

Color Feature-based Pillbox Image Color Recognition

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Abstract: Patients, their families and caregivers routinely examine pills for medication identification. Key pill information includes color, shape, size and pill imprint. The pill can then be identified using an online pill database. This process is time-consuming and error prone, leading researchers to develop techniques for automatic pill identification. Pill color may be the pill feature that contributes most to automatic pill identification. In this research, we investigate features from two color planes: red, green and blue (RGB), and hue saturation and value (HSV), as well as chromaticity and brightness features. Color-based classification is explored using MatLab over 2140 National Library of Medicine (NLM) Pillbox reference images using 20 feature descriptors. The pill region is extracted using image processing techniques including erosion, dilation and thresholding. Using a leave-one-image-out approach for classifier training/testing, a support vector machine (SVM) classifier yielded an average accuracy over 12 categories as high as 97.90%.

1 INTRODUCTION

The use of prescription drugs is increasing generally, especially among older persons, who are often burdened with polypharmacy. (Gu, Dillon, & Burt, 2010; Schumock et al., 2015; Thielke et al., 2010). Almost 60% of adults took prescription pills in 2012, a figure which was only 50% in 2000 (Kantor, Rehm, Haas, Chan, & Giovannucci, 2015). The possibility of pill misidentification, and possible adverse drug events, has therefore increased. Automatic pill identification would help reduce the possibility of pill misidentification. Because there are so many different medications and generic varieties of each medication, it would be extremely difficult for anyone to identify all pills, without specific background knowledge. The National Library of Medicine (NLM) hosted a Pill Image Recognition Challenge as part of its research and development in Computational Photography Project for Pill Identification (C3PI). In this research, we analyze the pill images presented in this challenge, using color features and a support vector machine (SVM) learning algorithm.

The research began with the pill recognition aspect of the project. Utilizing the NLM curated Pillbox images, which also included metadata information of the physical attributes of each pill,

enabled the development of a baseline recognition algorithm which performed well under controlled conditions. Generalization for the algorithm required accounting for real-world factors such as lighting condition, camera resolution, and non-homogeneous backgrounds.

Previous work in this domain (Madsen et al, 2013) and (Wan et al., 2015) yielded good results, but were limited to using images of similar quality as the Pillbox images. In this study, we expand the number of target color to be recognized from 7 to 12 and increase the number of Pillbox images to approximately 2100.

Using an SVM classifier, we were able to achieve a recognition accuracy based on 12 color categories of 97.90%.

2 METHODOLOGY

The workflow of this research consisted of first determining perceived five color component values (red, green, blue, yellow, white) and twelve perceived actual color values. There were 2151 high resolution pill images in the Pillbox database as of December 2014. The Pillbox images are of very high quality, with high resolution, controlled illumination, and uniform background. The high quality of the

database allows segmentation using a simple threshold to separate the pill object from the background for almost all pills. Using the segmented pill, the color classification process was performed using a four-step approach which is outlined in Figure 1 and summarized as:

- Step 1:** Segment the pill from the Pillbox image.
- Step 2:** Determine the best axis to divide the segmented pill image into two halves.
- Step 3:** Extract features from each half of the segmented pill region.
- Step 4:** Classify the segments into a color category (classification)

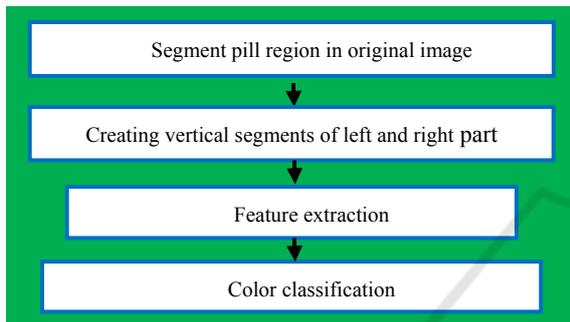


Figure 1: Pill color classifier development.

2.1 Segmentation of Pill Region

The Pillbox images are all dimensional similar; each being 768×1024 . Demonstrated in Figure 2, the colored background, front and back of each pill are included in the Pillbox images. Since the background color can influence color detection it is not used for pill color analysis. As such, a reliable segmentation algorithm of pill from background is needed.

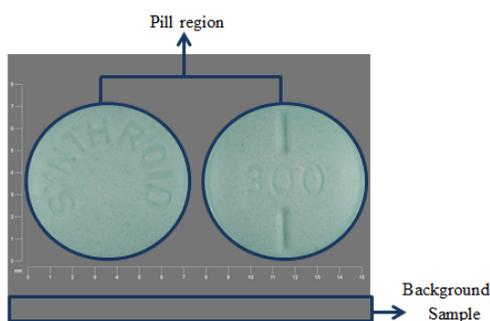


Figure 2: Example of a Pillbox image.

The algorithm to segment the pill image is as follows:

- Step 1:** Load red, green and blue (RGB) image

- Step 2:** Take a sample of the background pixels (10 lines of pixels, shown in the Figure 2) and calculate the mean intensity of background.
- Step 3:** Threshold the image based on the calculated mean intensity value
- Step 4:** Repeat Step 2-3 for Green and Blue color channels
- Step 5:** Use erosion to eliminate noise and dilation to fill holes
- Step 6:** Combine the binary mask that was generated for each color plane using a union operation.

Because the pill color is uniform on both sides of the pill in this data set, only one side of the segmented pill region (top-left side was arbitrarily chosen) is used for feature analysis. The segmentation of pill region is shown in Figure 3, with background color set to be black (pixel value is 0 in RGB color space) for convenience of feature calculation shown later.



Figure 3: Segmentation of pill region.

2.2 Creation of Vertical Segments of Pill Region

In this process, the segmented pill region obtained in the previous step is divided into two vertical segments, left segment and right segment. The reason for creating two vertical segments instead of analyzing the whole segmented pill region is that some pills have two or more colors (see Figure 4). To avoid classification errors that would occur with whole-pill color analysis, the pill is divided into vertical two segments.

After the pill region of interest is obtained through segmentation, a vertical central axis needs to be located. The central axis is simply defined as the middle column in the segmented pill region because of the accuracy of the segmentation. For a segmentation mask image of size $[M \times N]$, the middle column is defined as column $[N/2]$. The central axis location and vertical segments can be viewed in Figure 5.



Figure 4: A two-colored Pillbox image.

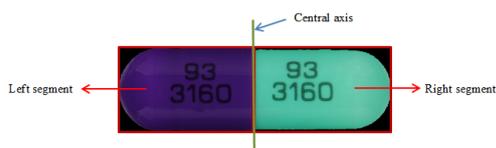


Figure 5: Central axis and left/right vertical segments.

2.3 Feature Extraction

For each vertical segment of the pill region image, there are five different categories of color features computed from the segmented pills, including: (1) RGB intensity, (2) HSV intensity, (3) Chromaticity, (4) Left-Right averages, and (5) Brightness. An overview of the features extracted for each feature category is presented in Table 1. The algorithms for computing each feature are given in detail following Table 1.

Table 1: 20 Color Features.

Feature Category	Label	Measure	Description
RGB Mean And Std. Dev.	F1	Red intensity	Red, Green and Blue color space statistics
	F2	Green intensity	
	F3	Blue intensity	
	F4	Std. Dev. Red intensity	
	F5	Std. Dev. Green intensity	
	F6	Std. Dev. Blue intensity	
HSV Mean And Std. Dev.	F7	Hue Mean	Hue, Saturation and Value color space statistics
	F8	Value Mean	
	F9	Saturation Mean	
	F10	Hue Std. Dev.	
	F11	Value Std. Dev.	
	F12	Saturation Std. Dev.	

Chromaticity Means	F13	Red chromaticity Mean	Chromaticity measures color quality and overall values of brightness. Red chromaticity = $R/(R+G+B)$; green and blue are similar. Chromaticity combines the features of saturation (color purity) and hue (color specificity) in a single value.
	F14	Green chromaticity Mean	
	F15	Blue chromaticity Mean	
	F16	Yellow chromaticity Mean	
Combination	F17	RGA	Averages of colors for each two-color combination.
	F18	GBA	
	F19	BRA	
Brightness	F20	Intensity	$\frac{R + G + B}{3}$

2.3.1 RGB Intensity

The RGB color model is additive in the sense that the three primary color spectra are added together, wavelength for wavelength, to make the final color spectrum (Boughen & Gross, 2003; Poynton, 2003).

After the pill region image is obtained, the color image is decomposed into red, green and blue images (figure 6). The background pixels are set to 0. All nonzero pixel values indicate pill region pixels; for this region, SumRed, SumGreen and SumBlue represent the summation of intensity values for pill region pixels. The number of pill region pixels is found by NumRed, NumGreen and NumBlue.

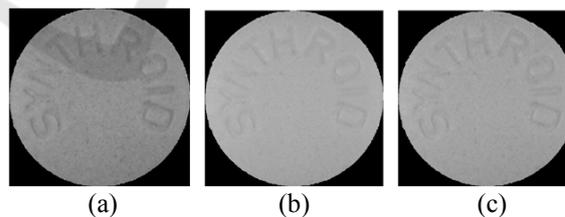


Figure 6: The grayscale images of pill region. a) red channel, b) green channel, c) blue channel.

In each of the three channels, the mean of red intensity (F1), green intensity (F2) and blue intensity (F3) are calculated according to the equations 1-3.

$$Red\ intensity = \frac{SumRed}{NumRed} \quad (1)$$

$$Green\ intensity = \frac{SumGreen}{NumGreen} \quad (2)$$

$$\text{Blue intensity} = \frac{\text{SumBlue}}{\text{NumBlue}} \quad (3)$$

The standard deviation for the three channels of the RGB color space, denoted as Std Red (F4), Std Green (F5) and Std Blue (F6) are calculated using the Matlab® function “std.”

2.3.2 HSV Intensity

The hue, saturation and value (HSV) color space represents colors in a way that is similar to the way that humans perceive colors. HSV attempts to separate chroma and luminance such a particular hue is the same independent of luminance. The conversion from RGB to HSV color space is provided by Matlab® with the function “rgb2hsv” which is detailed on Matlab official document webpage (MathWorks, 2016). The given pixel value represents the current pixel parameter (hue, saturation or value), as the entire image is distributed in these three channels. Figure 7 gives an example of a pill region in HSV color space.

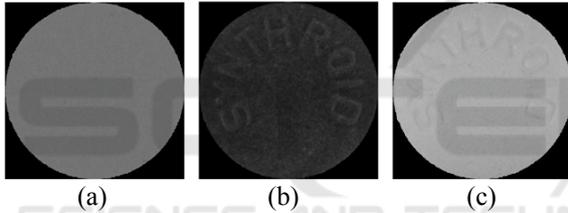


Figure 7: Illustration of grayscale image of HSV color space. a) hue, b) saturation, c) value.

The pixel value sums for each of the three channels, SumHue, SumSat and SumVal, can be obtained by summing the non-zero pixels (black pixels also have 0 values in HSV color space). The counting of pill region pixels NumHue, NumSat and NumVal is similar to RGB pixel counting. Hence, the HSV feature are also extracted using equations 4-6, similar to RGB feature extraction.

$$\text{Hue intensity} = \frac{\text{SumHue}}{\text{NumHue}} \quad (4)$$

$$\text{Saturation intensity} = \frac{\text{SumSat}}{\text{NumSat}} \quad (5)$$

$$\text{Value intensity} = \frac{\text{SumVal}}{\text{NumVal}} \quad (6)$$

Note that the HSV calculations are also accomplished with the Matlab® function “std,” and are processed in all three HSV color space channels.

2.3.3 Chromaticity and Brightness Features

For each channel of the HSV color space image, along with red, yellow, and blue chromaticity (See Equations 7-10) features were calculated for every pill. As an objective specification of the quality of a color regardless of its luminance, chromaticity can give us another view of the color being recognized and help in the color classification. And for this category of feature, four chromaticity features are defined: red, green, blue and yellow chromaticity. Each of these features represents a different aspect of color according to the color space we have here. Chromaticity features were among the most useful features in previous works on pill color recognition (Lee, Park, Jain, & Lee, 2012; Madsen, Payne, Hagerty, Szanto, Moss, Wronkiewicz, Stoecker, 2013; Wan, Woods, Salgado-Montejo, Velasco, & Spence, 2015).

$$C_r = \frac{R}{R + G + B} \quad (7)$$

$$C_b = \frac{B}{R + G + B} \quad (8)$$

$$C_g = \frac{G}{R + G + B} \quad (9)$$

$$C_y = \frac{R + G}{2(R + G + B)} \quad (10)$$

The brightness feature F20 is calculated as the average of the brightness in the red, green and blue channels (equation 11). Brightness is needed to better classify achromic colors, such as gray and white

$$\text{Brightness} = \frac{R + G + B}{3} \quad (11)$$

3 CLASSIFICATION

The left and right pill region vertical segments each have a specific color category. In the classification process, the left and right vertical segments are trained and tested separately in order to avoid the issue of color mixture when treating the pill region as a whole. However, the left part and right part in classification steps are the same regardless of the variation of color; hence, for the experiments, we consider just the left part as an example.

The labels for vertical segments were assigned manually by two of the authors (J.G.C. and P.G.) according to the 12 FDA colors (Julie N. Barrows Arthur L. Lipman, 2009) listed in table 3 below. The

entire database is labelled in 12 groups with one color in each. Take red for example, all the red pills are labelled as “positive (1)” for red color; all other pills are labelled “negative (0)” to complete the red color labels; the same labelling is done for all 12 colors.

Table 3: FDA Pill Color Classification Labels.

FDA Pill Colors			
Black	Pink	Gray	Turquoise
Blue	Purple	Green	White
Brown	Red	Orange	Yellow

In the first stage, twenty features (F1-F20) were extracted and used for color-based classification based on a leave-one-out method. A Support Vector Machine (SVM) classifier was investigated to take the input of twenty feature columns for individual pill classification (Cortes & Vapnik, 1995).

As 12 color are treated as the target color in this study, 12 different binary classifiers are built, the classification for a single color is carried out with the following steps:

- Step 1:** Train the SVM classifier algorithm using a leave-one-image-out approach. The classifier is trained based on the left vertical segment feature vectors for all except the left-out pill image, which is used for testing.
- Step 2:** Classify the pill left-out pill test image using the SVM classifier.
- Step 3:** Assign class labels (1 for target color confirmed, 0 for not target color) to the test segment image.
- Step 4:** Repeat steps 1-3 for all the segmented images in the experimental data set.
- Step 5:** To finish classifications for all the 12 colors, Step 1 to Step 4 above are repeated for all color labels (total 12 iterations).

For the SVM classifier, the LIBSVM(Chang & Lin, 2011) implementation is employed in this paper. This SVM tries to find an optimal hyperplane for linear inseparable classes which acts as a decision function to classify data in high dimensions. A linear kernel is used for the SVM to update the penalty parameter by a leave-one-image-out method, as explained in the paper of (Guo et al., 2015), (De et al., 2013). The implementation is completed with Matlab® and presented in (Guo et al., 2015).

4 EXPERIMENTS PERFORMED

Twelve color categories are defined for the classification target. The entire database of 2140 pillbox images are vertically segmented into two groups, each group of pill region segments (2140 for either left or right segments) will be assigned one of twelve color labels automatically by the classifier. The twelve target FDA color categories in Table 3 are manually assigned as the training and testing targets by the author. In the classification process, a leave-one-out approach is employed where 2139 images are used for training and the single left-out image is tested.

In the scoring used for classification accuracy, the percentage of rightly classified images is calculated for every color category. If the class label automatically assigned to the test image is the same as the manual class label, then the image is considered to be correctly labelled. Otherwise, the image is considered to be incorrectly labelled.

4.1 Experimental Results and Analysis

As previously stated, we obtained the vertical segment image classifications using the SVM classifier with a leave-one-image-out approach based on all the twenty features generated. Then the vertical segment classifications are compared with the target color truth label and finally calculated the percentage of right classification accuracy. We evaluated performance of these pill image classifications using the three approaches that is presented in Section 3. Table 4 shows the classification results obtained with the SVM classifier, for all twelve color categories.

Table 4: Classification results obtained for all color categories.

Color	Red	Green	Blue	Yellow	Black	White
Accuracy	98.46%	99.44%	99.21%	99.07%	100%	95.14%
Color	Gray	Pink	Cyan	Purple	Brown	Orange
Accuracy	90%	100%	99.47%	99.39%	96.78%	97.85%

As can be observed in Table 4, the highest accuracy of classification for all the color categories are the black and pink color classification, which both were 100% correct. Additionally, cyan has an accuracy of 99.47% (2129/2140), green classification is found to be 99.44% correct (2128/2140), 2127/2140 of purple pills are classified correctly, followed by blue follows with a classification accuracy of 99.21% (2123/2140). For yellow, 2120 pills are correctly recognized giving an accuracy of 99.07% (2120/2140). Red is recognized

in 98.46% (2107/2140) in classification and Orange as 97.85% (2094/2140).

However, white and gray give confusing classification results of 95.14% (2036/2140) and 90% (1926/2140) since manual labelling consistency is difficult for these colors with identical hues. After adjusting Pillbox image labelling using the output results, manually misclassified images can be corrected, which improves classification accuracy to as high as 99%. However, until labelling is further investigated, the lower white and gray results are used in calculating overall accuracy.

5 CONCLUSIONS

Under the idea of basic component colors for classification, the features are extracted as the basis of red, green and blue color related features. Furthermore, the chromaticity, since it combines saturation and hue (measuring color proportion over all values of luminance), provides a simple model for the color perceived by humans. Because of uncertainty regarding labelling of white and gray, performance ranged from over 98% for nine of the colors to 97.85% for orange, 95.14% for white, and 90% for gray. Perfect accuracy (100%) is yielded as the classification result for both cyan and pink color Pillbox images. Overall, the classification accuracy obtained from all the 12 color categories is 97.90% which is higher than results obtained by (Madsen et al, 2013) and (Wan et al., 2015).

Future research can be focused on principal feature analysis to find the most significant features, accuracy obtained from different current feature groups. Additional data could enable classification by unsupervised learning algorithms such as deep learning. And, as to make the algorithm more generalized and applicable in real world conditions, a noise level study on the pill images should be performed, taking into account non-optimal condition such as uneven illumination, image blur and heterogeneous backgrounds, etc.

As the first step in computing the visual content in pill color recognition, we have already made progress in reference image-based classification. Additional research should also focus on imprint identification, score marks and analysis of consumer-quality pill identification, to enable identification of pills under real-world conditions.

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