Clothes Matching for Blind and Color Blind People

Yingli Tian and Shuai Yuan

Electrical Engineering Department
The City College of New York
New York, 10031
{ytian,syuan00}@ccny.cuny.edu

Abstract. Matching clothes is a challenging task for blind people. In this paper, we propose a new computer vision-based technology of clothes matching to help blind or color blind people by using a pair of images from two different clothes captured by a camera. A mini-laptop or a PDA can be used to perform the texture and color matching process. The proposed method can handle clothes in uniform color without any texture, as well as clothes with multiple colors and complex textures patterns. Furthermore, our method is robust to variations of illumination, clothes rotation, and clothes wrinkles. The proposed method is evaluated on a challenging database of clothes. The matching results are displayed as audio outputs (sound or speech) to the users for "match (for both color and texture)", "color match, texture not match", "texture match, color not match", or "not match (for both color and texture)".

Keywords: Computer Vision, Clothes Matching, Color Matching, Texture Matching, Blind, Color Blind.

1 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]. In everyday life, people need to find appropriate clothes to wear. It is a challenging problem for blind people to find clothes with suitable color and texture. Most blind people manage this problem through the following ways: 1) Through help from their family members; 2) through using plastic Braille labels or different types of stitching patterns which are tagged on the clothes to represent different colors and appearances [16]; 3) through choosing clothes with simple colors.

In this paper, we develop a computer vision-based method to detect if a pair of images of two clothes matches for both texture and color. The image pair is captured by a wearable camera which is connected to a computer or a PDA. To our knowledge, there is no device on the market with this function. The function of matching clothes will also benefit people who are color blind. Figure 1 demonstrates the concept for clothes matching. By performing the texture and color matching to a pair of images from different clothes, our algorithm can detect: 1) colors of the clothes; 2) the texture of the clothes; 3) whether the colors match; and 4) whether the textures match. The matching results can be communicated to the user auditorily as "match (for both color and texture)", "color match, texture not match", "texture match, color not match", or

K. Miesenberger et al. (Eds.): ICCHP 2010, Part II, LNCS 6180, pp. 324–331, 2010.

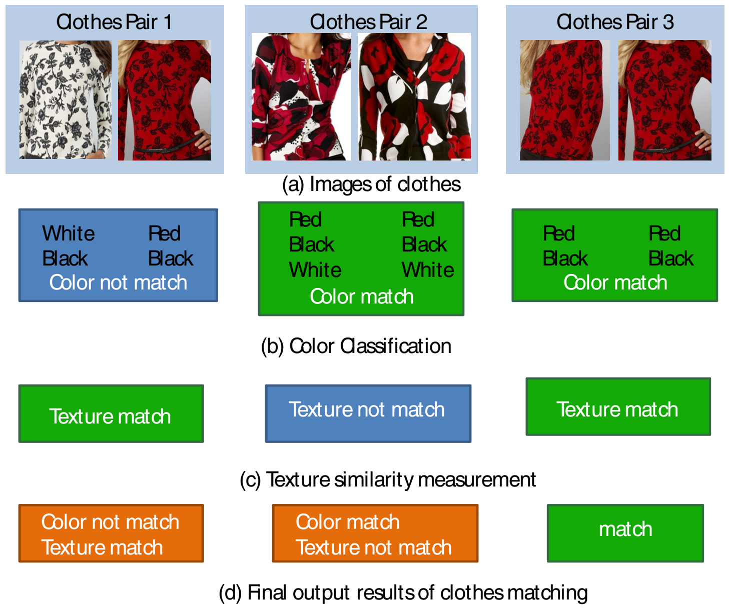

Fig. 1. Matching clothes with multiple colors and complex patterns by using color and texture information. (a) Three pairs of images of clothes. (b) Color classification results. (c) Texture similarity measurement results. (d) Final audio outputs.

"not match (for both color and texture)". Since most cell phones are with built-in cameras, the algorithm can also be integrated into cell phones.

2 State-of-the-Art

In the current market, there is no device for clothes matching. However, some color identifiers are available but they can only detect primary colors present in a very small region. Figure 2 shows the color identifier manufactured by BRYTECH [2]. This device cannot correctly classify colors of clothes containing multiple colors and complex patterns.

In computer vision and image processing research, many methods were developed for texture and color matching [3-15]. There are three critical issues for successful clothes matching. The first is the issue of color constancy. People perceive an object to be the same color across a wide range of illumination conditions but the actual pixels of an object, which are perceived by a human to be the same color, may have values (when sensed by a camera) that range across the color spectrum depending on the lighting conditions. Secondly, shadows and wrinkles are often part of the texture of clothes and cause errors. Lastly, many clothes have designs with complex patterns and multiple colors. To overcome the above issues, our method is designed to handle clothes with multiple colors and complex patterns by using both color and texture information. In addition, our method can deal with illumination changes, clothes wrinkles, and clothes rotations.

Fig. 2. Color identifier manufactured by BRYTECH [2]

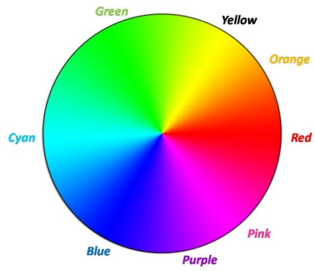

Fig. 3. Basic color space quantization based on Hue for pixels meet constrains of saturation and luminance

3 Methodology for Clothes Matching

3.1 Color Classification and Matching

Our color classifier is based on acquiring a normalized color histogram for each image of the clothes in bi-conic (hue, saturation, luminance) HSI space. The key idea is to intelligently quantize color space based on using the relationships between hue, saturation and luminance. As color information is limited by both lack of saturation and intensity, it is necessary to separate chromatic from achromatic space along surfaces defined by a function of saturation and intensity in the bi-conic space. In particular, for each image of the clothes, the color classifier creates a histogram of the following colors: ***red, orange, yellow, green, cyan, blue, purple, pink, black, grey***, and ***white***. These colors are selected based on the empirical distribution and our ability to discern. Each image of an article of clothing is first converted from RGB to HSI color space. Next, HSI space is quantized into a small number of colors. If the clothes contain multiple colors, the dominant colors will be outputted.

In our color classification, we first detect colors of "*white*", "*black*", and "*gray*" based on saturation S and luminance I. If the luminance I of a pixel is larger than 0.75, and saturation $S<0.25+3(0.25-(1-I))$, then the color of the pixel is defined as "*white*". Similarly, the color of a pixel is "*black*", if the luminance I of a pixel is less than 0.25 and saturation $S<0.25+3*(0.25-I)$. For color "*gray*", the saturation S and luminance I should meet following conditions: $0.25 \leq I \leq 0.75$ and $S < 1/5*I$. For other colors (e.g. ***red, orange, yellow, green, cyan, blue, purple, and pink),*** hue information is employed. As shown in Figure 3, hue is displayed as a 360° color wheel. We define the color "*red*" between 345°--360° and 0--9°, "*orange*" in the range of 10°--37°, "*yellow*" between 38°--75°, "*green*" between 76°--160°, "*cyan*" between 161°--200°, "*blue*" in the range of 201°--280°, "*purple*" between 281°--315°, and "*pink*" between 316°--344°.

The dominant colors will be communicated auditorily to the blind user. As shown in Figure 4, both Figure 4(a) (with texture) and 4(b) (without texture) show examples of clothes in color of light blue. However, the user will not be able to figure out whether the white and blue colors are mixed together only based on the colors classification results. To avoid this kind of confusions, we detect if the clothes have texture patterns by using the method described in Section 3.2.

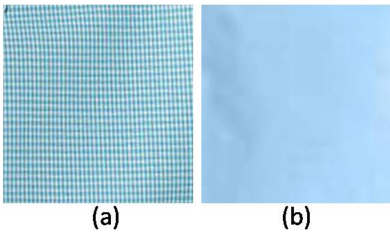

Fig. 4. (a) An example of clothes with texture and mixture colors (64.7% cyan, 27.6% white, 4.6% gray, 3% blue); (b) an example of clothes without texture but with mixture colors (9% blue and 90% white)

3.2 Texture Detection

Figure 5 shows the basic method to detect if the clothes have texture patterns. Based on the color classification results, if there is only one dominate color, the input image of clothes has no texture. Only for the images with multiple dominate colors, we continue to check if the multiple colors are caused by texture patterns. To detect if an image has texture or not, we first transfer it to gray scale image, and then perform Gaussian smoothing to reduce noises. Next Canny edge detection is applied to detect the edges in the image followed by a morphology processing to remove the edge pixels with small areas. At each edge pixel, we check the neighbor pixels around it by using a 3x3 mask to get the directions of the edge. Along the edge direction, we calculate the color values on the both sides of the neighbor's position in the original image. If the colors from both sides do not match each other, the edge is more likely caused by texture. Otherwise, the edge pixel is removed from further processing. Finally, we calculated the total edge ratio with the image having texture if the edge ratio is larger than a threshold. If both images from the image pair are without textures, we treat them as "texture match". For images with texture, we will continue to perform texture matching as described in Section 3.3.

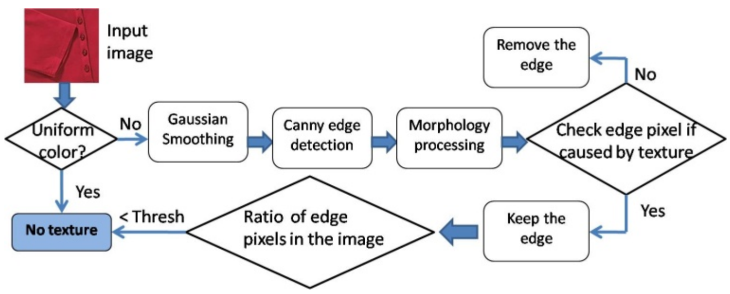

Fig. 5. Flowchart of proposed texture detection method

3.3 Texture Matching

For clothes with complex texture patterns, we develop a new approach for texture analysis by using Radon transform, wavelet features and co-occurrence matrix to handle illumination changes and rotations. Wavelet features provide spatial and frequency information which can be easily used to analyze texture features. However, wavelet features are stable for lighting changes but sensitive to the orientation of textures. In order to develop methods that work successfully for texture orientation-invariant, we employ Radon transform for estimating the orientation of texture patterns then rotate the image with main orientation of texture as 0•. Histogram equalization is performed to decrease illumination changes. Next, Haar wavelet transform is applied to obtain features on three directions (horizontal, vertical and diagonal). For each wavelet sub images, co-occurrence matrix for gray texture analysis is calculated. Finally, the texture matching is performed based on statistical classification included six features, e.g. mean, variance, smoothness, energy, homogeneity, and entropy.

4 Experiment Results

4.1 Databases

To validate the effectiveness and robustness of our method, we have performed evaluation on 3 datasets: 1) Brodatz album texture database [13]; 2) color and texture matching (CTM) dataset for clothes; 3) texture detection (TD) dataset for clothes. We collect datasets of clothes images with variety of colors and texture patterns. The Brodatz album texture database [13] is a public available standard dataset for texture analysis. We have used it to compare our method to state-of-the-art methods. The CTM database contains 128 images of clothes with complex patterns, multiple colors, and lighting changes. The TD dataset contains 45 clothes images with different patterns and colors. Among these images, 23 of them have textures and 22 images without texture.

4.2 Color and Texture Matching Results

Texture classification results on Brodatz album dataset: To make the results comparable, we apply exactly the same experimental setting on Brodatz album dataset as in [13]. Since we do not have the source code of [13], we implement their algorithm for the comparison. For Brodatz album dataset, there are 60 different textures and each texture is treated as a class. Our method achieves average classification rate of 97%. The method of Khouzani and Zadeh [13] achieves average accuracy of 96.7%.

Color and texture matching results on CTM dataset: Our CTM dataset contains 128 clothed images with complex patterns and colors. Among these images, 76 of them are matching and 52 images are non matching. In our test, we selected 50 matching pairs and 83 non-matching pairs. For texture matching, the method of Khouzani and Zadeh [13] achieves 67.7% matching rate and our method achieves 82.7% accuracy rate. Table 1 shows that our method achieves the state-of-the-art results on the standard Brodatz album dataset and significantly outperforms existing methods on our CTM dataset containing images of clothes with complex patterns and lighting changes. Table 2 shows the confusion matrix of our method for texture matching on CTM dataset. For color detection and matching, our algorithm achieves correct classification and matching rate at 99.2%. Figure 6 displays some examples of the results for clothes matching by using both color and texture information. The first row in Figure 6 shows the original image pairs. The second row displays the Radon transform image for texture orientation estimation. The third row and the fourth row demonstrate the wavelet features and the co-occurrence matrix images respectively.

Table 1. Comparison with the state-of-the-art results of texture matching on Brodatz album dataset and CTM dataset

Methods	Khouzani and Zadeh [13]		Our method	
Datasets	Brodatz	CTM	Brodatz	CTM
Accuracy	96.7%	67.7%	97%	82.7%

Table 2. Confusion matrix of clothes texture matching by our method on CTM dataset

	Number of matching pairs	Number of non matching pairs
Number of matching pairs	**42**	7
Number of non matching pairs	16	**68**

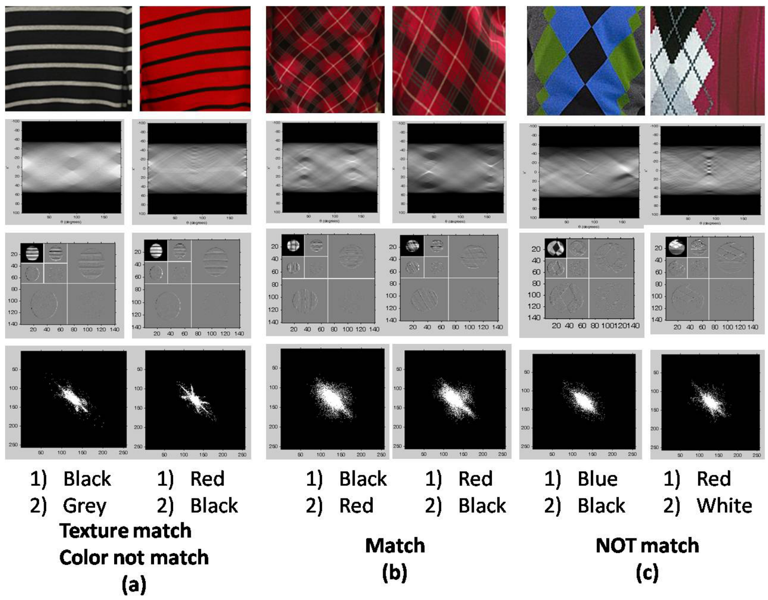

Fig. 6. Examples of results for clothes matching. (a) The clothes images are texture match, but color doesn't match; (b) the clothes images are match for both texture and color; (c) the clothes images are NOT match for both texture and color. The first row shows the original image pairs. The second row displays the Radon transform image for texture orientation normalization. The third row and the fourth row demonstrate the wavelet features and the co-occurrence matrix images respectively.

Fig. 7. Example results of texture detection. The top row shows the clothes without texture and the bottom row shows the example clothes with texture patterns.

Texture detection results on TD dataset: Our TD dataset contains 45 clothes images with different patterns and colors. Among these images, 23 of them have textures and 22 images without texture. In our test the accuracy of our texture detection is 100%. Figure 7 demonstrates some example results of texture detection. Our method can handle wrinkles and lighting changes.

5 Conclusion and Future Work

We have developed a new method to match clothes with multiple colors and complex patterns to assist visually impaired and blind people by distinguishing both texture and color information. To handle complex texture patterns and lighting changes, we combine Radon transform, wavelet features, and co-occurrence matrix for texture matching. Our algorithm for color matching is based on normalized color in HSI color space. We develop a color classifier to detect multiple colors including *red, orange, yellow, green, cyan, blue, purple, pink, black, grey*, and *white*. We also develop a simple edge-based texture detection method. The texture matching is only performed for the images with texture patterns. The proposed clothes matching algorithm is evaluated by three databases. Two of the databases contain clothes images with a variety of texture patterns, colors, and illumination changes. The results demonstrate that our method is robust and accurate for clothes with complex patterns and multiple colors.

The proposed color matching and detection function will also benefit color blind people. This research has the following impacts: (1) It enriches the study of texture matching, and leads to significant improvements over existing methods in handling images with lighting changes and complex texture patterns with different directions; (2) The method developed in this paper provides new functions to improve the quality of life for blind and visually impaired people; and (3) The research will benefit many other important areas including object detection and industry inspection, etc.

Our future work will focus on classifying more colors and 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.

Acknowledgments. This work was supported by NSF grant IIS-0957016.

References

1. Resnikoff, S., Pascolini, D., Etya'ale, D., Kocur, I., Pararajasegaram, R., Pokharel, G., et al.: Global data on visual impairment in the year 2002. Bulletin of the World Health Organization 82, 844–851 (2004)
2. Color identifier manufactured by BRYTECH, http://www.brytech.com/
3. Akhloufi, M.A., Ben Larbi, W., Maldague, X.: Framework for color-texture classification in machine vision inspection of industrial products. IEEE International Conference on System, Man, and Cybernetic (2007)
4. Caelli, T., Reye, D.: On the classification of image regions by color, texture and shape. Pattern Recognition (1996)
5. Charalampidis, D., Kasparis, T.: Wavelet-Based Rotational Invariant Roughness Features for Texture Classification and Segmentation. IEEE Trans. on Image Processing 11(8) (2002)
6. Dennis, D., Higgins, W.E., Wakeley, J.: Texture segmentation using 2D Gabor elementary functions. IEEE Trans. On Pattern Analysis and Machine Intelligence 16(2) (1994)
7. Do, M.N., Vetterli, M.: Texture similarity measurement using Kullback-Leibler distance on wavelet subbands. In: Proc. IEEE Int. Conf. on Image Proc., ICIP (2000)
8. Do, M.N., Vetterli, M.: Rotation invariant characterization and retrieval using steerable wavelet-domain Hidden Markov Models. IEEE Trans. Multimedia 4(4) (2002)
9. Van Gool, L.J., Dewaele, P., Oosterlinck, A.: Texture analysis. Compute Vision, Graphics, and Image Processing 29 (3) (1985)
10. Haley, G.M., Manjunath, B.S.: Rotation-invariant texture classification using a complete space-frequency model. IEEE Trans. Image Process. 8(2) (1999)
11. Hanbury, A., Kandaswamy, U., Adjeroh, D.A.: Illumination-invariant Morphological Texture Classification. In: International Symposium on Mathematical Morphology (2005)
12. Jalil, A., Manzar, A., Cheema, T.A., Qureshi, I.M.: New Rotation- Invariant Texture Analysis Technique Using Radon Transform and Hidden Markov Models. IEEE, Trans. INF&SYST. E91-D(12) (2008)
13. Khouzani, K.J., Zaden, H.S.: Radon Transform Orientation Estimation for Rotation Invariant Texture Analysis. IEEE. Trans. on pattern analysis and machine intelligence 27(6) (June 2005)
14. Varma, M., Ziisserman, A.: Texture Classification: Are Filter Banks Necessary. In: IEEE Conference on Computer Vision and Pattern Recognition (2003)
15. Wu, W.R., Wei, S.-C.: Rotation and gray-scale transform invariant texture classification using spiral resembling, subband decomposition, and Hidden Markov Models. IEEE Trans. Image Process 5(10) (1996)
16. How Blind People Match Clothing? http://www.associatedcontent.com/article/1788762/how_blind_people_match_clothing.html