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A Model for African Fabrics Analysis and Recognition

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ABSTRACT
In this paper, a model to analyse and distinguish traditional African fabric patterns is presented. The model can be a valuable tool in image retrieval systems. Selected African fabric patterns were analysed using image processing and wavelet analysis techniques to extract relevant features for the recognition purpose. The recognition model consisted of multiple multi-layered artificial neural networks that used statistical and structural properties to recognize African fabrics' patterns. The model was simulated in MATLAB environment and its performance with respect to the accuracy of the recognised fabrics patterns was evaluated using the following metrics sensitivity, specificity and efficiency.

General Terms
Pattern Recognition, Neural network, Clusters, Wavelet decomposition, Statistical and geometry measures

Keywords
African fabric patterns analysis, search engines, information challenged community,

1. INTRODUCTION
The decision making processes of human being are related to the recognition of patterns. African people have developed rich textile traditions and distinctive forms of fabrics to communicate and enhance cultural meanings [16]. These textiles have an exceptional significance as a means of communication, information and mutual association in communities [1]. The history of textiles across Africa has been richly innovative, and has contributed to the development of a myriad of distinct genres of cloth and design. Their patterns are original artistic explorations of sophisticated visual paradigms with shimmering luminosity, dense composition, and its immense rippling effect viscerally engaging the viewer. Figure 1 depicts examples of African woven and tie-dye fabrics from Nigeria (Figure 1a,1b,1f), Ghana (Figure 1c,1d), South Africa (Figure 1e), Côte d'lvoire (Figure 1g), and Mali (Figure 1h). These fabrics do feature bright colors, complex geometric and aesthetic features, thus making it difficult for potential buyer to pick from varied choices available. In addition, knowing the particular style of cloth and where to purchase the item is a huge task, for there is information access dilemma, as buyers and sellers suffer from lack of information. Besides, due to the complexity in these designs, existing search engines may not achieve accurate results, the impact of which is to constrain commerce development.

In the present harshly competitive world of business, availability, quality of information, and the ability to communicate that information, are the critical foundations for all trades and enterprises. Hence, obtaining relevant information (usage, origin, price, historical proverbs, etc) on fabrics on a timely basis will prevent these attributes (risk, cost, and time constraints) from affecting trade in information challenged communities.

Fig 1: Examples of African fabrics

This study proposes a framework for fabric patterns analysis and visual recognition framework that can infer properties from images. To distinguish among the different African fabric categories and designs (within each category), as a result of their complexity, this study employed a two level classification schemes (one to classify among the categories and the other to classify within the fabric category) using two feature sets. The first classification scheme is a simple algorithm we developed to cluster the fabrics into categories using the mean computed from a fraction of dataset representing the filter responses of an image through Principle Component Analysis (PCA) and multi-level 2-D wavelet decomposition. The second scheme uses multiple multi-level perceptron networks with first order statistics and eccentricity measure (performed on image maps) to classify fabric designs within a given fabric category.

The rest of this paper is organized as follows. Section 2 reviews the related work. In section 3, the proposed fabric analysis and recognition model is described in details. Simulation results and performance evaluation of the model are discussed in section 4. Finally, some concluding remarks are provided in section 5.

2. RELATED WORK
Several researches for automatic recognition of fabric structures have been reported. Gabor filters was applied to automatically segment defects on nonsolid fabric images having variety of interlacing patterns [4]. Though, Gabor filter is a widely feature extraction method, especially in image texture analysis, the selection of optimal filter parameters is usually problematic and unclear. An automated vision system for detecting and classifying surface defects on leather fabric using geometric and statistical features segmentation procedure based on thresholding and morphological processing was proposed in [12]. In [22], an automated colour separation algorithm for fabric colour pattern analysis using self-organizing map neural network and fuzzy c-means to partition the patterns was developed. Though, colour histogram is robust to background complications and independent of image size and orientation, its sparsely nature makes it sensitive to noise. Fourier analysis and neural

network was used in [2] to detect and classify defects in knitted structures. Fourier analysis however, suffers from the sinusoidal bases which can only capture information in the frequency domain. In [23], an integrated Gabor filters with labelling algorithm for edge detection and k-means clustering with simulated annealing for image segmentation was proposed. However, the classic Gabor expansion is computationally expensive. A design of a simulation environment for electronic textiles [15] was described, but the design had a greater dependence on physical locality of computation. A worked on retrieval of Songlet patterns based on their shapes using geometric shape descriptors from gradient edge detector was discussed in [9], while in [21], image processing techniques were used to determine the amount of fuzz value on the fabric surface and artificial neural network and regression analysis methods applied to predict the fuzz on the fabric surface to prevent defects on fabrics. In [11], genetic algorithm for color separation in printed colour fabrics was used with fuzzy c-means to classify pixels colours. A regular texel level for textile recognition model was used in [7].

Many of these previous works, however, are computationally demanding and are not adequate to recognise African fabric patterns due to their complexity (patterns with encoded complex messages at various levels of abstraction), richer colours, and more variations than other kinds of textiles. A robust but simplified model which combines statistical and structural information as feature sets, PCA combined with wavelets; and multiple multi-level perceptron networks as classification algorithms are used to analyse and recognize the patterns. Reasons supporting the choice of these algorithms include wavelet transform is more preferable in texture analysis and in particular for, fabric classification. It has gained a lot of attention for texture classification and other related applications [8, 14, 18]. Artificial neural networks are widely used in many applications and have been applied to different textile problems [2, 10, 20]. Finally, the local statistical features require the least computational burden compared to other approaches.

3. MODEL DESCRIPTION

A simplified diagram depicting the model is depicted in Figure 2. From the diagram, fabric images are first processed and then multi-level decomposition algorithms (PCA and 2D wavelet transforms) applied for dimensionality reduction. In the first level classification, the mean, computed from a fraction of dataset representing the filter responses of an image through PCA and multi-level 2-D wavelet decomposition will be used with our classification algorithm to cluster the fabrics into categories$\left(CAT_j, j = 1, n-1\right)$. For the second level classification (within fabric designs), the first-order statistics and geometric measures are computed and fed into multiple multi-layer perceptron networks ($MLP_i, i = 1, n$) as inputs to recognise the matching fabric designs. Key modules of the framework are discussed in the subsections following.

3.1 Image Processing

A pre-processing algorithm was developed to correct the orientation of the fabric images and also to convert them into same size images. Furthermore, to improve the qualities of the images, histogram equalization was used to enhance their appearances. The images are then converted into grey scale to eliminate hue and saturation information while retaining the luminance.

3.2 Principle Component Analysis

Principle Component Analysis (PCA) is a feature extraction technique by which information regarding component factor variation which serves as response variable predictors is determined. PCA is used to project a set of images from a high dimensional space of pixels to a lower dimensional space which has the set of images as its main component. This linear transformation produces weights according to feature importance. Assume points in n-dimensional space, and suppose there are n points $X_i = (x_1, x_2 \dots, x_n)^T$, $1 \le i \le n$ satisfying E[Xi] = 0. PCA rotates the points on the space such that the points only spread out along axes.

Mathematically, define Q= $(X_1, X_2, \dots X_m)$, Q is an n*m matrix containing information on a given data. The covariance matrix of these points on the space is thus

$$C_x = \frac{1}{m} QQ^T \qquad (1)$$

A linear transform orthonormal matrix P can be computed to transform Q to Y by $Y = PQ$. The rows of P are the principal components of Q. However, PCA cannot eliminate out noise well enough so a combination of wavelet analysis with PCA is made to improve the result of feature extraction.

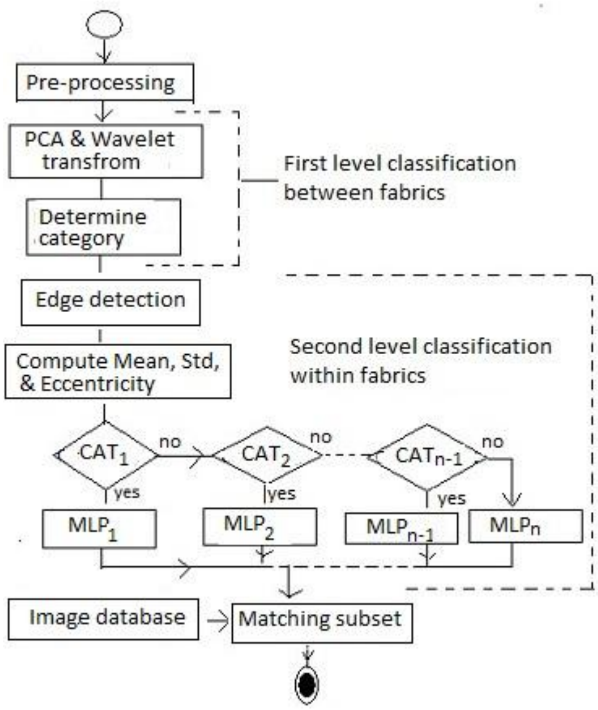

Fig 2: Model description

3.3 Discrete Wavelet Transform

A Discrete Wavelet Transform (DWT) signal is decomposed into coarse approximation coefficients at the first level by filtering it using a low-pass filter and into detail coefficients by passing it through a high-pass filter. In subsequent levels, the decomposition is done recursively only on the low pass approximation coefficients obtained at the previous level. The process is continued for the required number of levels. Wavelet decomposition technique has a better performance than others in the area of signal processing due to its multilevel decomposition with variable trade-off in time and frequency resolution [5,17]. Wavelet decomposition of a signal f(x) is obtained by convolution of the signal with a family of real orthonormal basis $\omega_{a,b}(x)$. The basis function is obtained through translation and dilation of the mother wavelet $\omega(x)$ defined as $\omega_{a,b}(x) = 2^{-a/2}\omega(2^{-a}x - b)$, where a,b ϵ R and a≠0 are the dilation and translation ;parameters. The mother wavelet can be reconstructed from a scaling function, $\tau(x) = \sqrt{2}\sum_n h(n)\tau(2x-n)$, where h(n) is the impulse response of a discrete filter. There exists an algorithm similar to the one-dimensional case for 2d signals. This two dimensional wavelet transform leads to a decomposition of approximation coefficients at level j-1 in four components: the approximations at level j, and details in horizontal, vertical and diagonal orientations. In terms of two-dimensional wavelets, at each stage, a matrix f(x,y) is decomposed into four quarter-size matrices

$$f^1(m,n) = \langle f(x,y), \tau^1(x-2m, y-2n)\rangle,$$
$$f^2(m,n) = \langle f(x,y), \tau^2(x-2m, y-2n)\rangle,$$
$$f^3(m,n) = \langle f(x,y), \tau^3(x-2m, y-2n)\rangle,$$
$$f^4(m,n) = \langle f(x,y), \tau^4(x-2m, y-2n)\rangle$$

In feature extraction tasks, the commonly adopted approach is to select the sub-band image that contains the highest energy distribution. Therefore, low frequency sub-band is selected upon high frequency sub-bands for fabric image structure representation in this research. In this specific application we performed multi-level 2-D wavelet decomposition on fractions of the principal component scores of fabric images at level 1 using the Discrete Haar Transform.

3.4 Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) networks are composed of many simple elements inspired by biological nervous systems operating in parallel. Within MLP system (Fig 3), there exist three types of units: input, hidden, and output units. The input layer transmits signals to the neurons in the hidden layer, which in turn extracts relevant features from the received signals. The features considered important are then directed to the final layer (output layer) of the network. The input layer distributes the inputs x_i to the weights w_{ji}^h of the hidden layer using:

$$net_j^h = \sum_{i=1}^{N} w_{ji}^h x_i + \theta_j^h \qquad (2)$$

where θ is the bias term and h refers to quantities on the hidden layer. The weighted sum of the inputs in the neurons of the hidden layer is computed using (3) and are then passed to a nonlinear *activation* function, (such as the tangent hyperbolic) given in (4).

$$Z_j = \sum_{i=1}^{p} w_{ij}^h x_i = {w_j^h}^T x, \qquad j = 1,..,m \quad (3)$$

$$v_j = \frac{1-exp(-2z_j)}{1+exp(-2z_j)}, j = 1,..,m \qquad (4)$$

Other typical activation functions are the threshold function (hard limiter) and the sigmoidal function. The neurons in the output layer are linear, in that they only compute the weighted sum of their inputs. Training is the adaptation of weights in a MLP network such that the error between the desired output and the network output is minimized. The two steps involved are (1) *Feed forward computation*.

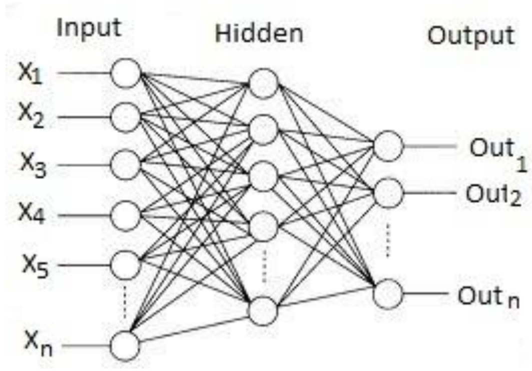

Fig 3: MLP layers

Using the network inputs x_i, the outputs of hidden layer are first computed, and they are passed as inputs to the second layer, the outputs of this layer are computed, and so on until the output of the network is obtained. (2) *Weight adaptation*. The output of the network is compared to the desired output. The difference (error) of these values is used to adjust the weights in the output layer first, then in the preceding layers to decrease the error (gradient-descent optimization).

The design of the MLP to recognise African fabric patterns is a simple structure, which consists of one input layer, one hidden layer, and one output layer. The MLP used a hidden layer of log-sigmoid neuron followed by an output layer of linear neuron. Since a typical African fabric may have several variants or designs we employed multiple MLPs to identify patterns from varied fabric designs. Each MLP received input as a 3 by 1-element vector (mean, standard deviation, and eccentricity measure), representing the feature vector of the image.

3.5 Classification Algorithms

Feature extraction acts as a vital role for a recognition system, and given a set of training patterns from each class, the objective is to establish decision boundaries in the feature space which separate patterns belonging to different classes. For feature extraction, the PCA algorithm was first applied to the image pixels $\sum_i^n \sum_j^m x_{i,j}$ to compute the principal component scores, thereafter; a 2D wavelet transform was applied on a fraction of the principal component scores, say $\sum_i^n \sum_j^k x_{i,j}$, $k < m$, where much of the columns contributing less to the feature space were ignored. This was done to achieve better accuracy with lesser storage and computational complexities. The degree of similarity among classes can be calculated by using a suitable distance measure. A two level classification schemes were employed in this study. In the first scheme, a simple algorithm to partition the fabrics according to designs (or category) follows.

Consider a set of M feature spaces representing fabric patterns classified into c categories, with each category containing n fractions of the principal component scores representing set of images, $y_1, y_2, \ldots, y_n$. Let the mean of principal component scores in each fabric category and the mean of the principal component scores of all images be represented by $\bar{m}_c$ and $\bar{\bar{m}}_a$, respectively. For each fabric, the following expression gives a measure of how related the fabric is to each of the fabric design types (category).

$$c_i = |(y_i - \bar{m}_c)/\bar{\bar{m}}_a|, \qquad i = 1, n \qquad (5)$$

The following control structure was used to partition fabrics into appropriate category:

If c_i*< threshold_value then*
  return $fType_1$
else if c_i *threshold_value then*
  return $fType_2$
else if c_i *threshold_value then*
  return $fType_3$
  :
  :
endif

where $fType_i$, i=1,M may represent designs of African fabrics (i.e. *'Adire', 'Aso-oke', 'Kente', 'Mudcloth',* etc.). For example, Figure 4 illustrates how four fabric categories are clustered into partitions (Category A to Category D). The threshold, carefully selected is used to determine the degree of closeness of each fabric mean to its category mean ($\overline{m}_c$). High tolerance value will have members overlapping multiple categories and low tolerance value will eliminate valid members from a given category. Expression given in (5) was used to calculate the degree of closeness of a typical fabric design to its category mean. Fabrics with values below the threshold 0.1 (dashed line) as depicted in Figure 4 are closely similar to the appropriate category and are saved, while fabrics not related (having values above the threshold), are ignored.

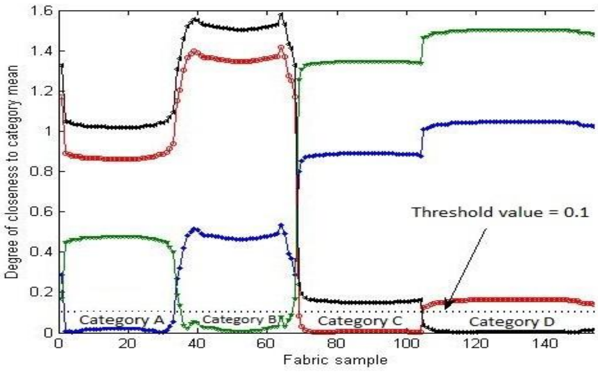

Fig 4: Classification function among categories

In the second classification scheme for within fabric designs, the feature vector used was computed by first applying the canny edge detection algorithm [3] on grey scale image of the fabric. The first-order statistics (mean and standard variation) were computed using the following:

$$\mu = \frac{1}{N}\sum_{i=1}^{n}\sum_{j=1}^{m} f(i,j)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\sum_{j=1}^{m}(f(i,j)-\mu)^2} \qquad (6)$$

where f(i, j) is the grey-level of the $(i, j)^{th}$ element of a $n \times m$ image and N is the total number of pixels in the image.

Another important feature extraction approach is to extract structural information, like lines, eclipses, and circles, from the images to aid recognition. This information is calculated using the eccentricity analysis. Eccentricity gives the ratio of the distance between the foci of the ellipse and its major axis length. An ellipse whose eccentricity is 0 is a circle, while an ellipse whose eccentricity is 1 is a line segment. The eccentricity measure is given as

$$C = \frac{P^2}{A} \qquad (7)$$

where P and A are an object's perimeter and area, respectively. This measure has found many applications as a geometric feature because it usually represents well the degree of the eccentricity of an object. Equations (6-7) are used as textual representation of the fabrics and they serve as input to the multiple MLP networks for the final classification.

4. MODEL SIMULATION

According to [13], MATLAB enjoys popularity in many different disciplines due to its multi-platform, broad support base of active user community and sample code repositories. MATLAB software was adopted because of its user friendliness, scalability, popularity, and many other support features it provides.

4.1 Data Sample Used

Eight hundred (800) samples of images representing selected African fabric designs were digitally collected from contemporary artists (experts) from Nigeria, Ghana, and South Africa meaningfully engaging in their production. The four fabrics used in this study are:

i). Adire is a tie-dye fabric made by the Yorubas. The different design types are *Eleko* (designs stencilled or painted onto the cloth with starch), *Oniko* (tying patterns into the fabric); and *Alabere* (stitching designs using raffia on the fabric).

ii). Kente (Ewe) is a probably the best known of the woven fabrics, worn by political authorities and high-ranking officials of the Ashanti people in Ghana.

iii). Amafu is a colourful 100% cotton fabric from South Africa, which can either be a subtle Damask or plain weave. Its basic designs are the hand-dyed screen prints (available in vibrant colours) and the subtle discharge prints (available in copper and silver).

iv). Aso-oke is a traditional woven fabric of the Yoruba. The three design types are *etu* (a dark blue indigo dyed cloth), *sanyan* (a brown cloth woven from the beige silk); and *alaari* (woven from Southern European silk obtained from the Saharan via Tripoli). The fabric is considered trendy in countries like Europe, United States, Brazil, Cuba, and other West Africa countries.

4.2 Training and Test Sets

The image database was randomly divided into two groups - the training set (70% of the data) and the test set (30% of the data), with no repetition. The training method used was supervised [6] using a high performance and faster adaptive learning rate in place of the standard gradient descent to train the network. Each MLP was trained for a maximum of 1000 epochs or until the network sum-squared error falls beneath 1e-2. Considering the sizes of the multiple MLP networks (the largest had 3 inputs, 9 hidden neurons, and 1 output), it is probably evident that the smaller multiple MLP networks will be easier to simulate. The training procedure was repeated k times, each time using training set. The multiple MLPs grouped similar patterns into clusters using the Euclidean distance measure defined as follows:

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (8)$$

Once the network was constructed (and trained), the test set, consisting of pre-processed greyscale fabric images (from the four fabric types discussed above) were used in the simulation to test the model. In the simulation, fabric images were randomly chosen from the test set as queries; and the similar images returned were counted as relevant images. Figure 5 illustrates sample outputs from the proposed model, the ability of the model to recognise among fabric categories (see Figure 5a) and within category (design) shown in Figure 5b, where the model was able to identify and extract fabrics matching a given *Adire-eleko* design, used as query. Simulation results showed that the model performs recognition of the different fabric designs reasonably.

5. PERFORMANCE EVALUATION

A complementary issue to performance is correctness. The central question is whether a system is conforming to the requirements and does not contain any flaws. Standard technique for evaluating the performance of image retrieval algorithms was used to evaluate the framework developed in this study. We computed sensitivity and specificity values for random queries belonging to different fabric categories and designs, the following types of errors (Table 1) were used.

i). Correct Detection (CD)- the system recognizes a given fabric when indeed one was present.

ii). Correct Rejection (CR)- the system recognizes the absence of a given fabric when indeed it was absent.

iii). False Positive (FP)- the system recognizes a fabric that was not present.

iv). False Negative (FN)- the system fails to recognize a fabric that was present

Similarly, the performance of the system was evaluated in terms of sensitivity (S), specificity (SP), and efficiency (E). Sensitivity (S) measures the ability of the model to recognize fabric patterns, while specificity (SP) gives a measure of the ability of the model to identify a typical African fabric. The mathematical representation of sensitivity(S), specificity (SP), and efficiency (E) [19] are defined as follows:

$$S = \frac{CD}{CD + Fn}$$

$$SP = \frac{CR}{CR + CD} \qquad (9)$$

$$E = \frac{CR + CD}{CD + FN + FP + CR}$$

The efficiency, sensitivity, and specificity of the recognition system is shown in Table 2, the model produced a reliable and consistent result in recognising the patterns. Generally, the results obtained indicated that the model has a strong capability to recognize the patterns of all the four fabrics used in this study. Based on the similarity, data vectors are clustered such that the data within a cluster are as similar as possible, and data from different clusters are as dissimilar as possible. As indicated in Table 2, the model was able to accurately recognize *Kente* patterns due to its relative simplicity compared to other fabric designs used in this study.

Table 1. Confusion Matrix

		Recognition State	
		Present	Absent
Decision	Present	CD	FP
	Absent	FN	CR

(**a) Recognition among fabric categories**

(b) Recognition within category

Fig 5: Sample classification results

Table 2. Model Performance

Fabric Category	Recognition Present	Absent	S	SP	E
Adire	99 1	3 97	0.99	0.49	0.98
Aso-oke	100 0	15 85	1.00	0.46	0.93
Amafu	98 2	6 94	0.98	0.48	0.96
Ewe	100 0	0 100	1.00	0.50	1.00

6. CONCLUSION

In this paper, a model to analyse and recognize traditional African fabric patterns has been presented, and it is expected to provide a valuable tool in image retrieval systems. The model used a two level classification scheme. In the first scheme, principal component analysis and Discrete Wavelet Transform (DWT) were combined for multi-level decomposition and classification among the different fabrics category, while at the second level, multiple multi-layer perceptron networks that accept a three by one element vector representing the statistical and geometric measures as feature set was used to classify designs within fabric category. The applicability of the model was demonstrated using samples of traditional African fabrics.

7. REFERENCES

[1] Akinwumi, T. M. 2008. The “African Print” hoax: machine produced textiles jeopardize African print authenticity. The Journal of Pan African Studies, 2(5), 179-192.

[2] Cali S., Ertuğrul Ş., and Ucar N. 2004. Fault detection and classification in knitted structures using Fourier analysis and neural networks. 9th Mechatronics Forum International Conference, Ankara, Turkey, 445-448.

[3] Canny, J. 1986. A computational approach to edge detection. TPAMI, 8(6):679–698

[4] Escofet J., Navarro R., Millán M.S., and Pladellorens J., 1998. Detection of local defects in textile webs using Gabor filters, Opt. Eng. 37(8), 2297-2307

[5] Gokmen G. 2011. Wavelet based reference current calculation method for active compensation systems. Electronics and Electrical Engineering, 2(108), 61–66.

[6] Hagan, M. T., Demuth, H. B., and Beale, M. 2002. Neural Network Design. Boston: Campus Publishing Service, University of Colorado.

[7] Han, J. and Mackenna, S. J. 2009. Classifying and Comparing Regular Textiles for Retrieval Using Texel Geometry. International Conference on Computer Vision, Theory and Applications, Portugal.

[8] Jafari-Khouzani, K and Soltanian-Zadeh, H. 2005. Radon transform orientation estimation for rotation invariant texture analysis. IEEE Trans. 27 (6), 1004-1008

[9] Jamil N., Baker Z. A., and Senbok, T. M. T. 2006. Image Retrieval of Songlet Motifs using Simple Shape Descriptors. Geomtric Modelling and Imaging New Trends (GMAT’ 06). London, pp. 171-176

[10] Kumar A. 2003. Neural network based detection of local textile defects, Pattern recognition, 36, 1645-1659.

[11] Kuo, C. F., Shih, C. Y. and Lee, J. Y. 2008. Separating color and identifying repeat pattern through the automatic computerized analysis system for printed fabrics. Journal of Information Science and Engineering, 24, 453-467.

[12] Kwak, C., Ventura, J. A., and Tofang-Sazic, K. 2001. Automated defect inspection and classification of leather fabric. Intelligent Data Analysis, 5,355–370.

[13] Larkins, D. B. and Harvey, W. 2009. Introductory computational science using MATLAB and image processing, Procedia Computer Science, 1–9.

[14] Li, S. and Taylor, J. S. 2005. Comparison and fusion of multi-resolution features for texture classification. Pattern Recognition Letters, 26, 633– 638.

[15] Martin, T., Jones, M., Edmison, J., Sheikh, T., and Nakad, Z. ”Modeling and Simulating Electronic Textile Applications”, LCTES, USA, 2004

[16] Perani, J. and Wolff, N. H. 1999. Cloth, dress, and art patronage in Africa, Berg Publishers.

[17] Popov A., Kanaykin A., Zhukov M., and Panichev O., Bodilovsky O. 2010. Adapted mother wavelets for identification of Epileptiform complexes in Electroencephalograms. Electronics and Electrical Engineering, 8(104), 89–92.

[18] Sastry, C. S., Pujari, A.K., Deekshatulu, B. L., and Bhagvati, C. 2004. A wavelet based multi-resolution algorithm for rotation invariant feature extraction. Pattern Recognition Letters. 25 (16), 1845–1855.

[19] Subasi A. 2007. EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications, 2(4), 1084-1093.

[20] Tilocca A., Borzone P., Carosio S., and Durante A. 2002. Detecting fabric defects with a neural network using two kinds of optical patterns. Textile Research Journal, 72(6), 545-550.

[21] Uçar, N. and Ertuğrul, S. 2007. Prediction of fuzz fibers on fabric surface by using neural network and regression analysis. Fibers & Textiles in Eastern Europe, 15(2), 58-61.

[22] Xu B. and Lin, S. 2002. Automatic color identification in printed fabric images by a Fuzzy-Neural network. AATCC Review, 2(9), 42-45.

[23] Yiming J, Kai H. C. and Chi-Cheng H. 2004. Efficient Edge Detection and Object Segmentation Using Gabor Filters. ACMSE '04, Huntsville, Alabama, USA, 454-459.