Rotation and Illumination Invariant Texture Analysis

Matching Clothes with Complex Patterns for Blind People

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Abstract—**Matching clothes is a challenging task for blind people. In this paper, we describe a new texture analysis approach which is robust to variations of rotation and illumination for matching two images of clothes with complex patterns. The approach integrates Radon transform, wavelet transform, and co-occurrence matrix for texture analysis of clothes images. We first calculate directional properties of texture pattern in each image by applying Radon transform. The directional properties are used to rotate the clothes image with the dominant orientation of the texture patterns as horizontal. To handle illumination changes, we perform Haar wavelet transform to extract texture features on three directions (horizontal, vertical and diagonal). For each wavelet sub image, grey level co-occurrence matrix for texture analysis is calculated. Finally, texture matching is performed based on six statistical features (i.e. mean, variance, smoothness, energy, homogeneity, and entropy). The robustness and effectiveness of the proposed method are evaluated on our database which contains 128 images of complex pattern clothes. The matching results are presented for blind users as speech outputs.**

Keywords-clothes matching; Co-occurrence matrix; Radon transform; texture analysis; wavelet transform

I. INTRODUCTION

Based on the 2002 world population, there are more than 161 million visually impaired people in the world today, of which 37 million are blind [1]. It is a challenging task for blind people to choose suitable clothes in their daily life. Most blind people manage this task either through helping from their family members or through using plastic Braille labels or different types of stitching patterns tagged on the clothes which represent different colors and appearances [2]. Some blind people just choose clothes with very simple colors and patterns.

In this paper, we develop a new method for matching clothes with complex patterns to assist people who are blind or visually impaired by using a pair of clothes images. The image pair of clothes is captured by a camera. The matching results are presented for blind users as speech outputs. The function will be transferred to camera phones in future.

Texture analysis and classification has been widely used for applications of image retrieval and industry inspection. Some researchers applied statistical and mathematical techniques to analyze image textures [3-5]. Varma *et al.* [6] and Dennis *et al.* [7] proposed texture analysis methods by using filter banks. Hanbury *et al.* [8] proposed the standard morphological texture characterization methods by applying the granulometry and the variorum in the task of texture classification. Some attempts have been made for rotation invariant texture analysis by using different features with Hidden Markov Models [9-11]. However, they have experimented on a limited scale.

Wavelet transform provides spatial and frequency information which can be used to analyze texture features. But wavelet transform is sensitive to the orientation variant. Making texture rotation-invariant becomes the key point before wavelet transform. Some attempts tried to rotate the wavelets in order to get the whole information in the texture [17-19] and some authors proposed approaches for estimating the orientation information then used this particular direction for wavelet decomposition [12, 13]. Pun and Lee [17] employ log-polar transform before wavelet transform to create rotation and scale invariant features. To get rotation invariant features, Manthalkar *et al.* [18] combine multiple channels of the wavelet decomposition. Charalampidis and Kasparis [19] developed a rotation invariant method by using wavelet-based roughness features and steer ability.

The most related work to our approach is [13]. Khouzani and Zadeh [13] proposed preprocessing step to make the analysis invariant to rotation. They utilize the Radon transform to convert the rotation into translation and then apply translation invariant wavelet transform to extract rotation invariant features. However, since their classification is based on the average energy of all the sub-band of wavelets decomposition, their method fails if the total energies of the pair of clothes images are very similar. In addition, the performance of their algorithm on the clothes matching is not satisfying for the images with big lighting changes.

To address above issues, we propose a new approach for texture analysis by combining Radon transform, wavelet features and co-occurrence matrix. Figure 1 shows the system diagram. The input is a pair of images of two clothes. To decrease the effects of illumination changes and be prepared for further processing, image preprocessing is first performed on each image. The preprocessing step includes conversion color image to grey, histogram equalization, and selection of a circle region centered of the image which contains main information of the clothes. Then, we chose Radon transform to obtain the dominant orientation information of the image patterns and rotate it back to 0 degree to make the algorithm rotation invariant. Next, we employ Haar wavelet transform to extract features on 3 directions (horizontal, vertical, and diagonal) and calculate co-occurrence matrix for each wavelet sub images. Finally, the matching of clothes patterns is performed based on six statistical features (i.e. mean, variance, smoothness, energy, homogeneity, and entropy.) The matching results are provided as speech outputs for blind users.

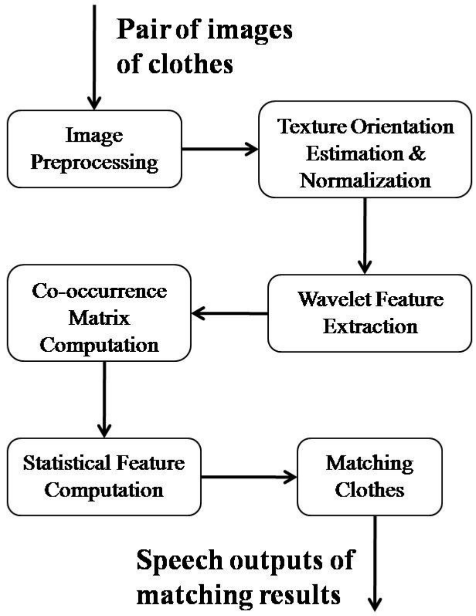


Figure 1. System diagram of matching clothes with complex patterns for blind people

II. .APPROACH TO ROTATION AND ILLUMINATION INVARIANT TEXTURE ANALYSIS

A. *Texture Orientation Estimation and Normalization*

In order to make the clothes matching algorithm invariant to texture orientations, Radon transform is applied on the maximum circle region which is centered in the input image *f* (*x*, *y*) for a given set of angles to estimate the dominant orientation of the texture. Here, the region with circle shape is chosen since it has the least direction interference comparing with other shapes. For each given angle, the radon transform can be thought of as computing the projection of the image along the given angle. The resulting projection is the sum of the intensities of the pixels in each direction. As depicted in Figure 2, the Radon transform $R(\rho, \theta)$ of the input image $f(x, y)$ can be defined as [16]:

$$R(\rho,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(\rho - xcos\theta - ysin\theta)dxdy$$

where $\rho = x\cos\theta + y\sin\theta$ is the perpendicular distance of a line from the original position and θ is the angle between the line and y-axis. $\delta(\,)$ is the Dirac delta function.

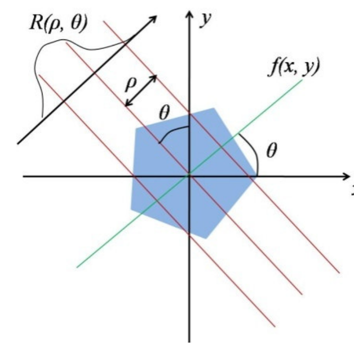
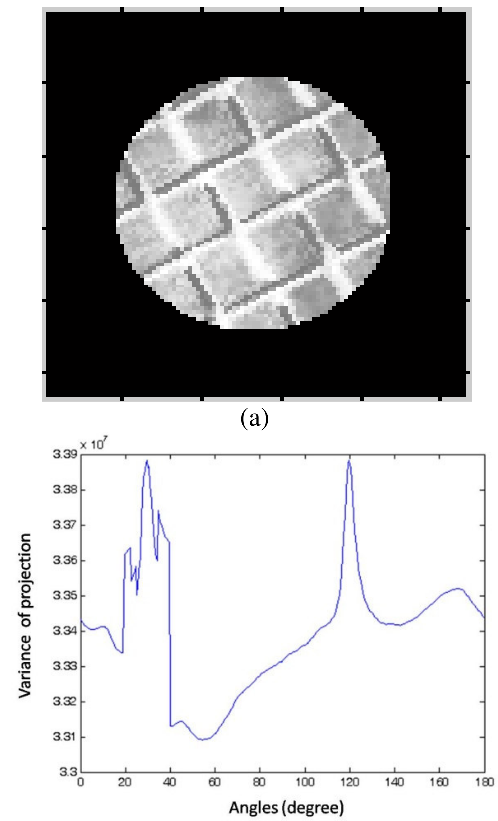


Figure 2. Radon transform of an image *f(x, y)*.



(a)

(b)

Figure 3. (a) An example of a texture image which have 2 maximum angles (30° and 120°); (b) variance of projections at different angles. We calculate the mean values from two sets [27, 28, 29, 31, 32, 33] and [127, 128, 129, 121, 122, 125]. The main orientation is corresponding to the angle of 30°.

Radon transform computes projections along θ, which varies from 0° to 180° in discrete steps of $\Delta\theta$. So for any $\Delta\theta$, the texture principal orientation can be estimated as the projection which has more straight lines. As shown in Figure 3, for the images with two or more main texture orientations, we determine the final dominant orientation by calculating the mean of the variance of projections at 6 neighbor angles around each local maxima variance. The orientation with largest mean value will be chosen as the final dominant orientation of the texture. In the example of Figure 3, there are two main texture directions (i.e. 30° and 120°) as shown in Figure 3(b) which displays the variance of projections at different angles. We calculate the mean values from two sets

[27, 28, 29, 31, 32, 33] and [127, 128, 129, 121, 122, 125]. The main orientation is corresponding to the angle of 30°. We then rotate the dominant orientation information of the image patterns back to 0 degree to make the algorithm rotation invariant.

B. Wavelet Transform

Wavelet transform is a local transformation of space (time) and frequency which can effectively extract information from the images. Wavelet transform can be represented by following formula:

$$f(x) = \sum_k c_{j0}(k)\varphi_{j0,k}(x) + \sum_{j=j0}^{\infty}\sum_k d_j(k)\psi_{j,k}(x)$$

where $c_{j0}(k)$ is the scaling coefficients and $d_j(k)$ is the wavelet coefficients. The scaling function φ (x) and wavelet ψ (x) are defined as:

$$\varphi_{j0,k}(x) = 2^{j0/2}\varphi(2^{j0}x - k)$$

$$\psi_{j0,k}(x) = 2^{j0/2}\psi(2^{j0}x - k)$$

where *j0* is an arbitrary starting scale. With the coefficients above we can easily obtain the two levels of wavelet decomposition. In our system, we use Haar function as the scaling function coefficient. Figure 4 shows the Haar wavelet transform resulted in 2 levels decomposition on three directions (horizontal, vertical and diagonal) for image of Figure 3(a).

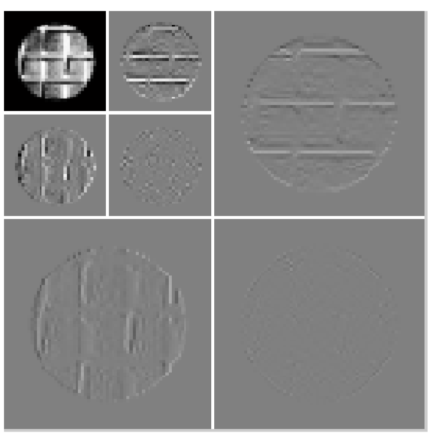


Figure 4. Example results of Haar wavelet transform results.

C. Grey Level Co-occurrence Matrix

Khouzani and Zadeh [13] classify texture patterns based on the average energy of all the sub-band of wavelets and their method fails if the total energy of one image of the pair of clothes images is very close to the energy of another image. Figure 5 shows examples of two image pairs with different texture patterns but same energy which method [13] fails. In our system, we employ grey level co-occurrence matrix for texture matching.

Grey level co-occurrence matrix depicts the spatial relationship for a pixel and its neighbors in an image. It has been used for texture measurements since 1973 [20]. Figure 6 shows an example of the co-occurrence matrix of an image with size 8x8. *Q* is an operator that defines the position of two pixels relative to each other in image *f*. Let *G* be a matrix whose element *g (i, j)* is the frequency of the pixel pairs with intensities *i* and *j* occur in image *f* in the positions specified by *Q*. The final matrix *G* is referred to as a Co-occurrence matrix. The number of possible intensity levels in the image determines the size of matrix G. For an 8-bit image, the maximum size of co-occurrence is 256x256.

Figure 5. Two image pairs with different texture patterns but with same energy.

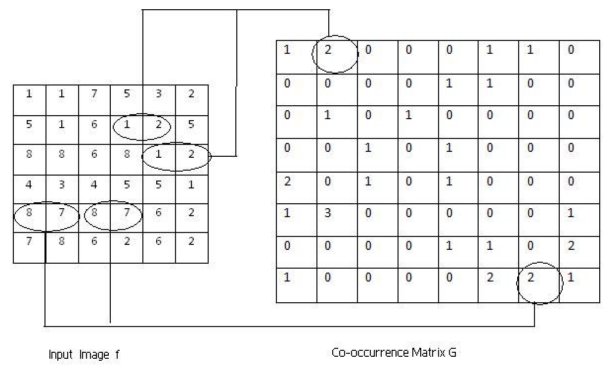


Figure 6. An example of a size 8*8 co-occurrence matrix by considering a pixel and its right neighbor. Element *G (1, 2)* is 2 because there are two occurrence in image *f* of a pixel valued 1 having a pixel valued 2 immediately to its right. Element *G (8, 7)* is 2 because there are 2 occurrences in *f* of a pixel with value of 8 having a pixel valued 7 immediately to its right.

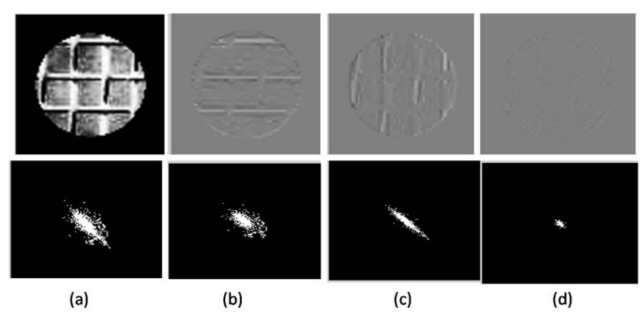


Figure 7. Co-occurrence matrices: (a) Input image & co-occurrence matrix; (b) Horizontal Wavelet & co-occurrence matrix; (c) Vertical Wavelet & co-occurrence matrix; (d) Diagonal Wavelet & co-occurrence matrix.

Since each pixel in the image has maximum 8 neighbor directions, we calculate the final co-occurrence as the sum of 8 occurrence matrices. Since we use a circle region to estimate the texture orientation, the circle will contributes to the calculation of the co-occurrence matrix for each sub-band decomposition of wavelet. To eliminate the effects of the circle shape, we only calculate the pixels inside the circle shape. Figure 7 shows the co-occurrence matrices of different sub-band of wavelet features and the final co-occurrence.

D. *Statistical Features for Texture Matching*

To classify texture, we compose 6 statistical features from co-occurrence matrices, i.e. *mean, variance, smoothness, energy, homogeneity* and *entropy*. They are calculated by the following formulas:

$$Mean = \sum_{i,j=1}^{L} (i) f(i,j)$$

$$Variance = \sum_{i,j=1}^{L} (i-m)^2 f(i,j)$$

$$Smoothness = \sum_{i,j=1}^{L} (i-j)^2 f(i,j)$$

$$Energy = \sum_{i,j=1}^{L} f(i,j)^2$$

$$Homogeneity = \sum_{i,j=1}^{L} \frac{f(i,j)}{1+(i-j)^2}$$

$$Entropy = -\sum_{i,j=1}^{L} f(i,j) \log_2 f(i,j)$$

where $f(i, j)$ is the ijth term of co-occurrence matrix G divided by the sum of the elements of G. L is the number of distinct intensity levels, m indicates the first feature mean. The distance to determine if a pair of images matching is defined as:

$$\Delta = \sum_{k=1}^{6} \frac{F_1(k)-F_2(k)}{F_1(k)+F_2(k)}$$

where F_1 and F_2 are the vector contains six statistical features of the pair of input images. If the distance is larger than a threshold, the image pair of clothes is not match. The threshold is selected based on experiments.

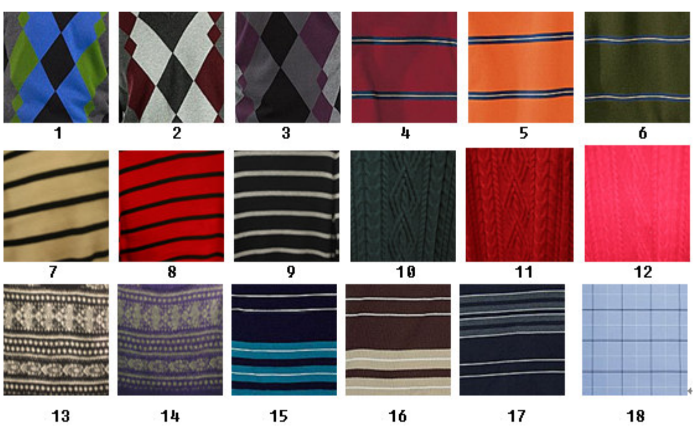


Figure 8. Examples of our clothes dataset with complex patterns.

III. EXPERIMENTS AND DISCUSSIONS

A. *Database*

To validate the efficiency and robustness of our method, we collected a dataset which contains 128 images of clothes with complex patterns and lighting changes. The resolution of the images is 140x140. Figure 8 shows some examples of our clothes matching dataset. The dataset with ground truth (image pairs that match or not) will be released to public at our website.

B. *Texture Classification and Matching Results*

Our dataset contains 128 clothed images with complex patterns and colors. Among these images, 76 of them have their match images and 52 images have not match images. In our test, we select 50 match pairs and 83 not match pairs. As shown in Table I, the method of Khouzani and Zadeh [13] achieves 67.7% matching rate and our method achieves 82.7% accuracy rate. Our method significantly outperforms existing methods on our dataset containing images of clothes with complex patterns and lighting changes. The detailed results of our method are presented in Table II. Figure 9 displays some examples of successful detection results.

TABLE I. COMPARISON WITH THE STATE-OF-THE-ART RESULTS ON OUR CLOTHES MATCHING DATASET

Methods	Results of 133 pairs
Method in [13]	67.7%
Our Method	**82.7%**

TABLE II. CONFUSION MATRIX OF CLOTHES MATCHING BY OUR METHOD

	# of match pairs	# of not match pairs
# of match pairs	**42**	7
# of not match pairs	16	**68**

Figure 9. Examples of successful detection results by our proposed method. The top row displays three pairs of matching clothes images and the bottom row displays three pairs of images for clothes which are not matching.

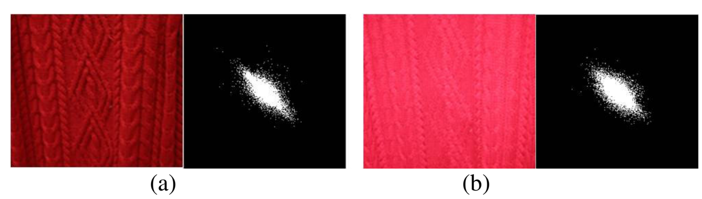
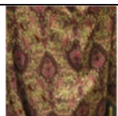
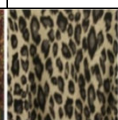
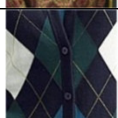
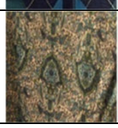


Figure 10. Our method handles illuminations changes. (a) Image 1 of a sweater and the corresponding co-occurrence matrix; (b) image 2 of the same sweater with large lighting change and the corresponding co-occurrence matrix. The distance between the image pair is very small and the image pair is detected as “match”.

C. Discussions

Our method is robust to rotation and illumination variances. Figure 10 shows one example of a pair images from the same clothes but with large lighting changes. The co-occurrence matrices of these two images are very close and our method successfully matches them.

TABLE III. EXAMPLES OF IMAGE PAIRS WITH SIMILAR ENERGY WHICH METHOD [13] FAILS FOR CLASSIFICATION BUT OUR METHOD CORRECTLY MATCHES THEM.

Image pair		Energy of Img 1 & 2 ($x\ e^6$)	Distance of classification method [13] (Th=2.4)	Distance of our method (Th=0.15)
Img1	Img2			
		e1=1.7791 e2=1.7781	0.2131 (Match)	**1.442 (Not Match)**
		e1=1.1710 e2=1.1755	1.0808 (Match)	**0.6177 (Not Match)**
		e1=2.0164 e2=2.0247	0.4924 (Match)	**0.1877 (Not Match)**

As we indicate in Section II, the method of Khouzani and Zadeh [13] fails for images with different texture but similar energy. Table III demonstrates some examples in our dataset and compares the distances of texture classification for our method and [13]. In Table III, *e1* and *e2* represent the energy of the image pair. The threshold of distance for texture classification in method [13] is showed in Table I which achieves the best matching results on our dataset (67.7% ccuracy). In our method, the threshold is 0.15 which achieves 82.7% matching rate. Our method can successfully classify them while [13] fails. The main errors in our method are happened to the images with very similar texture patterns such as samples 9, 15, and 17 as shown in Figure 8.

IV. CONCLUSIONS

We have presented an approach to matching clothes with complex patterns for blind or visually impaired people. The approach combines Radon transform, wavelet features, and co-occurrence matrix for texture analysis. Our approach significantly outperforms existing methods on our dataset containing images of clothes with complex patterns and lighting changes. The detection results demonstrated that our method is robust and effective to handle rotation and illumination changes. The matching results are displayed as speech outputs to help blind/visually impaired users. Our future work will focus on transferring the function to cell phones. We will also address the human interface issues for image capture and auditory display of the clothes matching on computers and cell phones.

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