Clothing Matching for Visually Impaired Persons

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Abstract. Matching clothes is a challenging task for many blind people. In this paper, we present a proof of concept system to solve this problem. The system consists of 1) a camera connected to a computer to perform pattern and color matching process; 2) speech commands for system control and configuration; and 3) audio feedback to provide matching results for both color and patterns of clothes. This system can handle clothes in deficient color without any pattern, as well as clothing with multiple colors and complex patterns to aid both blind and color deficient people. Furthermore, our method is robust to variations of illumination, clothing rotation and wrinkling. To evaluate the proposed prototype, we collect two challenging databases including clothes without any pattern, or with multiple colors and different patterns under different conditions of lighting and rotation. Results reported here demonstrate the robustness and effectiveness of the proposed clothing matching system.

Keywords: Blind, Color Blind, Computer Vision, Clothing Matching, Color Matching, Pattern Analysis, Visually Impaired

1. Introduction

Based on statistics from the American Foundation for the Blind and the National Health Interview Survey, there were, as of 1994-1995, approximately 275,000 people in the US with bare light perception or less [1, 25]. While a small percentage of the 1.3 million people who qualify as legally blind, this is the population who are most in need of vision substitution systems, since many people with low vision can accomplish visual tasks with magnification and other aids.

In everyday life, people need to find appropriate clothes to wear. This is a very challenging task for blind people to choose clothes with suitable color and pattern. Most blind people manage this problem either through aid from family members or through using plastic Braille labels or different types of stitching patterns which are tagged on the clothes to represent different colors and appearances [3]. This method also requires aid in labeling. And some blind people solve the matching problem by keeping only clothing with very simple colors and patterns in their wardrobes.

Although many methods have been developed for texture matching and color detection in the computer vision and image processing research [4-7, 9-20, 22, 27-29], currently there is no device that can effectively supply matching choices for blind people. A good solution to this problem could help not only blind persons, but those who are severely color deficient, though in most cases the color deficiency is confined to one axis in color space (e.g. reds confused with greens). There are some portable electronic color identifiers available but they can only detect primary colors present in a very small region [8]. One example is displayed in Figure 1. Unfortunately, this kind of device cannot correctly classify colors of clothes that containing multiple colors and complex patterns.

There are several critical issues for successful clothes matching. First, people perceive an object to be the same despite even very large changes in the spectral composition of light reflected from the object. (Conversely, objects that reflect identical spectra are often reported as being of different colors, depending on lighting conditions and color adaptation state.) Thus, object colors determined from a camera

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image may not always correspond perfectly to those reported by a human observer. Secondly, shadows and wrinkles may be confused as part of the texture patterns or imagery of the clothing and thus cause errors. Thirdly, the images of clothes can be imaged from arbitrary viewing directions. Methods of matching patterns require the input pair of images must be pattern rotation-invariant. Lastly, many clothes have designs with complex patterns and multiple colors, which increase difficulty of identifications.

Fig. 1. Color identifier manufactured by BRYTECH [8].

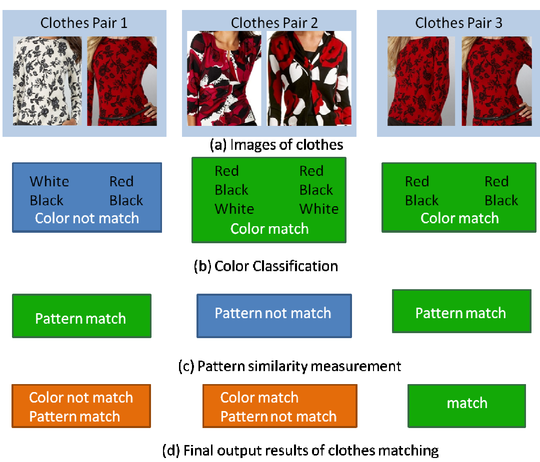


Fig. 2. Matching clothes with multiple colors and complex patterns by using color and texture information. (a) Three pairs of images of clothes. (b) Color classification results. (c) Pattern similarity measurement results. (d) Final audio feedback.

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 this paper, we develop a computer vision-based prototype to match a pair of images of two clothes for both pattern and color. The image pair is captured by a camera which is connected to a computer. Results of the matching algorithm are reported via text-to-speech outputs. Figure 2 demonstrates the concept of the proposed system. To configure and control the system, users can simply speak out the commands to switch on/off the system, execute corresponding functions, and adjust the volume of audio outputs. Our algorithm can detect: 1) colors of the clothes; 2) whether the clothes have pattern or have homogeneous color; 3) whether the colors match for a pair of images; and 4) whether the patterns match for a pair of images. Finally, the detection results can be communicated to the user verbally as "The dominant colors are …", "No pattern", "match (for both color and pattern)", "color match, pattern not match", "pattern match, color not match", or "poor match (for both color and pattern)".

2. System and Interface

As shown in Fig. 3, the computer vision-based clothes matching prototype for blind persons integrates different sensors (i.e. a camera, a microphone, and audio output devices which can be an earphone, blue tooth, or speakers). A camera is used to capture images of clothes. A wearable computer (can be a PDA or a smart phone) is used to capture and analyze data. The detection and matching results are described to the blind user by verbal display with minimal distraction of the user's hearing sense. The user can control the system by speech via microphones. The information is processed by the computer.

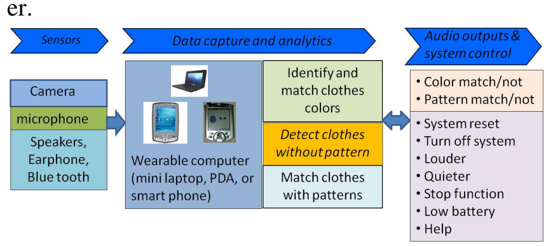
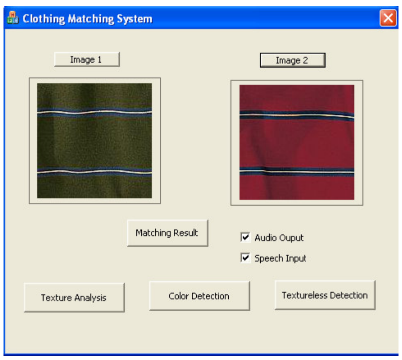
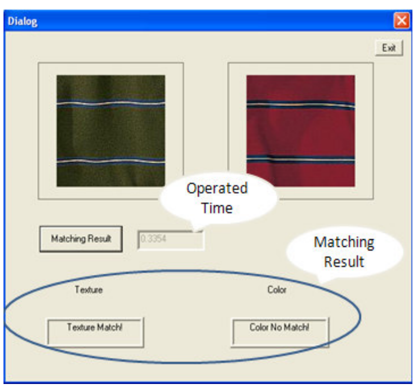


Fig. 3. Prototype hardware and architecture design of computer vision-based clothes matching aid for blind persons.

In our prototype, we develop a program based on Microsoft SDK tools for speech recognition and audio feedback to make it easily to use by blind users. As a user gives simple speech commands through a microphone, the system can directly recognize input commands, execute corresponding functions, and provide final audio outputs. In addition, can be set by a number of high priority speech commands such as "System Reset", "Turn off system", "Stop function", "Repeat result", "Help", and speaker volume and speed control commands (e.g. “Louder”, “Quieter”, “Slower”, “Faster”). The speech commands with can be used at any time. To protect privacy and minimize masking environmental sounds, bone conduction earphones or small wireless blue tooth speakers can be used. The system will also check battery level and send out an audio warning when the battery level is low. Figure 4 shows the system interface for development.



(a)



(b)

Fig. 4. System interface for development to verify our method. (a) A image pair of clothes with same pattern in different colors for test; (b) the matching results are displayed.

3. Methodology for Clothes Matching

As show in Figure 5, there are three main components in our methodology for clothes matching: 1) color detection and matching, 2) pattern detection, and 3) pattern matching. In this section, we describe the algorithms for each component.

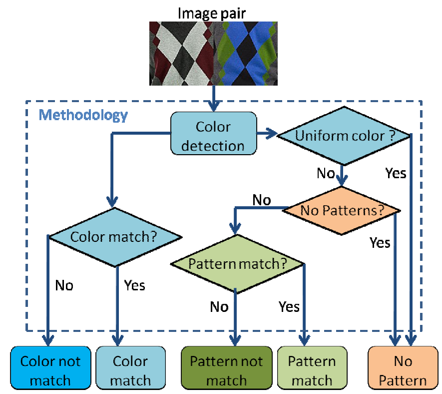


Fig. 5. System flowchart for clothes matching. From top to bottom, the system input (image pair), methodology, and matching results are displayed. In the methodology, there are three main components: color detection and matching, pattern detection, and pattern matching.

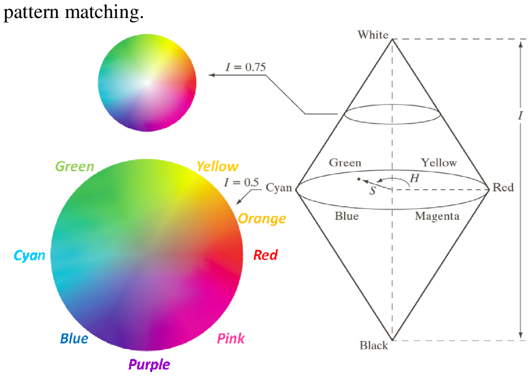


Fig. 6. HSI color space and the basic color space quantization based on Hue for pixels meet constrains of saturation and luminance.

3.1. Color Detection and Matching

Our color detection is based on acquiring a normalized color histogram for each image of the clothes in bi-conic (hue, saturation, luminance) HSI color space as shown in Figure 6. The key idea is to intelligently quantize color space based on 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 classifies the pixels in the image to the following colors: ***red, orange, yellow, green, cyan, blue, purple, pink, black, grey***, and ***white***. Each image of an article of clothing is first converted from RGB to HSI color space. Then, 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 large enough, and saturation S is less than a special threshold, then we define the color of the pixel as “white”. Similarly, the color of a pixel “black”, can be determined if the luminance I of a pixel is less enough and saturation S is also satisfied with the condition. Under the rest values of the luminance I, pixel of color “gray” could be found in a defined small S radius range. For other colors (e.g. ***red, orange, yellow, green, cyan, blue, purple, and pink*****)**, hue information is employed.

As shown in Figure 6, 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 in auditory to the blind user. If there is only one dominant color, which means the clothes has uniform color without patterns. If both images from the image pair have uniform colors, then no further pattern matching processing is needed because we can easily know the clothes pair is match or not only based on the color detection and matching. However, for clothes with multiple dominant colors, 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. As shown in Figure 7, both Figure 7(a) (with patterns) and 7(b) (without pattern) show examples of clothes in colors of blue and white, but they are totally different as showed one is with patterns and another one is without pattern. To avoid this kind of confusion and provide the user clear information, we further detect if the clothes have patterns by using the method described in next Section.

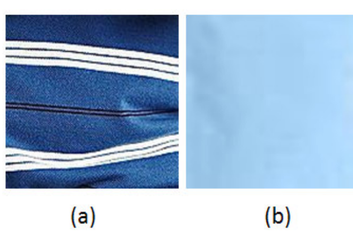


Fig. 7. (a) An example with patterns and mixture colors (74.5% blue, 18.7% white, 3.5% black, 1.7% gray) (b) An example without pattern and mixture colors (5% blue, 94% white).

To detect the colors of a pair of clothes image, the dominant colors are compared. If the categories and the order of the first 3 dominant colors are same, the color of the pair of clothes is match. If the categories of the first 3 dominant colors are same but in different orders, the output can be “color does not match exactly but in same color series”. This part can be turned based on feedback from blind users.

3.2. Clothing Patten Detection

Our method for detecting if an image of clothes has patterns is illustrated in Figure 8. Based on the color detection results from previous section, if there is only one dominant color, the input image of clothes has no pattern. Only for the images with multiple dominant colors, we continue to check if the multiple colors are caused by patterns.

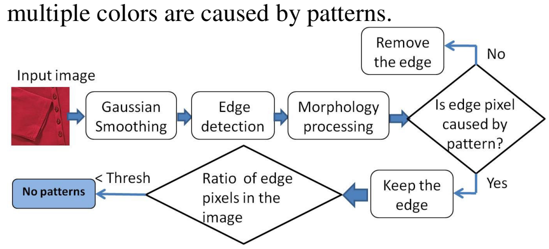


Fig. 8. Flowchart of proposed pattern detection method.

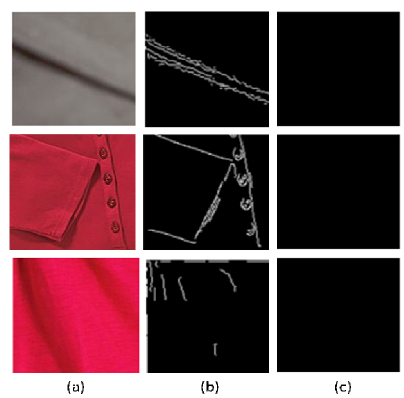


Fig. 9. Examples of successfully handle edge noises caused by folders, sleeves, and wrinkles of clothes for pattern detection. (a) Original clothes images; (b) edge maps from Canny edge detector; (c) edge maps after removing edge noises by checking color values on the both sides of the neighbor’s of each edge pixels.

To detect if an image has patterns or not, we first transfer it to gray scale image, and then perform Gaussian smoothing to reduce noise. Next Canny edge detection is applied to detect the edges (i.e. pixels has intensity discontinuities) 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 are different, the edge is more likely caused by pattern. Otherwise, the edge pixel is removed from further processing. Finally, we calculate the total edge ratio with the image having pattern if the edge ratio is larger than a threshold (given by a parameter). Figure 9 displays several successful examples to handle edge noises caused by folders, sleeves, and wrinkles of clothing for pattern detection. If both images from the image pair are without patterns, we treat them as a "pattern match". For images with patterns, we will continue to perform pattern matching as described in Section 3.3.

3.3. Clothing Pattern Matching

Texture analysis and classification has been widely used for applications of image retrieval and industry inspection. For pattern matching for clothes, the following main factors have to be addressed: 1) rotation invariance. The method should be able to analyze the patterns when the clothes images are in arbitrary orientations. 2) Insensitivity to lighting changes; and 3) the method should be simple enough so that to be transferred to devices having less computational power.

Some attempts have been made for rotation invariant texture analysis [7, 12, 20, 23-24, 28]. 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 [22, 24] and some authors proposed approaches for estimating the orientation information then used this particular direction for wavelet decomposition [7, 22].

Inspired by [22], we develop a new texture pattern analysis approach which is robust to variations of rotation and illumination in the system. In application of clothes matching, we found that illumination changes significantly affect the matching results during the experiments. For an input image pair of 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 a Haar wavelet transform to extract features on 3 directions (horizontal, vertical, and diagonal) and calculate co-occurrence matrix for each wavelet sub images. The Haar wavelet is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Finally, the matching of clothes patterns is performed based on six statistical features which are commonly used for texture analysis. Compare to existing methods, our method is robust to match clothes with complex texture patterns, as well as to handle clothes with large lighting changes.

3.1.1 Radon Transform for Pattern Orientation Estimation and Normalization

In order to make our algorithm invariant to pattern orientations, we apply Radon transform 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 patterns. Radon transform can be thought of as computing the projection of the image along the given angles which varies from 0° to 180° [19]. In our system, we choose a region with circle shape since it has the least direction interference comparing with other shapes. For each given direction, the radon transform can be thought of as computing the projection of the image along the given direction. The resulting projection is the sum of the intensities of the pixels in each direction.

The 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 pattern principal orientation can be estimated as the projection which has the straightest lines. We determine the final dominant orientation by calculating the mean of the variance of projections at 6 neighbor angles around each local maxima variance if there are two or more principal orientations. The orientation with largest mean value will be chosen as the final dominant orientation of the texture pattern. In the example of Figure 10, 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 corresponds to the angle of 30°. We then rotate the dominant orientation information of the image patterns back to 0 deg to make the algorithm rotation invariant.

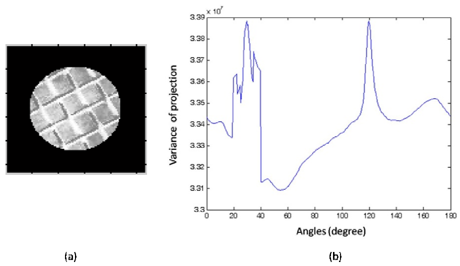


Figure 10. Example of pattern orientation estimation by Radon transform. (a) A texture image with 2 maximum angles (30° and 120°); (b) variance of projections at different angles. The main orientation is corresponding to the angle of 30°.

3.1.2 Wavelet Feature Extraction

Wavelet transform is a local transformation of space and frequency which can effectively extract information from the images for texture analysis. The wavelet series expansion of function can be defined with respect to a scaling function and a wavelet function with different scaling and wavelet coefficients. With the coefficients we can easily obtain the different levels of wavelet decomposition. In our system, we use two levels of decomposition. Figure 11 shows an instance of Haar wavelet transform resulted on three directions (horizontal, vertical and diagonal) of the image.

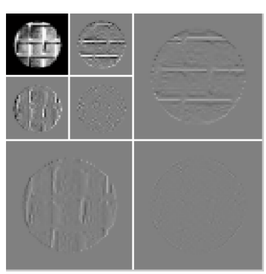


Fig. 11. Examples results of Haar wavelet transform results.

3.1.3 Grey Level Co-occurrence Matrix

Khouzani and Zadeh [22] 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 another image. Wavelet energy is the most popular feature used in wavelet texture analysis. Figure 12 shows an image pair with different texture patterns but same energy which method [22] fails. In our system, we employ a grey level co-occurrence matrix for pattern matching.

Figure 12. An image pair with different texture patterns but with same energy.

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 [18]. The co-occurrence matrix of an image calculates the frequency of a pixel pairs with intensities i and j occur in an image at each specified position. The number of possible intensity levels in the image determines the size of the co-occurrence matrix. For an 8-bit image, the maximum size of co-occurrence is 256x256.

Since each pixel in an image has maximum 8 neighbor directions, we calculate the final co-occurrence as the sum of 8 occurrence matrices. In virtue of we use a circle region to estimate the pattern 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.

3.1.4 Pattern Matching

To match patterns, we compose 6 statistical features from different order moments of the co-occurrence matrices. A distance function is defined from the about six statistical features between the input image pair to determine if the pair of images matches. If the distance is larger than a threshold, the image pair match is rejected. The threshold parameter is selected based on experiments.

4. Experiment Results and Discussions

4.1. Databases

The robustness and effectiveness of the proposed method are evaluated on two datasets of clothes we collected: 1) color and matching (CTM) dataset; 2) pattern detection (TD) dataset. The CTM dataset is collected for pattern and color matching, which contains 128 images of clothes with complex patterns, multiple colors, and lighting changes, 76 of them have their match pattern pairs and 52 images have not match pattern pairs. The TD dataset is collected for pattern detection, which contains 45 clothes images with or without patterns and in uniform color or multiple colors. Among these images, 23 of them have patterns and 22 images without pattern. The size of all images is 140x140 pixels. Figure 13 shows some examples of the two datasets. The datasets with ground truth will be released to public at our website.

(b)

Fig. 13. (a) Examples from the CTM dataset with complex patterns and multiple colors; (b) examples from the TD dataset, the top row shows the clothes without pattern and bottom row shows the example clothes with texture patterns.

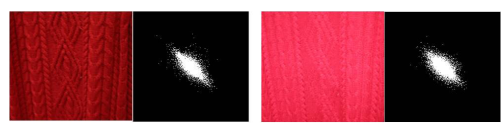
4.2. Clothes Matching Results

In our test, we evaluated the proposed method for pattern detection (i.e. to determine if the clothing image has patterns or not), color matching, and pattern matching. The testing results are summarized in Table 1. For pattern detection, we use all the images in TD dataset. Among the TD dataset, the rate of pattern detection is 100%. For pattern matching, we select 50 matching pairs and 83 non-matching pairs from CTM dataset. Our method achieves 85% accuracy rate and is robust to clothes with complex texture patterns, multiple colors, and variances of rotation and lightings. Some successful results of pattern matching are displayed in Figure 14. As shown in Figure 15, our method can handle large illumination variances. Figure 15 presents a pair images from the same clothes with flash light on and off respectively. The co-occurrence matrices of these two images are very close and our approach successfully matches them. For color matching and detection, we select 48 matching pairs and 52 non-matching pairs from CTM dataset. Our method achieves correct classification and matching rate at 99.0%. Figure 16 displays two test examples with matching colors but different patterns.

Table 1. Results of pattern detection, pattern matching, and color matching

Test	Accuracy	Dataset
Pattern detection	100%	TD: 45 images
Pattern Matching	85%	**CTM:** 50 matching pairs, 83 non matching pairs
Color Matching	99.0%	**CTM:** 48 matching pairs, 52 non matching pairs

Fig. 14. Examples of image pairs of successful pattern matching.



(a) (b)

Fig. 15. 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 co-occurrence matrices of these two images are very close and our method successfully matches them.

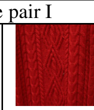
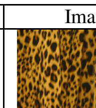
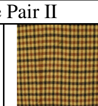
Detected Colors (%)	Image pair I		Image Pair II	
				
Red	**98.47**	**98.51**	0.0	0.0
Orange	0.0	0.0	**35.21**	**36.31**
Yellow	0.0	0.0	**31.65**	**48.91**
Green	0.0	0.0	0.0	0.0
Cyan	0.0	0.0	0.0	0.0
Blue	0.0	0.0	0.0	0.0
White	0.0	0.0	0.0	0.0
Black	0.0	0.0	**22.41**	**9.33**
Gray	0.0	0.0	0.0	0.0
Pink	0.0	0.0	0.0	0.0
Purple	0.0	0.0	0.0	0.0

Fig. 16. Examples of color matching. Our color detection method can handle both single color (Image pair I with single dominant

"red" color) as well as complex colors (Image pair II with three dominant colors of "Orange", "Yellow", and "Black").

4.3. Result Analysis

For pattern matching, the main errors in our test occurred with images with very similar texture patterns such as samples 9, 15, and 17 as shown in Figure 13(a).

For color matching in 100 image pairs, only one pair does not correctly match due to the background distraction in "Image on the right" which shown in Figure 17. The three dominant colors for "Image on the left" are 'black", "red", and "pink", while for "Image on the right" are 'black", "red", and "orange".

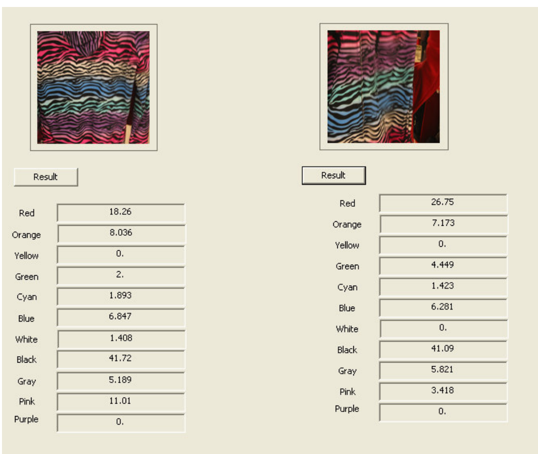


Fig. 17. The image pair of our color match fails.

4.4. System Efficiency

The proposed algorithm is very efficient. For a pair of clothes images in resolutions of 140x140, the processing time, which includes all the testing components of pattern detection, pattern matching, and color matching, is about 0.35 seconds (not including audio output). Our system is implemented in C++ and tested on a 2GB Pentium IV machine.

4.5. Discussion

The proposed clothes matching algorithm can handle large illumination variances, multiple colors, and complex patterns. The color matching and detection functions may also benefit some people with color deficiencies [23]. This research has the following impact: (1) It enriches the study of pattern 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 may benefit many other important areas including object detection and industry inspection, etc.

The proposed system is very efficient and takes about 0.35 seconds to match a pair of images on a standard PC in C++ without code optimization. There is no large memory required by the algorithm. The proposed algorithm can be applied to off-the-shelf smart camera phones. Compared to a standard PC, the computer in a mobile phone has less computational power and lacks a floating point processing unit (FPU). However, computational power is rapidly increasing on smart phones. With optimized code in Symbian C++, which is the most efficient language currently available for the mobile phone, there are no obstacles to transferring the proposed technology to a smart phone.

5. Conclusions and Future Work

We have presented an efficient computer vision-based system to match clothes with multiple colors and complex patterns to assist visually impaired and blind people by distinguishing both pattern and color information. To handle complex texture patterns and lighting changes, we combine techniques using the Radon transform, wavelet features, and co-occurrence matrix for pattern matching. Our algorithm for color matching is based on normalized color in HSI color space and is able to detect multiple colors including *red, orange, yellow, green, cyan, blue, purple, pink, black, grey*, and *white*. To make the algorithm more efficient, we further developed a simple edge-based pattern detection method. The pattern matching is only performed for the images with texture patterns. The evaluation results on clothes datasets demonstrate that our method is robust and accurate for clothes with complex patterns and multiple colors. The matching outputs are provided to the user in audio (speech or sound).

"Fashion sense" and personal preferences for matching would be obviously useful things to add to our system since they can vary so much over different cultures, time and personal taste. In the practical assistive system, a configuration step could be added to allow the user to select a number of preferences, such as acceptable or appropriate color and/or pattern matches. For example, the system could be configured to accept homogeneous achromatic colors (white, gray, black) as a "fashion" match with any other color. Similarly, the dominant color of a patterned article of clothing could be configured to indicate an acceptable personal taste match against another color (e.g. yellow against green).

Our future work will also focus on classifying more colors, recognizing clothes patterns, and transferring the function to smart 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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