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RECOGNITION OF CLOTH PATTERN FOR OPTICAL DEFECTIVE PERSONALITIES

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ABSTRACT

For the optically defective humanity choosing of cloth pattern and colour is a challenging task .In the computer vision this becomes a difficult in choosing cloth due to the large intra class pattern, scaling and rotation. The pattern of cloths is segregated into plaid, striped, pattern less irregular and handling complex patterns and colour that cannot be identified visually impaired people .This system integrates a camera, a microphone, a computer and a Bluetooth ear piece for audio description. Radon Signature descriptor is used to recognise the cloth pattern fuzzy clustering is adapted to capture the global features of cloth pattern and colour. Our approach achieves accuracy of 97% recognition of cloth and colour accuracy. It outperforms the texture analysis on clothing pattern recognition. This system would provide more support and independence in their daily life.

Index terms: clothing pattern recognition, texture analysis, clustering, optically defective people.

INTRODUCTION

From the statistics of World Health Organisation (WHO), about 166 million people around the world are optically defective and due to blindness 37 million people are blind around the world. Low vision is diabetics, infection, traumatic injuries, cataracts, macular degeneration, diabetic retinopathy, cataract and glaucoma these are reasons that lead to blindness. Colour plays a major role in everybody's life. This became a task in their day –to-day life for optically defective humanity.

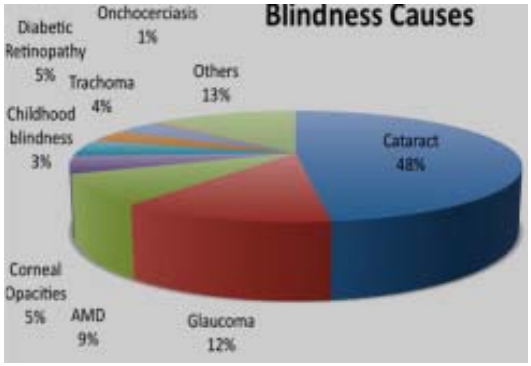

Figure-1. Blindness chart.

Levels of Visual Function include:

- Normal vision
- Moderate visual impairment
- Severe visual impairment
- Blindness

The prevalence of visual impairments increases with age i.e. about 16% of the people are in the 45-64, 18% of people in the range 65-74, 27% of the people of age 70 and older. The visual function is consisting of many other components. They include visual field, colour perception, stereo acuity, dark adaptation, glare recovery, contrast sensitivity function.

Hence, we introduced a system that helps visually impaired people to recognize cloth patterns and colours. This system contains of three major components 1.An sensor including camera is used to capture the cloth pattern, a microphone is involved for command input and for audio output speakers are used that can hear identically.2. Clothing pattern recognition, colour identification and Data capturing analysis by using a computer which can be a Smart phone or desktop.3. Audio outputs for the status of the colour and cloth pattern which they have chosen.

In an extension our system handles clothes with complex patterns and recognition of clothes in four such as plaid, striped, pattern less, irregular and different colour.

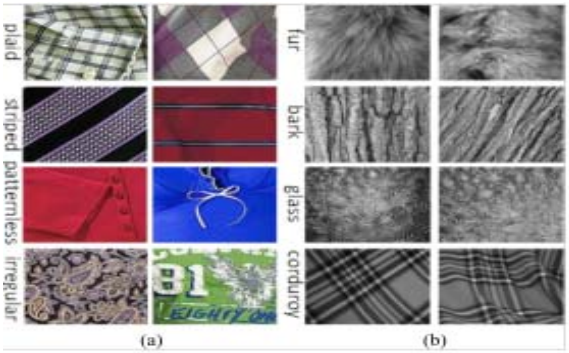

Figure-2. Interclass variations in clothing pattern images and traditional texture images. (a) Clothing pattern samples with large interclass pattern and colour variations. (b) Traditional texture samples with less interclass pattern and intensity Variations. Clothing pattern recognition including four-pattern categories of plaid, striped, pattern less.

RELATED WORK

Recognition of cloth pattern are being developed to improve the quality of life and their safety [2], [7], [6], [16], [17], [27], [28], [30], [31] reading a display, indoor

navigation an finding rehabilitation, banknote recognition. Hidayati *et al* [14] proposed a method for generic classification of upper cloths. Liu et al [12] proposed a method of clothing for specific occasions. These systems are designed for blind users. Yuan et al [31] developed a system to assist visually impaired people to match cloths from the pair of clothing images. This system can provide a user with the information about whether or not the clothing patterns and colours match.

Texture provides essential information for many image classification tasks including cloth pattern recognition. Some early research on texture mainly focused on the analysis of global two-dimensional image transformations including scaling and rotation. Due to the lack of invariance in cloth to geometric transformations, this cannot efficiently represent texture images with 3-D transformations such as view point and surface deformation. Lazebnik *et al.* [11] Based on affine-invariant detectors and descriptors (RIFT and SPIN) a texture representation method is used. Zhang *et al.* [32] also Combined scale invariant feature transform (SIFT) and SPIN for Texture classification.

Unlike existing traditional texture images, clothing patterns presents very larger intra class variations are present within each pattern category. Although many computer vision technology and image processing techniques have been developed for texture analysis and classification, traditional texture analysis methods cannot recognize clothing patterns effectively. Hence, we develop a camera-based prototype specifically for optically defective people to recognize clothing patterns and colours.

IMAGE FEATURE EXTRACTION FOR CLOTHING PATTERN RECOGNITION

The clothing patterns present visual pattern recognition and it is as characterized by the few basic primitives (e.g., plaids or stripes). The local features are effective to extract the structural information of primitives. Due to large intra class variance, local primitives can vary significantly of same clothing pattern (see Figure-2). Global features including directionality and statistical properties of cloth Pattern is more stable within the same category. Therefore, they able to provide complementary information to local structural features. Next, we present extractions of global and local features for clothing pattern recognition, i.e., Radon Signature, Fuzzy clustering and SVM classifier.

A. Pre-Processing

The input image is get converted into grey-scale image by eliminating hue and saturation points in the image, While retaining the luminance. So, that the radon signature can be applied on the image .Gaussian filter is used to blur images and to eliminate noise. Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rising and falling time. This is closely connected to the fact that the Gaussian filter has the minimum possible group delay. It is considered to be a time domain filter, just as the sinc function is the ideal frequency domain filter. It is used in various research purposes such as probability distribution for noise, as a smoothing operator, in mathematics. It has its basis in the human visual perception system.

RADON SIGNATURE

Clothing images present very large intra class variations, which is the major challenging for cloth pattern recognition. In a perspective, the directionality of the clothing pattern across the different categories is very consistent and this is used as an important property to distinguish the clothing patterns. As shown in the figure, the clothing patterns of plaid and striped are anisotropic in nature. The categories of pattern less and irregular are isotropic in nature. To characterize the directionality feature of clothing pattern a novel descriptor radon signature is used.

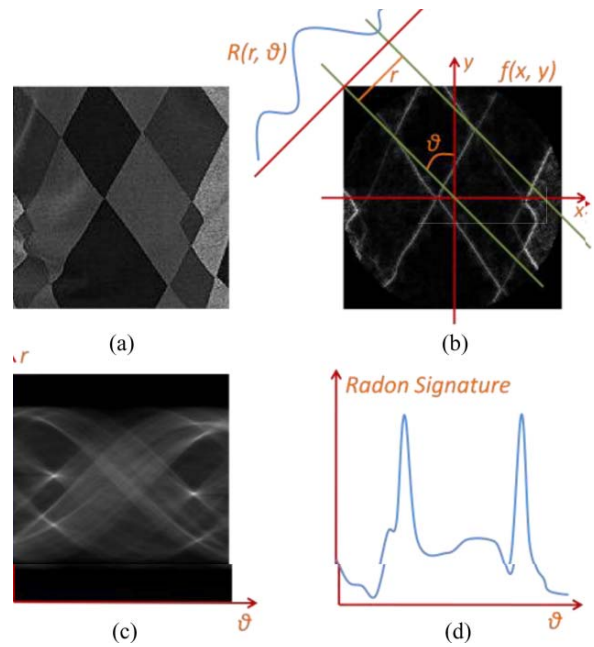

Figure-3. Computation of Radon Sig. (a) An intensity image of clothing pattern.(b) Radon transform performed on a maximum disk area within the gradient map of (a). (c) Result of Radon Transform. (d) Feature vector of Radon Signature.

The Radon signature is based on the radon transform, which is commonly used to detect the principle orientation of the image. Then the image is rotated accordingly to its dominant direction to achieve rotation invariance. The Radon transform of a 2-D function is given for f(x ,y) is defined as

$$R(r,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\,\delta(r - x\cos\theta - y\sin\theta)\,dxdy$$

Where r is the perpendicular distance of a projection line to the origin and the angle of the projection line is θ as shown in the Figure-3(b). The first advantage of radon transform is its robustness to zero mean white noise and the another advantage of this transform is

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rotation invariance. The large interclass variations of clothing pattern also reflect large changes in intensity and colour. Figure-3(b) illustrates the Radon transform over a disk area of gradient map. $R(r, \theta)$ in (1) is a function with two parameters of r and θ, as shown in Figure-3(c). The directionality of an image can be represented by Vary (r, θi), the variances of r under a certain projection direction θi. The number of sampling in each projection line is defined by N. The radon signature is generated by the variances of r under all the sampling projection directions.

$$[\mathrm{Var}(r, \theta 0), \mathrm{Var}(r, \theta 1), \ldots, \mathrm{Var}(r, \theta T-1)]$$

Where the number of sampling projection direction is T. It determines the feature dimension of radon signature. To normalize the feature vector we employ L2-norm vector. The principle directions of the image in Fig. 3(a) correspond to the two dominant peaks in the Radon Sig in Figure-3(d).

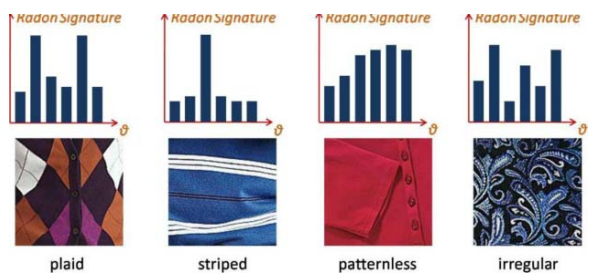

Figure-4. Clothing patterns samples and associated Radon Sig descriptors.

Figure-4 illustrates Radon signature descriptors of sample images from different four clothing pattern categories. The plaid patterns have two principle orientations; the striped have one principle orientations; for the irregular and the pattern less images have no dominant peaks, but the directionality of the irregular image presents a very large variations than the pattern less image .The radon signature of the pattern less image is smoother compared to the irregular image.

WAVELET SUBBANDS

The discrete wavelet transform decomposes an image S into low frequency image D(S) under multiple scales and multiple high frequency channels. It is a linear transform that operates on a data vector transforming it into different vectors of same length. It separates data into different frequency components. By using these wavelets the function can be analysed at the various levels of resolution. Wavelets seem to be very for the analysis of texture. It provides a multi resolution spectrum analysis tool. We extract the statistical features from the wavelets to capture the global statistical information of images at different scales.

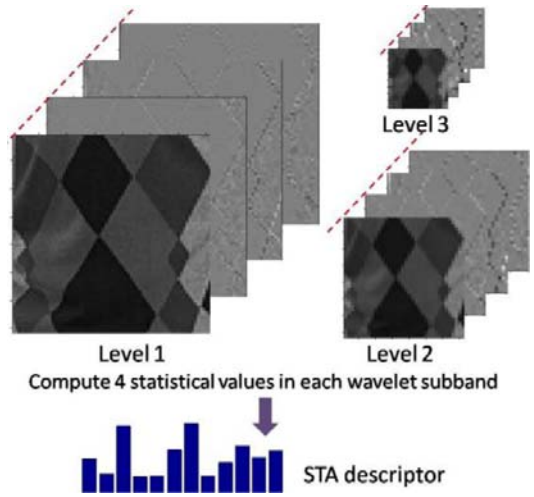

Figure-5. The computation of STA on wavelet sub bands.

Three levels of wavelet decomposition transform are applied to a clothing image. Each decomposition level includes four sub bands such as horizontal, vertical, original and diagonal components arranged from the close to the distant in each level. These statistical values are calculated in each wavelet sub band are concatenated to form the final descriptor.

FEATURE EXTRACTION AND COLORS

We propose an approach based on fuzzy clustering features for colour recognition. And from all the faces in the database the fuzzy clustering features can be extracted. Then, a new face is given, the features are extracted from that new face and it is compared against the features in the database. The face with the larger number of matching points is considered to be the nearest face, and this nearest face is used for the classification of the derived face. When the distance of the feature is less than a distance to the next nearest feature is said to be matched. From reducing the distance the number of false matches can be eliminated. In false match due to the high dimensionality of the features there will be a number of nearest features with close distances. Due to the high distinctive nature of fuzzy clustering features correct match has to find features that are very close to another feature. The cluster structure has different characteristic values in the evaluation of performance in order to detect that classifier has to be monitored regularly.

Accuracy of the approximation

Many classifiers respond output with approximated values rather than class labels. In the true output values the clusters will become know accuracy in the current time window, and it is defined as the difference between the output values from the clusters and the expected values corresponding to each cluster, it is compared against the previous time window for accuracy .If the difference increases it indicates a deterioration of the approximation and the classifier performance.

The number of misclassified objects

The true class labels of classified objects become known error rate of classification in the current window and it is compared with the average error rate of previous windows. This is one of the most common characteristics feature used to evaluate the performance of a each classifier. Error rates, which are very less or approximately equal to the average values, this provides evidence about the stable cluster structure and performance of the classifier. Changes in the cluster structure can be assumed when error rate is greater than the average values.

Unambiguity of the classification

In a classifier, a binary 1-out-of-c coding has been used to represent the existing c clusters the output with approximated values has highest value that determines the class label it is so called as winner take off principle. Under certain conditions, for each cluster the output values can be considered as probabilities. If the difference between two maximum output values is very small then the classifier is somewhat indifferent between the corresponding clusters. In most uncertain case where the each cluster is equally to all outputs take value 1/c.

Class distributions

The relative number of objects the percentage is assigned to each cluster during the current time window and it is compared to the average relative number of objects in previous time windows. The true class labels of previously classified objects are only required for the previous time windows. The number of objects in each cluster represents the class distribution and it describes a certain structure of the data. If the class changed after classification of new objects in the current window and if it is differs in average that indicates a change in cluster structure.

Means and variances of features

For each class and feature, the mean and variance values in the current window is compared corresponding to the values in the previous window .Based on the comparison measures a shift or drift in the feature values can be detected using values. To calculate this true class label is needed in order to calculate the each class separately

Unambiguity of fuzzy classification

The Performance of the fuzzy classifier based on the analysis of membership functions that represents fuzzy clusters. The difference between the two maximum degrees of membership of each object to the clusters can be considered to evaluate the quality of fuzzy cluster. If the difference of value is large than object and it can be assigned clearly to one of the clusters. If the value of difference is small an object belongs to both clusters to the same degree and very ambiguous By using, for instance, the maximum and average values of the difference between the two largest membership degrees over all objects the unambiguity is calculated for each window. If the maximum value of the difference over all objects in the current window is much smaller compared to the previous time windows, then the objects to clusters becomes very ambiguous. The ambiguous assignment can be distinguished based on the absolute degree of membership. The clusters which contain low degree of membership indicate that object do not belongs to any existing clusters in the window. Clusters contain equally high degrees of membership that indicate the objects belong to more than one cluster to the same clusters. These cases correspond to different kinds of changes in the cluster structure and lead to a decrease in classifier performance.

EXPERIMENTAL RESULTS AND OBSERVATION

To implement the algorithm MATLAB software tool is used. GUI interface is used to select the process. We have taken large number of images and tested using this algorithm. Identify cloth pattern and colour gives an accurate result using this algorithm. This provides greater result when compared to the existing methods and detecting damaged cloths is done effectively for the blind users. Compared to the earlier method the accuracy level is about 97%.The results are sketched below:

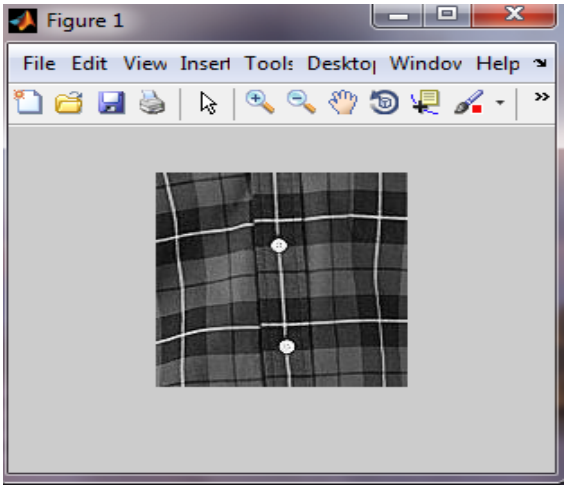

Figure-6. Input image converted to gray scale image.

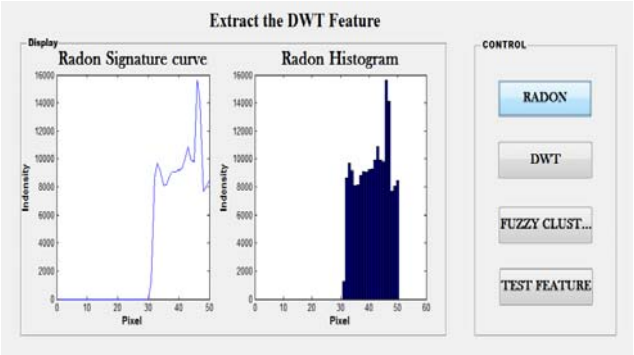

Figure-7. Radon signature and its histogram value for the cloth pattern.

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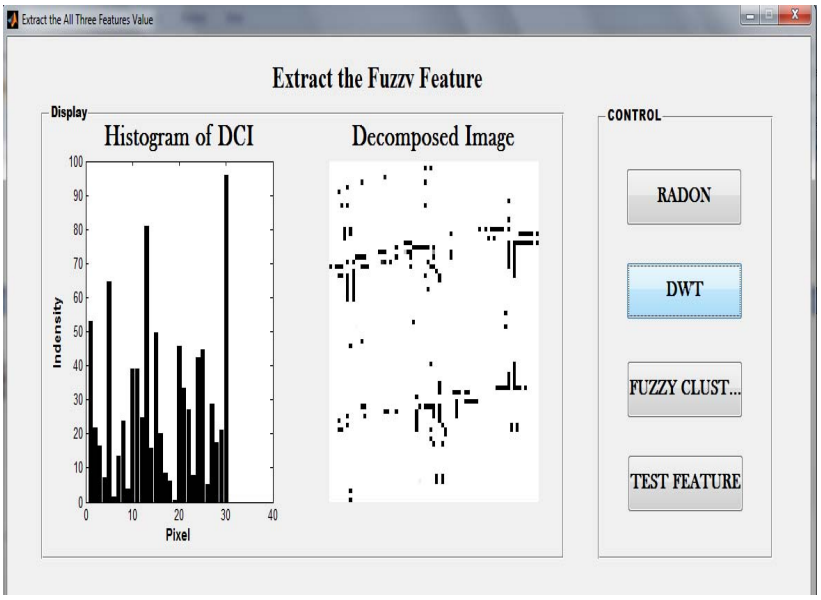

Figure-8. Histogram of DCT and its decomposed image.

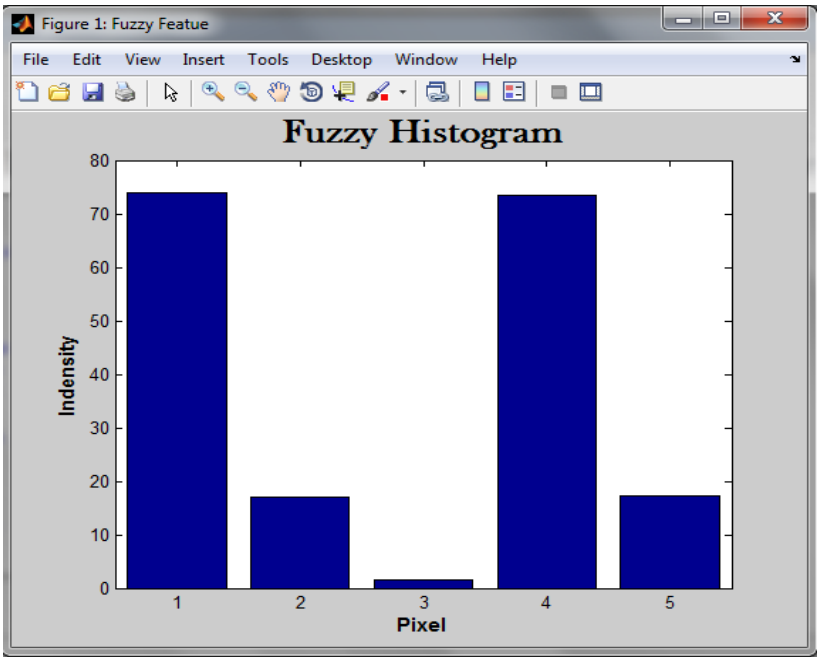

Figure-9. Fuzzy histogram value.

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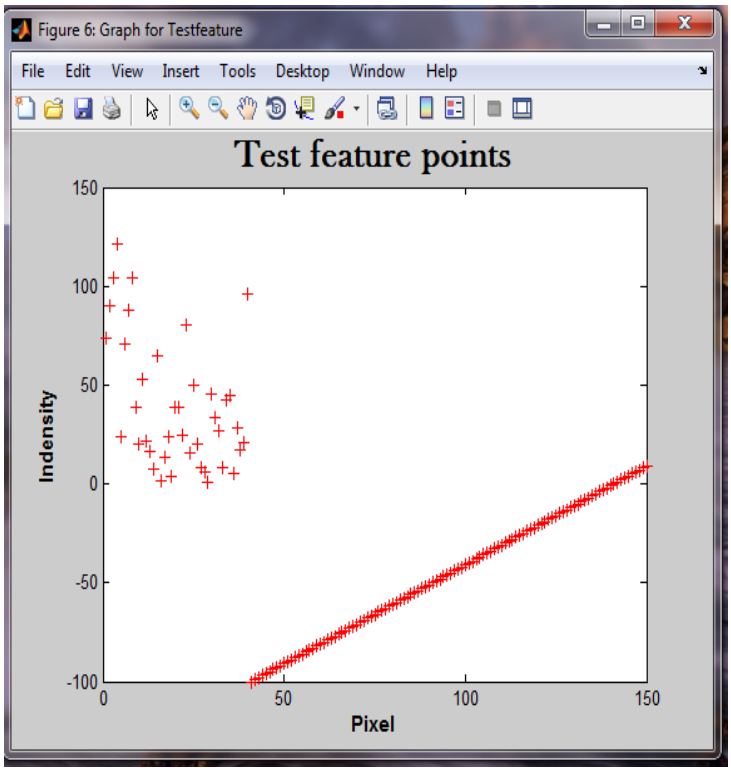

Figure-10. Test feature points for the cloth pattern for identifying colour.

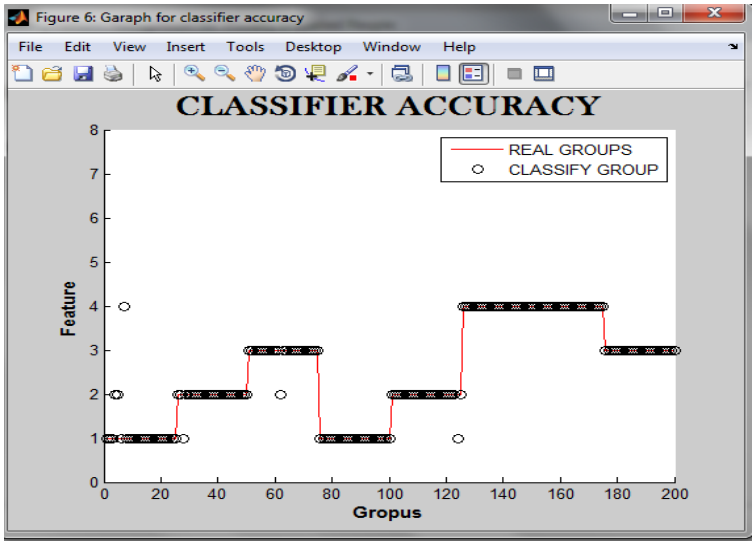

Figure-11. Classifier accuracy of colour.

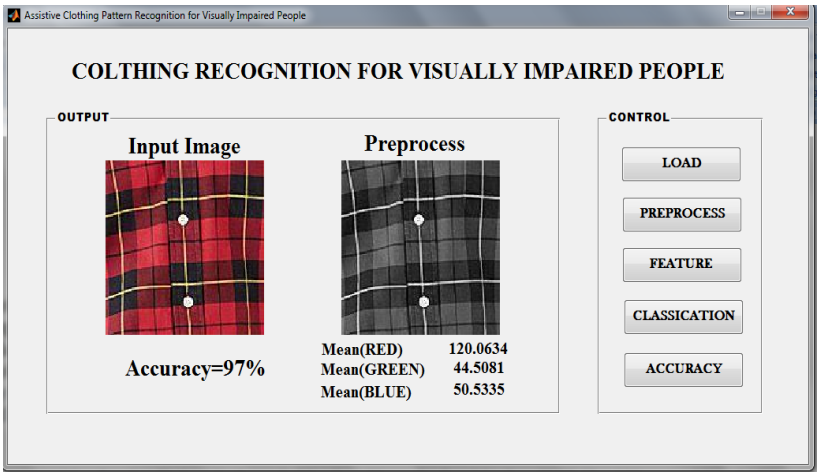

Figure-12. Accuracy and colour value for the pattern.

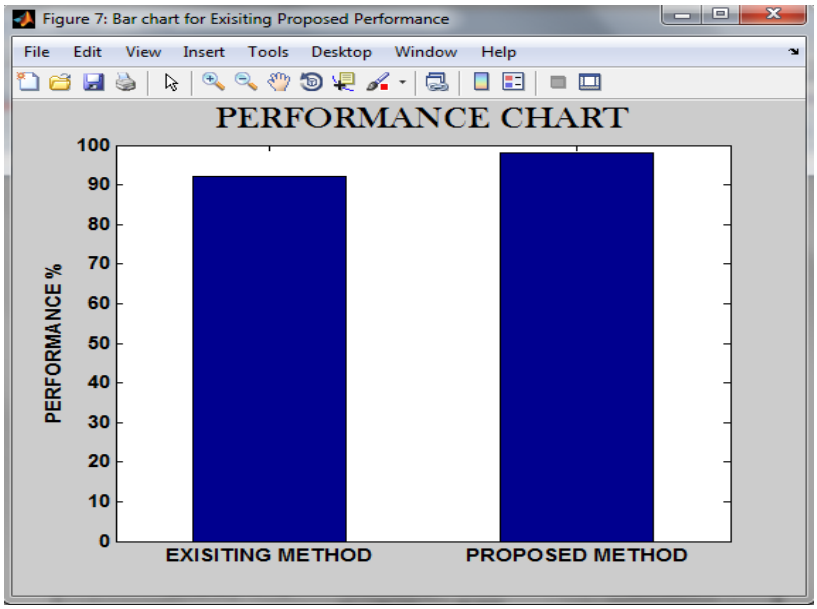

Figure-13. Performance chart for existing and proposed.

CONCLUSIONS

The main thought of this method to support the optically defective humanity for recognition cloth pattern and colours. The previously found methods they employ different algorithms for detection of pattern. We propose Radon signature is to capture global directionality features to recognise cloth pattern and fuzzy clustering helps in recognition of the colours. Detection of damaged cloth is effectively tested.The extracted global and local features are combined to recognize clothing patterns by using a support vector machines (SVMs) classifier. The accuracy level is increased when compared to other methods. The method would provide new functions to improve the quality of life for blind and visually impaired people.

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