International Journal of Engineering Research And Management (IJERM)
ISSN : 2349- 2058, Volume-02, Issue-01, January 2015

Recognition of Clothing Pattern for Visually Challenged People

K.Shoba, S.Gohisri, S.Sowndarya

Abstract— identifying the clothing pattern for visually all people is the difficult task. To avoid this problem our existing system introduces a technique called CCNY pattern recognition. This system has image-based prototype that recognizes clothing patterns in four categories (plaid, striped, pattern less, and irregular) and identifies 11 clothing colors like red, orange, yellow, green, cyan, blue, purple, pink, black, grey, and white. This approach introduce random signature to recognize the color pattern and the color identification is based on histogram of each clothing image in the HSI color space. Moreover, to increase the efficiency and accuracy of the system our proposed system introduces the fast texture feature extraction. This technique used to divide the image and analyze the texture by using Texture Estimation Algorithm. In addition, our system will convert the sound description of the pattern into text format. This approach will increase accuracy of the color identification for blind people and also the normal people.

***Index Terms*— Assistive system, clothing pattern recognition, global and local image features, texture analysis, visually impaired people**

I. INTRODUCTION

BASED on survey from the World Health Organization (WHO), more than 161 million visually challenged people and 37 million of them are blind among the world. Selecting clothes with suitable colors and patterns is a difficult task for blind or visually impaired people. Automatically observing the clothing patterns and colors may enhance their quality. Automatic camera-based clothing pattern identification is a difficult task owing to many clothing pattern and color designs as well as corresponding large changes in the intraclass. Prevailing texture estimation methods mainly focus on textures with more variations in viewpoint, orientation, and scaling, but with less intraclass pattern.

We introduce a system equipped with camera to help visually challenged people to identify the clothing patterns and colors. The three major components in the system are (see Fig. b): 1) sensors containing a camera for capturing clothing images, a micro-phone for input command and speakers for audio output; 2) data capture and analysis helps to perform command control, clothing pattern identification, and color recognition by using a computer and 3) audio outputs to provide system status and recognition results of clothing patterns and colors.

Manuscript received Jan 20, 2015
K.Shoba, Assistant professor,Information Technology,Jeppiaar Engineering College,Chennai
S.Gohisri, Information Technology,Jeppiaar Engineering College,Chennai
S.Sowndarya, Information Technology,Jeppiaar Engineering College,Chennai

Our system can handle clothes with complex patterns and identify clothing patterns into four divisions (plaid, striped, patternless, and irregular) to meet the basic requirements blind people. Our system is able to identify 11 colors: red, orange, cyan, blue, purple, yellow, green, pink, black, grey, and white. For clothes having multiple colors, the first several ruling colors are spoken to users. In order to handle the large changes in the intraclass, we introduce a novel descriptor, Radon Signature, to capture the global directionality of clothing patterns. The combination of local and global image features primarily outperforms the state-of-the-art texture analysis methods for recognition of clothing pattern.

This paper is structured as follows. In Section II, we summarize the related work on the research work on texture analysis and assistive techniques for visually impaired people and. The manipulations of local and global features for clothing pattern recognition are specified in Section III. Section IV deals with the system and interface design. The details of color identification and clothing pattern recognition and are rendered in Section V. Section VI presents our experimental outcome on a traditional texture dataset and challenging clothing pattern dataset. Section VII contains the conclusion part of the paper.

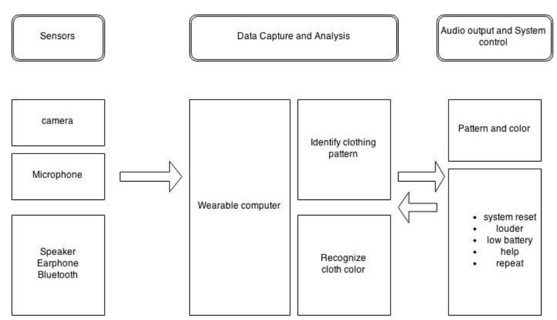

Fig. a. Overview and architecture design of the camera-based clothing pattern recognition system for blind and visually impaired persons.

II. RELATED WORK

Assistive systems are being established to improve the safety and life quality for those with special needs including indoor navigation and display reading, way finding, banknote recognition, rehabilitation, etc. Liu, built a clothing recommendation system for specific instances (e.g., wedding or dating).Hidayati et al, introduced a method for type division of clothes. The two systems are designed without considering key features for blind people. Yuan et al, proposed a system to help the blind people to match clothes from a pair of clothing images. This system can favor a user with the information about identify the clothing patterns and colors match. But, this system is still not able to automatically identify clothing patterns.

Texture gives essential information about clothing pattern identification. Some early research on texture identification focused on the estimation of two-dimensional (2-D) image transformations including plane rotation and scaling. These approaches cannot effectively represent the texture images with large 3-D transformations such as viewpoint change and nonrigid surface deformation due to the lack of invariance to general geometric transformation. Multi fractal analysis has gained better resilience towards3-D deformations.

For example, multi-fractal spectrum (MFS) proposed by Xu et al. Density functions and orientation templates are used to group the combined fractal dimensions of pixel sets. In order to make representations of texture more strong to 3-D image transformations and changes in the illumination, many of the recent techniques provides information on extracting local image features. Clustering the extracted local features generates the texton dictionary .However; properties of an image in different aspects are captured by multiple features. If different features are highly interrelating, their combination will enhance the feature representation. For example, Lazebnik et al introduced a texture representation method depends on affine-invariant descriptors and detectors (RIFT and SPIN). Zhang et al. also linked the scale invariant feature transform (SIFT) and SPIN for texture classification.

Unlike prevailing texture images, clothing patterns contain more changes in the intraclass within each pattern division. Although many computer vision and image processing techniques have been developed for texture evaluation and division, traditional texture evaluation technique cannot effectively identify the clothing patterns. Here, we introduced a camera-based system specifically for visually challenged people to help them identify clothing patterns and colors.

III. IMAGE FEATURE EXTRACTION FOR CLOTHING PATTERNIDENTIFICATION

Repetition of a few basic primitives represents some clothing patterns present as visual patterns (e.g., plaids or stripes). Accordingly, some local features are best to get the structural information of repetitive primitives. However, some local primitives of the same clothing pattern division can vary significantly, because of the larger changes in the intraclass (see Fig. a). Global features including statistical properties and directionality of clothing patterns are more stable within the same category. Therefore, they are able to provide complementary information to local structural features. Next, we present extractions of local and global features for clothing pattern identification, i.e., Radon Signature, statistical descriptor (STA), and scale invariant feature transform (SIFT).

A. Radon Signature

Clothing images provides larger changes in the intraclass, which results in the major challenge for clothing pattern identification. However, in a global point of view, the clothing Patterns directionality is more persistent across various divisions and can be used as an important proprietary to classify various clothing patterns. As shown in Fig. h, the clothing patterns of plaid and striped are both anisotropic. In variance, the clothing patterns in the division of patternless and irregular are isotropic. By make use of the novel descriptor, to show the difference of directionality, .i.e., the Radon Signature, to characterize the directionality feature of clothing patterns.

Radon Signature (RadonSig) which is commonly used to detect the principle orientation of an image that is based on Radon transformation. The image is then rotated according to this ruling direction. Inorder to achieve the rotation invariance. The Radon transform of a 2-D function f (x, y) is defined as

$$R(r,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(r - x\cos\theta - y\sin\theta)\,dxdy \quad (1)$$

Where r is the perpendicular distance of a projection line to the origin and θ is the angle of the projection line, as shown in Fig. c(b). To sustain the consistency of Radon transform for variety of projection orientations, we calculate the Radon transform based on the maximum disk area rather than entire image. The changes in the intraclass of clothing patterns also replicate as images in the same group present large changes of color or intensity. To minimize the intensity variations, we use the Sobel operator to calculate the gradient map as f (x, y) in (1). R (r, θ) in (1) is a function with two parameters of r and θ, as shown in Fig. c(c). The directionality of an image can be represented as Var (r, θi), the variances of r under a certain projection direction θi :

$$\mathrm{Var}(r,\theta_i) = \frac{1}{N}\sum_{j=0}^{N-1}(R(r_j,\theta_i) - \mu(r,\theta_i))^2 \quad (2)$$

$$\mu(r,\theta_i) = \frac{1}{N}\sum_{j=0}^{N-1} R(r_j,\theta_i) \quad (3)$$

Where R (rj , θi) is the projection value at perpendicular distance of rj and projection direction of θi ; μ (r, θi) is the expected value of R (r, θi); N is the number of sampling bins in each projection line. The RadonSig is formed by the variances of r under all sampling projections direction.

$$[\mathrm{Var}(r,\theta_0), \mathrm{Var}(r,\theta_1), \ldots, \mathrm{Var}(r,\theta_{T-1})]$$

Where T is the number of sampling projection directions. The principle directions of the image in Fig. c(a) correspond to the two dominant peaks in the RadonSig in Fig. c(d). Fig. d the four sample images from various clothing pattern group are illustrated by RadonSig descriptor .The plaid patterns have two principle orientations; the striped ones have one principle orientation; as for the patternless and the irregular images, they have no obvious dominant direction.

B. Statistics of Wavelet Subbands

The discrete wavelet transform (DWT) disintegrates an image multiple high-frequency channels under multiple scales Wk ,j (I); and into low-frequency channel Dj (I) under a coarser scale k = 1, 2, 3; j = 1, 2, . . . , J, where J is the number of scaling levels. For each level of j, the four wavelet subbands contains one low-frequency channel Dj (I) and three high-frequency channels Wk ,j (I).The high frequency channels Wk ,j (I) ; k = 1, 2, 3 encode the discontinuities of an image along horizontal, vertical, and diagonal directions, respectively. In this paper, we apply J = 3 scaling levels of DWT to disintegrates each clothing image, as shown in Fig. E.

Statistical features are well suited to estimate the texture which require a background clutter and will have uniform statistical properties.DWT gives a generalization of a multi resolution spectral analysis tool. Hence we excerpt the statistical features from wavelet subbands to grab global statistical information of images. It is customary to compute the single.

Energy value on each subband. In this paper, we employ four statistical values including energy, uniformity, variance and entropy.

Variance $=\sum_{i=0}^{L-1}(z_i - m)^2 p(z_i)/(L-1)^2$ (4)

Energy $=\sum_{i=0}^{L-1}(z_i - m)^3 p(z_i)/(L-1)^2$ (5)

Uniformity $=\sum_{i=0}^{L-1} p^2(z_i)$ (6)

Entropy $= -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_1)$ (7)

Where *zi* and *p* (*zi*) , *i* = 0, 1, 2, . . . , *L* − 1 is the intensity level and corresponding histogram; *L* is the number of intensity levels;

m $=\sum_{i=0}^{L-1} z_i\, p(z_i)$ is the average intensity level.

C. Scale Invariant Feature Transform Bag of Words

We select the SIFT descriptor as the representation of interest points based on the reasons: 1) the descriptor with 128 dimensions is fairly distinctive and compact; 2) the illustration with careful design is strong to variation in illumination and view points.3) The massive comparison against other local image descriptor realized that the SIFT descriptor performed well in the context of image mapping. The bag of words (BOW) technique is further applied to accumulation extracted SIFT descriptor by naming each SIFT descriptor has a visual word and calculating frequency of each visual word. Fig f. illustrates the process of local feature extraction.

IV. SYSTEM AND INTERFACE DESIGN

The clothing identification by the camera aid prototype for blind people merge a camera, a microphone, a computer, and a Bluetooth earpiece for audio description. A camera held upon a pair of sunglasses is used to take clothing images. The clothing patterns and colors are explained to blind people by hearing. Fig. g, shows the interface design includes *high priority commands and basic functions*.

High priority commands: A blind user can fix the system configuration by many high priority speech commands such as *system restart*, *turn-off system*, *stop function* (i.e., abort current task), speaker volume and speed control commands (e.g., *louder*, *quieter*, *slower*, and *faster*), and *help*.

The high priority commands can be employed at any fraction of time.

Basic functions: The recognition results will be presented to the blind user as audio outputs including *recognized*, *not recognized*, and *starts a new function.*

Audio output: For audio, we use a special operating system. A variety of configuration options are made available according to user preference, such as speech rate, volume and sound, and voice gender.

V. RECOGNIZING CLOTHING PATTERNS AND COLORS

The extracted local and global features are combined to identify clothing patterns by means of support vector machines (SVMs). The recognition of clothing color is implemented by quantizing clothing color in the HIS (hue, saturation, and intensity) space.

A. Clothing Pattern Identification

In our system, we set the size of the visual vocabulary to 100.The three scaling level is applied to disintegrate the clothing images. In the computation of the Radon Signature, we sample 60 projection directions from 1◦ to 180◦The vector feature of the RadonSig has a dimension of 60. The combined feature vector has a dimension of 208.

B. Clothing Color Identification

It is based on the normalized color histogram of each clothing image in the HSI color space. The main goal is to quantize the color space based on the relationship between hue, saturation and intensity. For every clothing image this technique quantize the following 11 colors red, green, blue, orange, yellow, purple, pink, cyan, black, gray and white. Based on the saturation value S and intensity I the white, black and gray are detected. I > I^U and S<S_T, then it is white color. If I < I^L and S<S_T then it is black color. For gray color, the remaining values of I, the value of S <S_T.

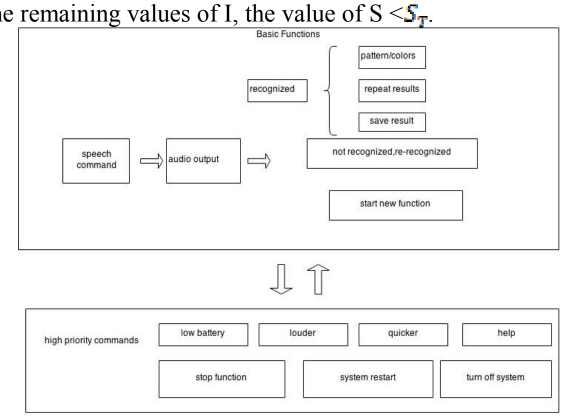

Fig c,system interface design for the proposed camera based clothing pattern recognition.

VI. CLASSIFICATION EXPERIMENTS

In this section, we calculate the performance of the new technique on two different datasets: 1) the CCNY Clothing Pattern dataset and 2) the UIUC Texture dataset .Our system focus on the evaluation of 1) the correlative relationships between the proposed local and global feature channels; 2) the advantage of our proposed method over the state-of-the-art texture classification approaches in the context of clothing pattern identification; and 3) the simplification of our approach on the traditional texture division.

A. Datasets

CCNY clothing pattern dataset: This dataset contains 627 images of four various clothing pattern designs: plaid, patternless, striped and irregular with 156, 157, 156, and 158 images.

UIUC texture dataset: The UIUC dataset is a well established traditional texture dataset. It includes 1000 uncalibrated and unregistered images with the resolution of 640 × 480. There are 25 texture classes with 40 images for each class.

B. Research and Review on Clothing Pattern Identification.

1) Experimental Setup: In this depiction, the fixed size random subsets are selected as a training set and the remaining images as the testing set.

2) Effectiveness of Different Combinations and Features::

The complementary relationships between global and local features on clothing pattern images are first evaluated. The better results are obtained by the multiple features.

To validate the effectiveness of the proposed features, the complementary relationships between different feature channels including global features of the RadonSig and the Statistics of wavelet subbands (STA), and local features (SIFT) are first evaluated. SIFT denotes the local structural features

STA is the global statistical characteristics; and RadonSig hold the property of global directionality. Fig. i shows the identification results of various features as a training set size. For each channels, SIFT and STA achieve comparable identification accuracies.

The comparisons of various feature channels and their combo validate our perception that the capability and complementarities of our proposed feature channels. The detailed identification accuracies of Fig. i. are listed in Table II. The percentages of training images per class are 10%, 30%, 50%, and 70%, respectively.

3) Comparison with the State-of-the-art Texture Analysis Technique the performance of the proposed system and the state of the art method are compared. It includes MFS, SIFT, (H+L) (S+R), and SIFT+S, main features to achieve the state-of-the-art performances.. MFS is an addition of the fractal dimension based on three density functions of image intensity, image Gradient, and image Laplacian. SIFT captures the local image structural information. (H+L)(S+R) is based on the extraction of SPIN and RIFT descriptors on affine Harris and Laplacian regions of an image.

Table III displays the identification accuracies of various methods on the CCNY clothing pattern dataset. The experiments are estimated by using 10%, 30%, 50%, and 70% of the dataset as training sets, and the rest as testing sets.

C. Experiments with the UIUC Texture Dataset

The suggested method extensively outperforms the texture division methods in identifying clothing patterns. In order to constitute the generalization of our method, we further compare our method with other state-of-the-art approaches on a traditional texture dataset, i.e., UIUC Texture dataset. Texture dataset while its performance on clothing pattern images is much worse. This is because the intraclass intensities of texture images in this dataset are much more persistent than that in clothing pattern images. SPIN provides complementary appearance feature to SIFT and the RadonSig needs a relatively large training set to model the directionality of texture images.

TABLE I

RECOGNITION ACCURACY (%) OF DIFFERENT FEATURE CHANNELS UNDER DIFFERENT VOLUMES OF TRAINING SETS (10%, 30%, 50%, 70% OF THE DATASET USED FOR TRAINING) ON CLOTHING PATTERN DATASET

Method	10%	30%	50%	70%
MFS[26]	56.71	66.68	72.39	75.80
SIFT[13]	69.42	80.45	84.50	87.73
(H+L)(S+R)[11]	52.71	60.34	62.65	64.69
SIFT+SPIN[32]	66.25	78.76	83.20	85.53
OUR METHOD	81.06	88.09	90.59	92.55

TABLE II

RECOGNITION ACCURACY (%) OF DIFFERENT METHODS AND VOLUMES OF TRAINING SETS (10%, 30%, 50%, 70% OF THE DATASET USED FOR TRAINING) ON CLOTHING PATTERN DATASET

Feature channel	10%	30%	50%	70%
SIFT	69.42	80.45	84.50	87.73
STA	69.45	80.65	84.28	86.94
RadonSig	69.24	75.41	79.93	82.44
SIFT+STA	75.80	84.03	87.09	88.68
SIFT+RadonSig	76.94	85.91	88.89	91.34
SIFT+STA+RadonSig	81.06	88.09	90.59	92.55

CONCLUSION

Here, we have suggested a system to identify clothing patterns and colors to help visually challenged people. We engaged RadonSig to capture the global directionality features; SIFT to represent the local structural features and STA to abstract the global statistical features; .The complementary information to improve recognition accuracy provided by the combination of multiple features. We gathered a dataset on clothing pattern identification including four-pattern categories of plaid, striped, patternless, and irregular. Experimental outcome illustrate that our proposed method efficiently outperforms in clothing pattern identification.

In addition, the performance estimation traditional texture datasets verifies the generalization of our technique to traditional texture analysis and classification tasks. This research also enriches the conversion of the speech commands into text format. It also enhances the performance of the recognition of the clothing pattern by including pixel by pixel identification. Study of texture analysis, and leads to improvements over prevailing technique in handling complex clothing patterns with huge changes in the intraclass. The process also provides new functions and methods to enhance the life quality for visually impaired people.

REFERENCES

[1] K. Khouzani and H. Zaden, “Radon transform orientation estimation for rotation invariant texture analysis,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 6, pp. 1004–1008, Jun. 2005.

[2] I. Kocur, R. Parajasegaram, and G. Pokharel, “Global data on visual impairment in the year 2002,” Bulletin World Health Org., 2004.

[3] S. Lam, “Texture feature extraction using gray level gradient based on co-occurrence matrices,” in Proc. Int. Conf. Syst., Man Cybern., 1996, pp. 267–271.

[4] S. Lazebnik, C. Schmid, and J. Ponce, “A sparse texture representation using local affine regions,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27,no. 8, pp. 1265–1277, Aug. 2005.

[5] S. Liu, J. Feng, Z. Song, T. Zhang, H. Lu, C. Xu, and S. Yuan, “Hi, magic closet, tell me what to wear,” in Proc. ACM Multimedia, 2012.

[6] D. Lowe, “Distinctive image features from scale-invariant keypoints,” Int. J. Comput. Version, vol. 60, no. 2, pp. 91–110, 2004.

[7] S. Hidayati, W. Cheng, and K. Hua, “Clothing genre classification by exploiting the style elements,” in Proc. ACM Int. Conf. Multimedia, 2012, pp. 1137–1140.

[8] V. Manian, R. Vasquez, and P. Katiyar, “Texture classification using logical operation,” IEEE Trans. Image Process., vol. 9, no. 10, pp. 1693–1703,Oct. 2000.