the formation of what we call woven cloth. In a powerloom, process of mechanization is further facilitated by providing either mechanical or electrical energy as motive power at strategic point or segment of the machine. In contrast, a handloom, as its very name suggests, is one where there is no provision of mechanical or electrical power. It is only the human effort that activates the machine parts into motion and accomplishes the weaving operation. Though both the machines follow the essentially same principles, handlooms are primitives in comparison with the powerloom counterparts in terms of structural and functional complexities.

Currently handloom products are engaged in an existential struggle against invading powerloom ones that undermine their exclusivity by cheap imitation that too often go shoddy beguiling unsuspecting customers who end up paying far more than what really it is worth for. Handloom fabrics differ from the powerloom ones in terms of uniformity of thread spacing, crimp evenness, cover variation etc. Handloom fabrics being woven manually always suffer from variation of picking force used for inserting weft threads as also uneven pressure on treadle pedal which make way for a shed formation where warp threads are unevenly tensioned. All such variations translate themselves in the formation of a fabric characterized by an uneven rugged appearance as opposed to a powerloom woven product which is far more even and uniform in appearance even when woven from the same yarns. This very appearance confers upon it an attribute that earns a rare ethnic appeal in its otherwise rugged texture that a similar powerloom product with identical structural and raw material specification can hardly match. Cheap inferior imitations from powerloom sector are eating into its pie of profits precipitating an ailing handloom sector. It is therefore crucial that such an unethical practice must be confronted effectively to salvage the handloom sector. This is what the background perspective of the present research that seeks a panacea for malady ridden handloom sector. It is true that naked human eye is too naïve to read through the texture of handloom and powerloom fabrics also there is no effective detecting mechanism or instrument that can classify or differentiate infallibly and universally between handloom and powerloom products.

Need of the hour is therefore an effective automatic recognition mechanism making distinction between handloom fabrics and their powerloom counterparts. With this urge before us, we present here an approach using linear proximal support vector machines

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(PSVM)[1,2] to study this distinction. As a well-established pattern recognition system, support vector machine (SVM)[3] in various incarnations has etched its footprints in carpet wear classification[4], fabric defect identification[5,6], fabric design categorization[7] and a host of other areas. While standard SVM performs as a rigid classifier tolerating no misclassification, its soft margin variant allows it[8]. Least-square support-vector machine (LS-SVM) simplifies the algorithms by introducing equality constraints rather than inequality ones and it involves solving a set of linear equations and not a quadratic optimization as in classical SVM[9,10]. PSVM used by us here wield a cutting edge, being a simple, efficient and very fast performer.

2 Theoretical Consideration

2.1 Outline of Proximal SVM[1]

Consider the problem of separating the set of training vectors belonging to two separate classes (x, y); $x \in \mathfrak{R}^n; y \in \{-1, +1\}$; i = 1, 2, ,…m. Theoretically, infinity number of hyper planes in $\mathfrak{R}^n$ which are parameterized by w and b can be conceived which separate the data into two classes. Our objective is to find a hyper plane that correctly classifies the data. To visualize it as a classification problem of m points in n dimensions (or attributes) of real space $\mathfrak{R}^n$ with their belongingness to either class $+1$ or -1, let us consider a standard soft margin support vector machine whose mathematical formalization with linear kernel may be represented by following quadratic problem[3]:

$$\text{minimize}_{\xi,w,b} \quad \frac{1}{2}\|w\|^2 + \frac{C}{2}\|\xi\| \qquad \ldots (1)$$

$$\text{subject to } y_i(\langle x.w\rangle - eb) + \xi \geq e \text{ and } \xi \geq 0$$

where c is the penalty term; ξ, the error variable; e is a vector of ones; and w geometrically represents normal to the hyper planes effecting separation of data. Two planes are defined as:

$$(x'w - b) = +1$$
$$(x'w - b) = -1 \qquad \ldots (2)$$

where b is a constant measuring distance of the hyper planes from the origin. We can therefore draw the conclusion that the plane situated in the mid region is:

$$x'w = b \qquad \ldots (3)$$

It can be shown that the distance of separation between the planes is $\frac{2}{\|w\|}$ and maximizing this distance will definitely improve the generalization capability of SVM. If first norm of the error variable ξ is minimized with c in Eq. (1), then we get an approximate plane as in Eq. (3) such that:

$$\begin{aligned} &x'w - b > 0, \text{then } y \in +1, \\ &x'w - b < 0, \text{then } y \in -1, \\ &x'w - b = 0, \text{then } y \in +1 \text{ or } -1 \end{aligned} \qquad \ldots (4)$$

At this juncture, problem of optimization can be modified as under:

$$\text{minimize}_{\xi,w,b} \quad \frac{1}{2}\|[{w \atop b}]\|^2 + \frac{C}{2}\|\xi\|^2 \qquad \ldots (5)$$

$$\text{subject to } y(\langle x.w\rangle - eb) + \xi \geq e$$

Here no explicit non negativity constraint is needed on ξ, second norm of the error vector ξ is minimized instead of first one, and margin between the hyper planes is also maximized with respect to w and b. This new formulation adds advantages of strong convexity of objective function without upsetting any other aspects of the standard formulations in Eq. (1).

We are now in a position to introduce PSVM by completely replacing inequality constraint by equality one, which (though simple) is very significant as it admits of explicit exact solutions of it in terms of available data, however in case of equations with inequality constraints this was impossible as their interdependence was too involved. From the perspective of geometry we can visualize PSVM as a classifier that does its task by judging the proximity of the test points to one of the twin hyper planes that are widened apart to the utmost. Mathematically, the distance between these twin planes are denoted by $\frac{1}{2}\|[{w \atop b}]\|^2$ which is also the reciprocal of the second norm distance squared (Fig. 1). Therefore, mathematically PSVM is an optimization problem with objective function, as given below:

$$\text{minimize}_{\xi,w,b} \quad \frac{1}{2}\|[{w \atop b}]\|^2 + \frac{C}{2}\|\xi\|^2 \qquad \ldots (6)$$

$$\text{subject to } y(\langle x.w\rangle - eb) + \xi = e \text{ and } \xi \geq 0$$

Now applying Karush-Kuhn-Tucker (KKT) conditions for optimality in our equality constraints, we get following differential equations or gradients, and equating each of them to zero we can write the following Lagrangian:

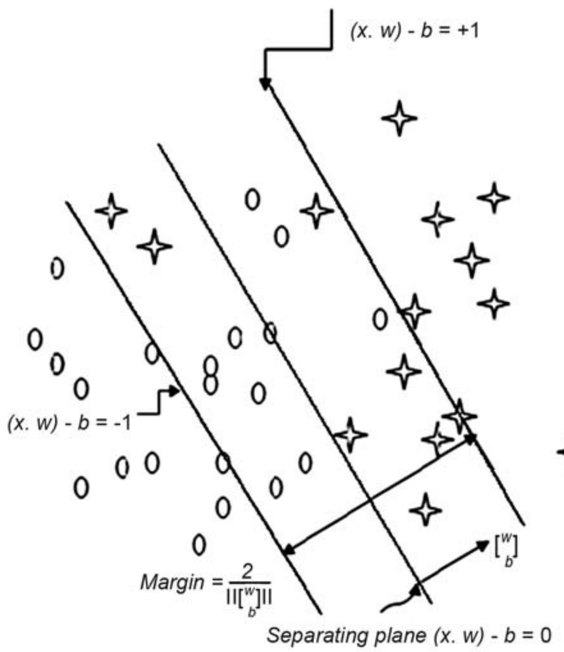

Fig. 1–Proximal support vector machine classifier in the (*w*, *b*)-space

$$L(w,b,\xi,\lambda) = C\frac{1}{2}\|\xi\|^2 + \frac{1}{2}\|[\begin{smallmatrix} w \\ b \end{smallmatrix}]\|^2 - \lambda\,(\,y(w.x-b) + \,\xi - e) \quad \ldots (7)$$

where $\lambda \in \Re^m$ is called Lagrange multiplier. Differentiating $L(w,b,\xi,\lambda)$ with respect to each variable we get:

$$\frac{\partial L}{\partial w} = w - xy\lambda = 0$$

$$\frac{\partial L}{\partial b} = \; b + \, e'y\lambda = 0 \qquad \ldots(8)$$

$$\frac{\partial L}{\partial \xi} = \; C\xi - \lambda = 0$$

$$\frac{\partial L}{\partial \lambda} = \; y(w.x-b) + \,\xi - e = 0$$

Thus we get,

$$w = xy\lambda,\;\; b = -e'y\lambda,\;\; \xi = \frac{\lambda}{C} \qquad \ldots (9)$$

Substituting these in the last equality of Eq. (8) we get a clear expression of λ in terms of problem variables x and y , as given below:

$$\lambda = (\tfrac{I}{C} + y(x.x' + ee')y)^{-1}e = (\tfrac{I}{C} + HH')^{-1}\,e \qquad \ldots (10)$$

where H is defined as

$$H = y[x-e] \qquad \ldots (11)$$

To avoid the inversion of matrix which is as massive as $m\times m$ in Eq. (10), we can circumvent this by

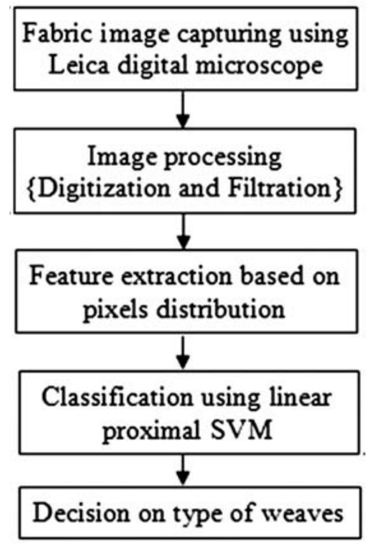

Fig. 2– Flowchart of the pattern recognition system for classifying handloom and powerloom fabrics

using Sherman-Morrison-Woodbury formula, giving following expression for λ (ref. 2):

$$\lambda = C(I - H\left(\tfrac{I}{C} - HH'\right)^{-1}H'\Big)\,e \qquad \ldots (12)$$

where *I* is an identity matrix.

3 Materials and Methods

A pattern recognition system for classifying handloom and powerloom woven fabrics can be partitioned into a number of components as illustrated in Fig. 2. At first, a digital camera captures the images of handloom and powerloom fabrics. Next the camera's signals are processed to simplify subsequent operations without losing relevant information. The information from each fabric image is then sent to a feature extractor, whose purpose is to reduce the data by measuring certain features or attributes. Proximal support vector machines (PSVM) use these features to evaluate the evidence presented and make a final decision as to the fabric type.

Plain woven 100% cotton fabrics were prepared from 30 tex warp and 20 tex weft both in handloom and powerloom. The threads per cm were 17 and 14 respectively in warp and weft directions for both the fabrics. Fabrics of 1 m width with 50 m and 20 m in length were woven in powerloom and handloom respectively. A light size was applied to all the yarns irrespective of the category they were meant for to minimize the hairiness. Such woven fabrics with a width of 1 m were subjected to random photographs.

Image captured in its various physical entities are the description of light intensities received as reflected energy from a real object and recorded in a suitable capturing device. Fabric images were captured using a LEICA camera (Model EZ-4D) with a magnification of ×25. Samples were illuminated by three halogen lights positioned approximately 20 cm above directly and to the right and left of the sample, to supply illumination in diagonal directions of 45°. Figure 3 depicts the typical images of handloom and powerloom fabrics. Altogether 160 images were captured for the experimentation, 80 from each category. Photo grabbing was done in reflected mode with ambient illumination. The digitized images were constituted of 2048 × 1536 pixels with subsequent conversion into gray level of 0-255 and stored as a two-dimensional gray matrix[11]. Once converted into gray level each image was enhanced by a median filter which eliminated undesirable noise. Except for median filters no other image quality enhancing method was used as it would have marred the essential features embedded in them.

It may intuitively be thought that though essentially made from same material with same design, structural difference in two different classes is bound to occur because in handloom fabrics, yarns are woven into fabric manually where variation in picking force and kick imparted on treadle are inevitable. On the other hand, automatic mechanization of them in powerloom leaves a powerloom fabric free from such variations. This fundamental aspect set off a structural difference between two fabric classes that are discernable even to a naïve eye. Handloom fabrics are thus rugged in appearance. Their ruggedness arising from loss of linearity of structural elements and minor aberration in design yet exhibits a rare beauty unique to themselves, while their powerloom counterparts are far less flawed. Thus, two visually different fabrics which are of the same material and same design would generate images in which reflected light intensity is variable due to variation of spatial disposition of yarns but each class exhibiting its own trend and this feature can be made tractable by measuring how pixel intensity changes over an image through statistical characterization.

For feature extraction, filtered grey image of fabric was considered. The values of the mean intensities as obtained from the data matrix of a gray fabric image for each column and each row correspond to the signals of warp and weft directions respectively. A plot of these signals both in warp and weft directions of the fabric as depicted in the Fig. 4 reveals the presence of periodic peaks, the positions of which lie approximately on the axes of warp and weft threads in the image. Thus, for every image, a grid was constructed out of a set of horizontal and vertical axes whose every point of intersection is the position of interlacement of warp and weft. Following four feature parameters are defined:

(i) RMS deviation of pixel distance for warps (σ_e) – This measures the root mean square deviation of pixel distance between the warps and have the expression:

$$\sigma_e = \sqrt{\frac{\sum(e_{i-}e)^2}{n-1}} \qquad \dots (13)$$

where e_i and e stand for any particular pixel distance and average pixel distance for warps.

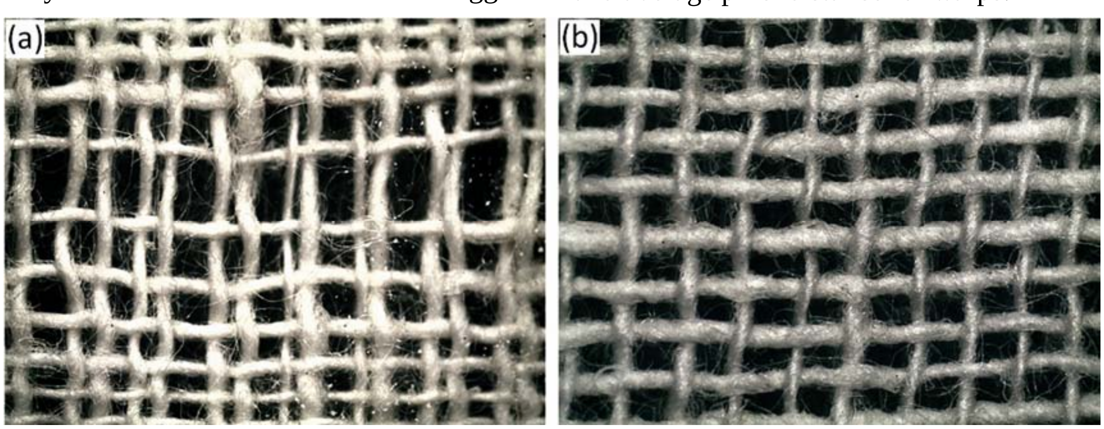

Fig. 3– Images of handloom (a) and powerloom (b) fabrics

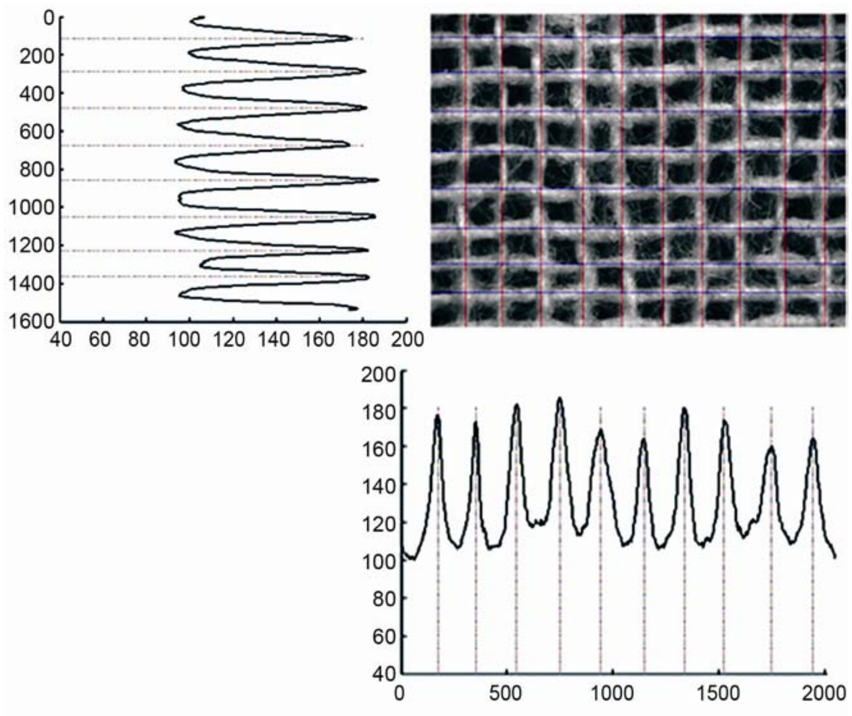

Fig. 4– Gray image of a powerloom fabric showing warp and weft lines

(ii) RMS deviation of pixel distance for wefts (σ_p) – This measures the root mean square deviation of pixel distance between the wefts and have the expression:

$$\sigma_p = \sqrt{\frac{\Sigma(p_{i-}p)^2}{n-1}} \quad \ldots (14)$$

where p_i and p stand for any particular pixel distance and average pixel distance for wefts.

(iii) Autocorrelation function between adjacent warps (r_e) – Assuming the variation in pixel distance between adjacent warps a stochastic process and taking lag at 1, it is defined as`

$$r_e = \frac{c_1}{c_0} \quad \ldots (15)$$

where c_1 is the estimation of auto covariance and c_0 is the variance for a stationary process. Thus, c_1 is defined as

$$c_1 = \frac{1}{N}\sum_{t=1}^{N-1}(d_t - d)(d_{t+1} - d) \quad \ldots (16)$$

where d the average pixel distance, d_t and d_{t+1} represent pixel distance at time t and t+1 respectively.

(iv) Autocorrelation function between adjacent wefts (r_p) – It can be defined for weft at lag 1 in the same way as above.

Having decided to work with above four features parameters or dimensions, we discern at our very image which is just a two dimensional representation of an otherwise spatial (3-dimensional) structure of fabric where pixel distance between adjacent warp is also affected by that between adjacent wefts, hence, the chosen dimensions are interdependent. In such a situation we invoke principal component analysis (PCA) to reduce data dimensions without sacrificing wealth of information substantially in the original data. Data, therefore, are re-expressed as first and second principal components that are linear combinations of original features or attributes. Apart from ensuring simplicity by reducing data dimensions, PCA can not only seek out the strongest pattern in original features but also tends to reduce the noise[12].

After the feature extraction of 160 samples from handloom and powerloom fabrics, linear PSVM was applied for their classification. The dataset was divided into training and testing data array using *k*-fold cross validation technique. In *k*-fold cross validation[13], the initial dataset is randomly partitioned into *k* mutually exclusive subsets or folds D_1, D_2, …, D_k, each of approximately equal size. The training and testing are performed *k* times. In iteration *i*, partition D_i is reserved as the test set and the remaining partitions are collectively used to train the model. In this method, each data point is used same number of times for training and once for testing. Therefore, the validation of the model becomes more accurate and unbiased. The grand mean of the percentage accuracies over k trials give an estimate of the expected generalization accuracy of the classifier. MATLAB 7.7 coding was used to execute the computational work.

4 Results and Discussion

The dataset comprises a total of 160 observations assigning classes to fabric images that belong to handloom and powerloom fabrics. Table 1 depicts only a subset of 20 data choosing 10 from each category representing 4 different features. Table 2 shows the first and second principal components for the data subset of Table 1.

A 10 fold cross validation was applied to assess the performance of the PSVM classifier for classifying two different fabrics. The classifier was trained using 9 of the folds and tested on the sample fold left out for each cycle, therefore, the training and testing were performed for 10 cycles. The expected generalization accuracies referring to training as well as testing was estimated as $\mu \pm \sigma$, where μ and σ are the mean and standard deviation of the accuracies over 10 trials. Standard soft margin SVM using linear kernel was also made to work upon with the same cross validation technique for comparing its performance with that of PSVM. Several values of the penalty term (C) were tried out and the best performance was obtained with C = 100. Table 3 shows a comparison of the results of training and testing accuracies as exhibited by the PSVM with its standard counterpart. The training accuracy was expectedly higher than the testing accuracy because latter is done on the unseen data. The average grand accuracies of training and testing dataset for PSVM are 99.375% and 98.75% respectively. On the contrary, standard SVM shows 99.31% and 98.75% accuracies respectively for training and testing dataset. The results show that the fabric classification accomplished by means of image recognition through PSVM is comparable with its standard counterpart and agree eminently well with only very little room for an error. It holds immense potentiality even when large scale exercise is required for classification of handloom and power loom fabrics. Nevertheless, the time required for execution of PSVM algorithm is fantastically small in

Table 1– Extracted features from the fabric images

Sl. No.	Input parameter				Output*
	σ_e	σ_p	r_e	r_p	
1	18.635	54.008	-0.2751	-0.882	1
2	17.332	83.395	-0.5653	-0.6038	1
3	19.302	56.474	0.3026	-0.6102	1
4	17.713	38.898	0.3203	-0.623	1
5	14.397	55.843	-0.0405	-0.8657	1
6	12.726	57.288	-0.3125	-0.9003	1
7	51.872	44.926	0.2337	-0.7389	1
8	30.331	65.963	-0.7359	-0.8818	1
9	29.348	67.969	-0.7516	-0.7179	1
10	27.231	50.54	0.0279	-0.7891	1
11	11.942	9.8894	0.1114	-0.0552	-1
12	7.6811	7.8098	-0.214	-0.4696	-1
13	11.487	9.0584	-0.008	0.0735	-1
14	13.479	5.7755	-0.4026	0.2167	-1
15	11.303	14.093	-0.2143	-0.183	-1
16	11.606	17.433	-0.0354	0.325	-1
17	14.937	13.507	-0.1889	0.2737	-1
18	18.44	17.199	0.0551	-0.1162	-1
19	9.6977	8.9249	-0.1916	-0.1693	-1
20	18.345	11.234	-0.1494	-0.0181	-1

*1= Handloom, -1= Powerloom.

Table 2– First and second principal components of input vector

Sl. No.	Input parameters		Output
	1st principal component	2nd principal component	
1	56.9662	-4.449	1
2	85.076	4.2067	1
3	59.5146	-4.4745	1
4	42.1056	-7.3586	1
5	57.6747	0.114	1
6	58.6544	2.0952	1
7	56.5339	-38.9022	1
8	71.4801	-12.7601	1
9	73.1723	-11.3037	1
10	55.7699	-13.6413	1
11	12.5748	-9.07	-1
12	9.4968	-5.4698	-1
13	11.6551	-8.8383	-1
14	8.9793	-11.5912	-1
15	16.4851	-7.3937	-1
16	19.7868	-6.8459	-1
17	16.8266	-11.0573	-1
18	21.2843	-13.52	-1
19	11.0796	-7.1403	-1
20	15.4875	-14.9282	-1

Table 3– Comparison of performance between PSVM and standard SVM

Parameter	PSVM	Standard SVM
Training accuracy, %	99.375 ± 0.30	99.31 ± 0.33
Testing accuracy, %	98.75 ± 0.64	98.75 ± 0.64

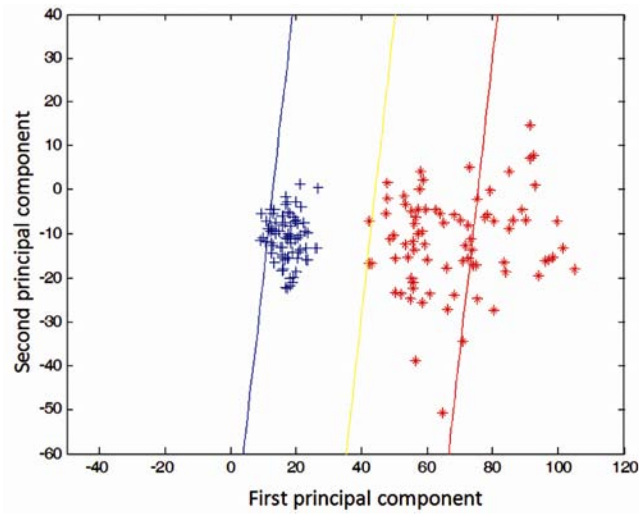

Fig. 5 – Classification of handloom and powerloom fabrics using PSVM

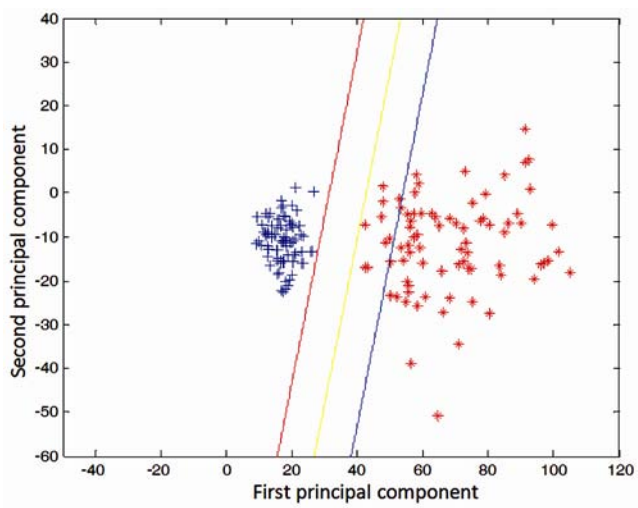

Fig. 6 – Classification of handloom and powerloom fabrics using standard SVM

comparison with that of standard SVM. While a standard SVM does its task in about 4 s, its proximal counterpart makes it in an awfully 0.01 s. This is ascribed to the fact that PSVM reduces the quadratic optimization problem in standard SVM to as simple as a system of linear equations.

Figures 5 and 6 illustrate the hyperplanes and margins for PSVM and standard SVM respectively for classifying the handloom and powerloom fabrics. Handloom fabrics are marked with (∗) symbol and powerloom fabrics are marked with (+) symbol (Figs 5 and 6). Margins by means of which data points are pushed apart by PSVM are wider than that drawn by standard SVM which is explainable on the basis of theoretical background algorithm works.

5 Conclusion

The present study holds the key of effective checking mechanism to differentiate handloom and power loom products to protect the interest of both customers and poor handloom weavers.

PSVM is a potential and efficient classifier to distinguish the handloom and powerloom fabrics. The time required for execution of PSVM algorithm is awfully small in comparison with that of standard SVM. While classifying handloom and powerloom fabric images, the performance rating of PSVM adjudged in terms of training and testing accuracy is in no way inferior to standard SVM. Moreover, PSVM is much less vulnerable to over fitting than its peers.

References

1 Fung G & Mangasarian O L, *Proximal support vector machine classifier*, paper presented at the International Conference on Knowledge Discovery and Data Mining, San Francisco, 26-29 August 2001.

2 Fung G & Mangasarian O L, *Machine Learning,* 59 (2005) 77.

3 Vapnik V, *The Nature of Statistical Learning Theory*, 2nd edn (Springer-Verlag, New York) 1999.

4 Orjuela V S A, Vansteenkiste E, Rooms F, Philips W, de Keyser R & de Meuleneester S, *Text Res J*, 80 (2010) 2132.

5 Ghosh A, Guha T, Bhar R B & Das S, *Int J Clothing Sci Tech*, 23 (2011) 142.

6 Bu H G, Huang X B, Wang J & Chen X, *Text Res J*, 80 (2010) 579.

7 Salem Y B & Nasri S, *Res J Text Apparel*, 13 (2009) 28.

8 Cristianini N & Shawe-Taylor J, *An Introduction to Support Vector Machines and other Kernel Based Learning Methods* (Cambridge University Press, Cambridge) 2000.

9 Suykens J A K & Vandewalle J, *Neural Processing Letters,* 9 (1999) 293.

10 Suykens J A K, Van Gestel T, De Brabanter, J, De Moor J & Vandewalle J, *Least Squares Support Vector Machines* (World Scientific Publishing Co., Singapore) 2002.

11 Gonzalez R C & Woods R E, *Digital Image Processing*, 3rd edn (Prentice Hall, New Jersey) 2009.

12 Johnson R A & Wichern D M, *Applied Multivariate Statistical Analysis,* 6th edn (Prentice Hall, New Jersey) 2007.

13 Han J & Kamber M, *Data Mining Concepts And Techniques*, 2nd edn (Morgan Kaufmann Publishers, San Francisco), 2006.