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THE DRUG TABLET IMAGE RETRIEVAL SYSTEM BASED ON CONTENT-BASED IMAGE RETRIEVAL

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Abstract. *Drug tablets morphology is important in illicit drug investigation. The tablet shapes and impressions can be used to classify drugs at crime scene. However, it is a difficult task for law enforcement officers to correctly classify drug tablets on site through naked-eye examination without utilizing proper drug tablet databases. To better assist investigators in drug classification, we have developed an online drug tablet image retrieval system based on content-based image retrieval techniques. The proposed system provides a practical and rapid tool for investigators to classify tablets by morphological characteristics. Traditional drug information query systems adopt text keywords as searching inputs. The correct retrieval results depend on the precision of keywords. However, it is also difficult for each user to describe an object using the same exact keywords. The proposed system uses features, extracted from the content of an image directly, as query data instead of human-described keywords. It can avoid the uncertainty caused from subjective keywords. From experimental results, the proposed system shows its capability of the drug tablet image retrieval.*
Keywords: Morphology, Drug tablet image, Content-based image retrieval

1. **Introduction.** At crime scene, drug tablet identification is now performed just by naked-eye examination. It is difficult for an officer (even well-trained and experienced one) to perfectly identify unknown drug tablets without the assistant of equipments. Occasionally, the officers fail to identify the illicit drug, the unknown tablets are considered legal, and then the suspect walks away. This can be a serious problem in illicit drug investigation. Instrumental chemical analysis can correctly identify drug tablets in forensic laboratory; however, it is not easy for laws enforcement officers to do such analysis at crime scene. Drug tablet morphology (shapes and impressions) is important in illicit drug investigation and it can be used to classify drugs at crime scene.

The drug tablet manufacturer identification is based on the trademarks and characters imprinted on the surface of tablets during production. These imprints of trademarks are considered as primary identification features. The public can use government-built on-line drug information query systems to obtain drug tablet information. The same problem of these systems is that users need to input precise retrieval keywords for obtaining correct information. Since users may use different keywords to describe the same object, these uncertain keywords will then cause different retrieval results. In recent years, SICAR®6 (the management system for shoe print and tire mark evidence) [1] has been developed for forensic applications. This system tries to use "feature-selecting" to improve the uncertain problem of text-description. However, the uncertainty still exists since the features are selected by examiners, even if the examiners are trained.

Content-based image retrieval (CBIR) methods show their capability of providing a way to input more direct and precise information for auto-identification [2-10]. Some commercial applications have been proposed, such as Nokia's Point & Find and Google's Goggles services. These services can provide the identification for various trademarks or barcodes in commercial purposes. The applications of CBIR in forensic science have been advocated by many researches and experts, such as forensic image databases [2-4], crime scene images [5,6], case-specific images and digital forensic investigation [7], and pistol image retrieval [8]. There are some drug tablet retrieval systems on websites [11,12]. These systems use human-described keywords to retrieve the interested drug tablet. These keywords include color, shape, letters or numbers of the tablet imprint. Geradts and Bijhold proposed a content-based method for forensic image databases [3]. They used features based on curvature scale-space representation. Chen et al. [13] used five features with the feature weights to identify the drug tablets. However, it is difficult for users to set proper feature weights. Besides, these two methods are sensible to light variation.

To assist law enforcement officer in illicit drug identification, we develop an online drug tablet image retrieval system based on CBIR techniques. In the proposed framework, officers can find information about suspected drug tablets from databases by taking pictures of the tablets at crime scene. The officers can use a handheld camera device to take pictures and submit the pictures to the remote retrieval system for querying with wireless communication (see Figure 1). In a short time, they can receive the retrieval results for identifying the suspect drug tablets. In addition, the drug database information can be updated frequently when any new or unknown types of illicit drug tablets are found.

The shape and imprint mark are usually used to distinguish the drug manufacturers, especially for the illicit drug identification task. In the proposed method, we use the signature feature to check the tablet shape and we extract the features of the imprint mark with the Gabor filters. The Gabor filters have three important properties: (1) they can be designed to be highly selective in frequency while displaying good spatial localization; (2) they resemble the receptive field profiles of the simple cells in the visual pathway; (3) they are band-pass filters; that is, they have tunable orientation and radial frequency bandwidth and tunable center frequency. With those properties, we can use the Gabor filters to extract a specific band of frequency components from the drug tablet images. The Gabor features are useful in the scaling, rotation, translation and side-light invariant recognition of the imprint mark [14].

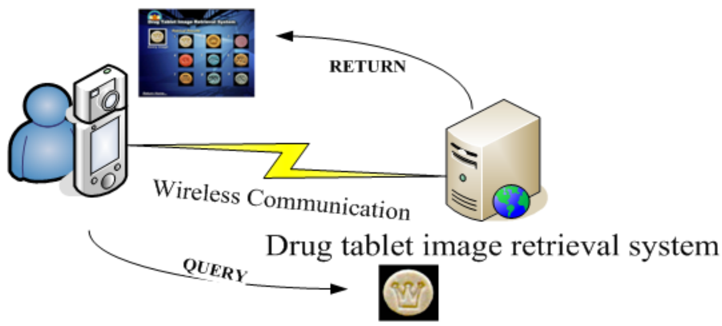


FIGURE 1. The framework of the proposed system

2. **Methods.** The proposed method uses the shape and imprint mark of a drug tablet to identify the drug. The procedures of the proposed method are shown in Figure 2. A drug tablet picture is taken by a handheld device and uploaded to the proposed retrieval system. In the system, each query drug tablet image is transferred into an image with the gray scale format. The shape detection and shape feature extraction procedures are performed. Then, some candidate drug tablet samples (twenty in our experiments) are picked out according to the shape similarity. In the imprint mark matching, we normalize the previous candidates and extract their features by using Gabor filters. We list nine samples which are most similar to the query tablet image as the retrieval results.

2.1. **Image color transformation.** To simplify the processes of the similarity matching in shape and imprint mark, we convert drug tablet images from color into gray scale [15] by the following equation:

$$b = 0.299R + 0.587G + 0.114B, \tag{1}$$

where b is denoted as the gray scale (R, G, and B are the red, green, and blue components respectively) at the pixel (x, y). An example of image color transformation is shown in Figure 3. The drug tablet image is captured by a phone camera with 256×256 pixels.

2.2. **Shape detection.** In order to simplify the shape detection, we place the drug tablet on a black plate and took the picture (see Figure 4(a)). In Figure 4(b), we use a threshold T to separate the drug tablet region $s(x, y)$ from the background with the following equation:

$$s(x, y) = \left\{ \begin{array}{ll} 1 & \text{if } b(x, y) \geq T \\ 0 & \text{otherwise} \end{array} \right\}, \tag{2}$$

where $b(x, y)$ is the original gray scale image, and the threshold T is calculated by using the Kapur threshold algorithm [16].

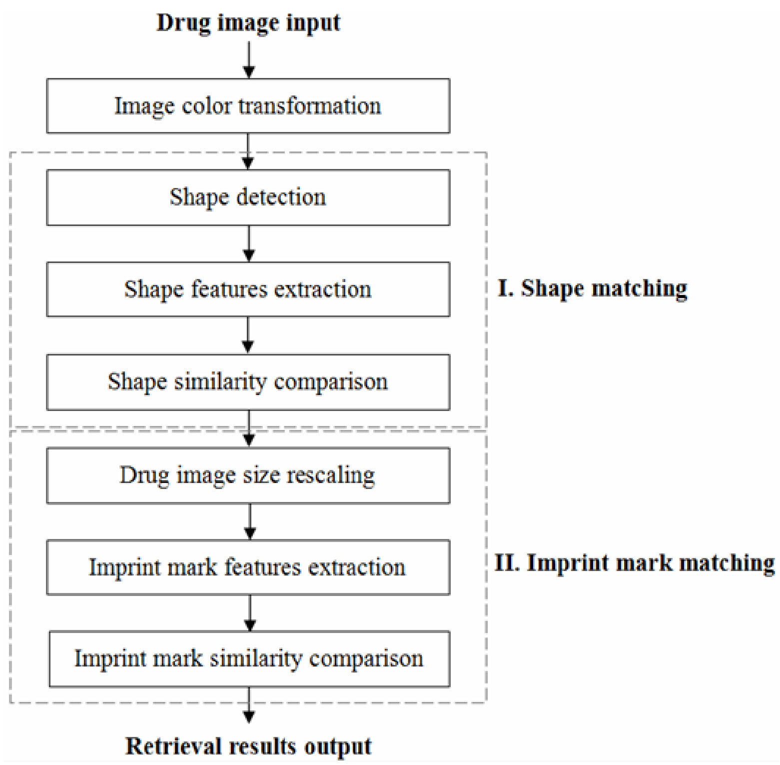
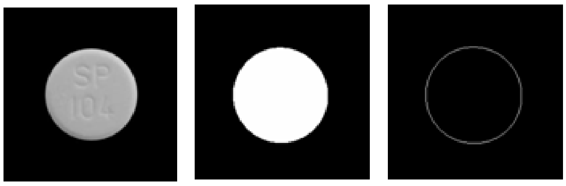


FIGURE 2. The procedures of the proposed method

(a) (b)

FIGURE 3. Image color transformation: (a) a color drug tablet image; (b) the converted gray scale image



(a) (b) (c)

FIGURE 4. Shape detection: (a) the original gray scale image $b(x, y)$; (b) the drug tablet region (white color $s(x, y) = 1$, $T = 77$); (c) the contour of the drug tablet $\tilde{s}(x, y) = 1$

After obtaining the drug tablet's region $s(x, y)$, shape detection is performed with the gradient operator. The gradient operator uses one 3×3 kernel (see Figure 5) which is convolved with the $s(x, y)$ to calculate approximations of the derivative $\tilde{s}(x, y)$ which is the contour of the drug tablet [15].

1	1	1
1	−8	1
1	1	1

FIGURE 5. A mask is used for detecting the contour of a drug tablet image

2.3. **Shape features extraction.** To extract the shape features, we use the 1-D signature representation to describe the tablet contour. We select the left most point in the contour $\mathbf{q}(= \{q_1, q_2, \ldots, q_\mathrm{H}\})$ as the starting point $q_1(x_{q1}, y_{q1})$, then follow the pixels in the contour one by one with the clockwise direction, and compute the distance, r, from the centroid, $\mathrm{C}(x_\mathrm{c}, y_\mathrm{c})$, to the points of the contour (see Figure 6(a)). The distance r(n) is defined as the following equation

$$\mathrm{r(n)} = \sqrt{(x_\mathrm{c} - x_{q\mathrm{n}})^2 + (y_\mathrm{c} - y_{q\mathrm{n}})^2}, \quad \mathrm{n} = 1 \sim \mathrm{H}, \tag{3}$$

where $(x_{q\mathrm{n}}, y_{q\mathrm{n}})$ is the coordinate of the n-th pixel q_n, H is the pixel number in the contour. In addition, r(n) is rescaled to $0 \sim 100$. The signature of Figure 6(a) is shown in Figure 6(b).

The mean μ and variance ρ of the signature r(n) are defined as

$$\mu = \frac{1}{\mathrm{H}}\sum_{\mathrm{n}=1}^{\mathrm{H}} \mathrm{r(n)}, \quad \rho^2 = \frac{1}{\mathrm{H}}\sum_{\mathrm{n}=1}^{\mathrm{H}} (\mathrm{r(n)} - \mu)^2. \tag{4}$$

We denote a vector $\boldsymbol{v} = (\mu, \rho)^T$ to represent the signature features of shape. The contours, signatures and feature vectors of some tablet samples are shown in Figure 7.

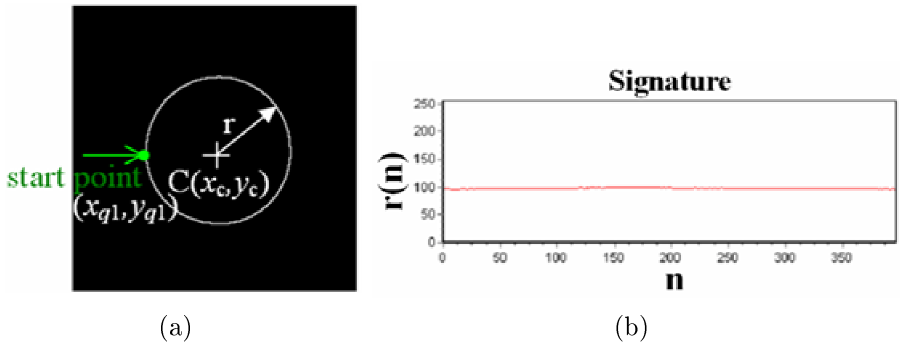


FIGURE 6. Shape and signature: (a) the start point in the contour; (b) the signature

2.4. **Shape similarity comparison.** After obtaining the feature vector $\boldsymbol{v}$, the shape similarity comparison is carried out to find twenty similar drug tablet samples. We use the Euclidean distance to compute similarity d_s between the query drug tablet image and the other drug tablet samples in the database. The similarity degree of the shape is defined as

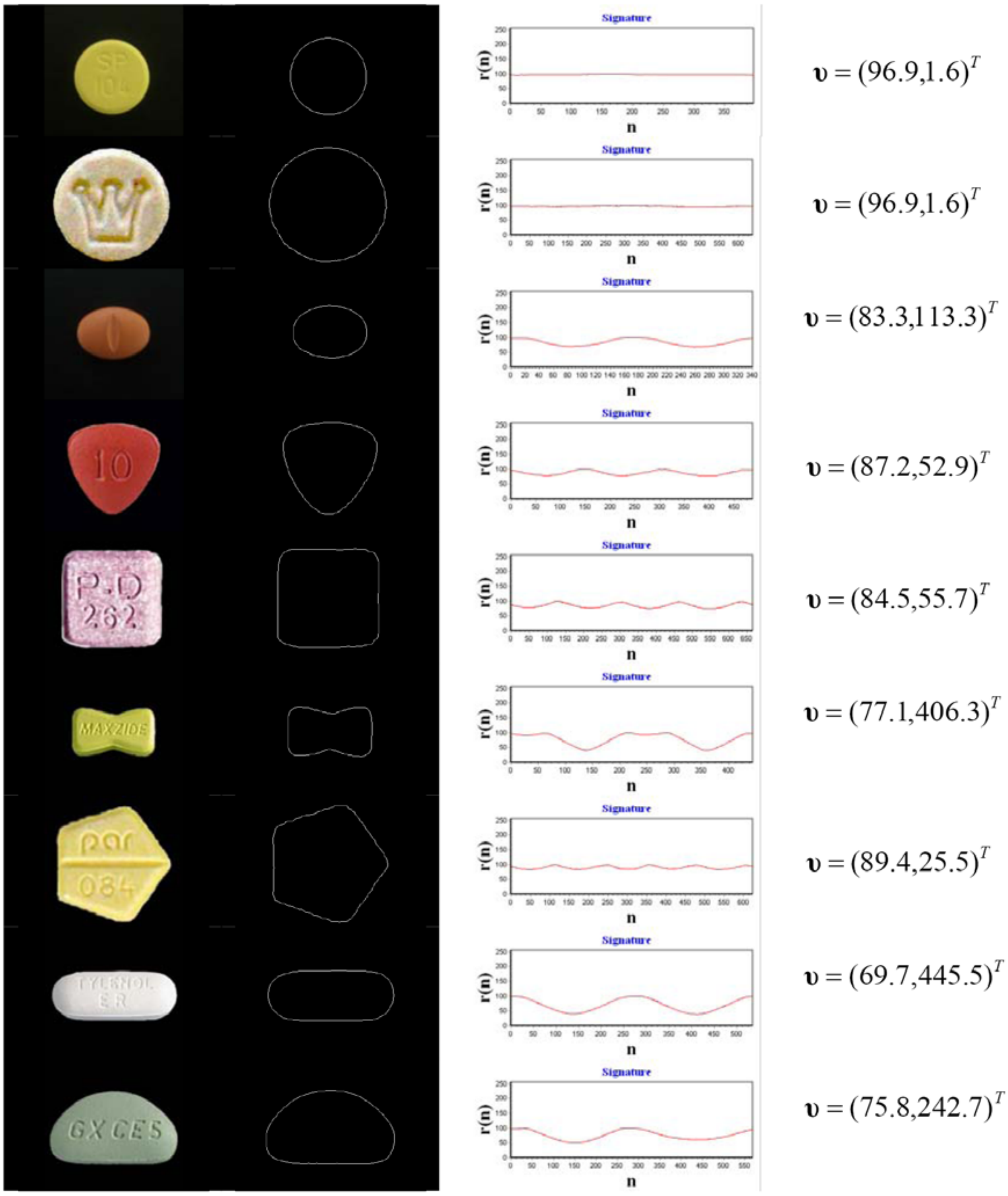
$$d_s^k = \|\boldsymbol{v}_k - \tilde{\boldsymbol{v}}\|, \quad k = 1, 2, \ldots, W, \tag{5}$$

where $\boldsymbol{v}_k$ is the feature vector of the kth drug tablet sample in the database, $\tilde{\boldsymbol{v}}$ is the feature vector of the query drug tablet image, W is the number of samples, and $\|\mathbf{a}\| = (\mathbf{a}^T\mathbf{a})^{1/2}$ is the Euclidean norm. The most similar drug tablet sample has the least value among others $(\min\{d_s^k\})$. The samples of the similarity are shown in Figure 8. Figure 8(a) is a query drug tablet image, and Figure 8(b) shows the matched samples in the database.

2.5. **Region size rescaling.** In the second step, the imprint mark similarity matching is done by Gabor features. In order to simplify the Gabor feature extraction, we need to rescale the region size of the drug tablet image. We use the spline interpolation to normalize the region as 600 pixels. An example is shown in Figure 9.

2.6. **Imprint mark feature extraction.**

2.6.1. *Gabor filtering.* Gabor filters have been applied to feature extraction in 1978. Recently, a novel framework of Gabor filters has proposed to construct the feature space. The feature space is constructed from Gabor filter responses and invariant search operations [17-24].



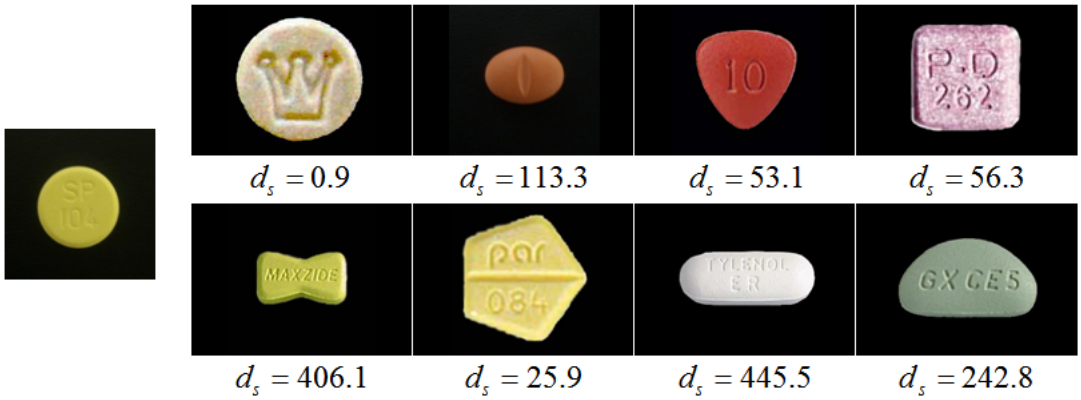
(a) (b) (c) (d)

FIGURE 7. The contours, signatures and feature vectors of drug tablet images: (a) drug tablet images; (b) contours; (c) signatures; (d) feature vectors $\boldsymbol{\upsilon} = (\mu, \rho)^T$

2.6.2. *Gabor functions and response.* The 1-D Gabor filter can be generalized to a 2-D function of space and spatial frequency. A normalized 2-D Gabor filter function ψ is defined as

$$\psi\left(x, y; f, \theta\right) = \frac{f^2}{\pi w \eta} e^{-\left(\frac{f^2}{w^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{j2\pi f x'}, \tag{6}$$

where $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\cos\theta$, f is the frequency of a sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian envelope and the sinusoid, w is the width of the filter along the plane wave, and η is the spatial width perpendicular the



(a) (b)

FIGURE 8. The similarity of the shape: (a) query drug tablet image; (b) eight matched examples

(a) (b)

FIGURE 9. Region size rescaling: (a) the original image region; (b) the rescaled image region

plane wave. The Gabor feature space consists of responses calculated with Gabor filters, invariant search operations can be established based on the properties of translation, rotation and scaling. The Gabor filter response γ_ξ can be calculated by convoluting ψ with the pixels ξ of the drug tablet region (see Equation (7)).

$$\gamma_\xi(x, y; f, \theta) = \xi(x, y) * \psi(x, y; f, \theta) = \int \int_{-\infty}^{\infty} \xi(x_\gamma, y_\gamma) \psi(x - x_\gamma, y - y_\gamma; f, \theta)\, dx_\gamma dy_\gamma, \quad (7)$$

where the symbol "$*$" denotes 2-D convolution operation. In Equation (7), Gabor filters provide a multi-resolution structure which consists of filters tuned to several different frequencies and orientations.

2.6.3. *The invariance theorems of Gabor filters.* The invariance theorems of Gabor filters are described in this section. The filter bank consists of several filters with different parameters. The selection of discrete rotation angles θ_i has been proposed [24],

$$\theta_i = \frac{i2\pi}{\alpha}, \quad i = \{0, \ldots, \alpha - 1\}, \quad (8)$$

where θ_i is the ith orientation and α is the total number of orientations. As a result of the responses of Gabor filters on angles $\pi \sim 2\pi$ are complex conjugates of responses on $0 \sim \pi$. In our experiments, $\alpha = 8$ is indicated. The frequencies f_j are defined as

$$f_j = \frac{f_{\max}}{\varphi^j}, \quad j = \{0, \ldots, \beta - 1\}, \quad (9)$$

where f_j is the jth frequency, $f_{\max}$ is the highest frequency and φ is the frequency scaling factor. $\varphi = 2$ and $\varphi = \sqrt{2}$ are for octave spacing and half-octave spacing, respectively. In our experiments, $\varphi = 2$ and $\beta = 5$ are used as the frequency parameters.

The feature space is constructed by using Equation (10) and the parameters are selected by Equations (8) and (9). A feature matrix G can be constructed from the interested orientations $\theta_0, \ldots, \theta_{\alpha-1}$ and frequencies $f_0, \ldots, f_{\beta-1}$ at the location (x_0, y_0),

$$G = \begin{pmatrix} \psi(x_0, y_0; f_0, \theta_0) & \psi(x_0, y_0; f_1, \theta_0) & \cdots & \psi(x_0, y_0; f_{\beta-1}, \theta_0) \\ \psi(x_0, y_0; f_0, \theta_1) & \psi(x_0, y_0; f_1, \theta_1) & \cdots & \psi(x_0, y_0; f_{\beta-1}, \theta_1) \\ \vdots & \vdots & \ddots & \vdots \\ \psi(x_0, y_0; f_0, \theta_{\alpha-1}) & \psi(x_0, y_0; f_1, \theta_{\alpha-1}) & \cdots & \psi(x_0, y_0; f_{\beta-1}, \theta_{\alpha-1}) \end{pmatrix}. \tag{10}$$

The feature matrix G can be used as a feature space for any classifier (see Figure 10).

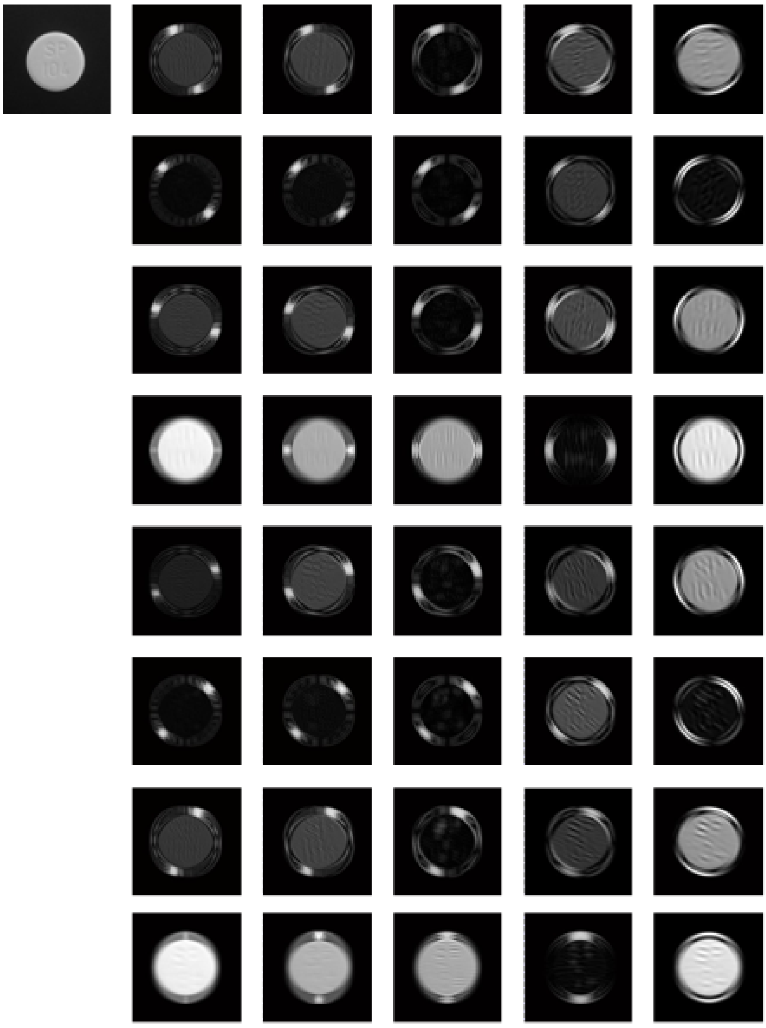


FIGURE 10. The magnitude of feature matrix G

Each of the Gabor filters has the real and imaginary parts that are conveniently implemented as the spatial mask of an $\alpha \times \beta$ size. For a given input image, the magnitude of a filtered image is obtained by using the Gabor filter as following:

$$Fs(i,j) = sum\left\{[\psi(x,y;f,\theta)_r * \xi(x,y)]^2 + [\psi(x,y;f,\theta)_i * \xi(x,y)]^2\right\}^{1/2}, \tag{11}$$

where $Fs(i,j)$ is the Gabor feature at the point (i,j) in the frequency plane for $i = 0, \ldots, \alpha - 1$ and $j = 0, \ldots, \beta - 1$. The $\psi(x,y;f,\theta)_r$ and $\psi(x,y;f,\theta)_i$ represent the real and imaginary parts of the Gabor filter which are separated from Equation (7). The Gabor magnitude feature is also related to the local power spectrum. As Equations (8) and (9), $i = 0, \ldots, \alpha - 1$, $\alpha = 8$ and $j = 0, \ldots, \beta - 1$, $\beta = 5$, the matrix G with 8×5 elements is defined in Table 1. That is, we use the matrix G as the Gabor feature space $Fs\,(i, j)$ of a drug tablet image. The 8×5 elements of a vector represent the magnitudes of the 8×5 filter bank, where each element holds the total amplitude of a filter response and is denoted as u. We use the symbol $\mathbf{u} = (u_1, u_2, \ldots, u_t, \ldots, u_{40})^T$, where $t = 5(i-1) + j$, to represent the vector of Gabor features.

Table 1. The magnitude of the feature matrix G

$Fs\,(i,j)$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	48186	64517	38745	99656	191022
$i=2$	23571	30313	31625	90254	63635
$i=3$	52021	68554	41614	108065	202136
$i=4$	25542	14122	17146	42834	300590
$i=5$	46071	62566	38126	95663	187203
$i=6$	20885	26726	29171	79562	57397
$i=7$	45942	62225	39256	95487	185397
$i=8$	254633	140255	168494	41513	294347

2.7. **Imprint mark similarity comparison.** We use the Euclidean distance d_I^k as the similarity between the query drug tablet image and the kth drug tablet sample in the database:

$$d_I^k = \|\mathbf{u}_k - \tilde{\mathbf{u}}\|, \quad k = 1, 2, \ldots, W, \tag{12}$$

where $\mathbf{u}_k$ is denoted as the Gabor feature of the drug tablet sample in the database, and $\tilde{\mathbf{u}}$ is denoted as the Gabor feature of the query image. The most similar target image has the least value among others $(\min\{d_I^k\})$, and other target images are shown by ranking the similarity degrees progressively.

3. **Experimental Results.** To evaluate the performance of our method in the practical illicit drug identification, the test image samples include clinical and illicit drug tablets in the experiments. The clinical drug tablet images (1073 samples) are collected from Deaconess Health System's drug tablet images database. And the illicit drug tablet images (207 samples) are captured from the seized illicit drug tablets at crime scenes. Five experiments are carried out to evaluate the proposed method as shown in Figures 11-15. In the experiments of Figures 11-14, the drug tablet samples are all without surface damage. Some drug tablets with surface damage are used in the last experiment of Figure 15. All sample images are captured with sufficient light by a handheld camera device with 256×256 pixels.

In Figure 11, the query image is a cold medicine tablet. Nine target images are ranked according to the similarity degrees. Figure 12 shows the query image with a different shape. Figure 13 shows the query image with translation. From Figure 12 and Figure 13, we can see the first two retrieval images are exactly the target images. That is, these two drug tablet images can be correctly identified even they are with translation, rotation or scale phenomenon. Figure 14 shows the retrieval results of the drug tablet image is obtained with a side-light condition. We can see target images are found. The first five ranked images belong to the same tablet and they are taken in different side-light conditions.

FIGURE 11. Retrieval results of a cold medicine tablet image

FIGURE 12. Retrieval results of the query image with a different shape

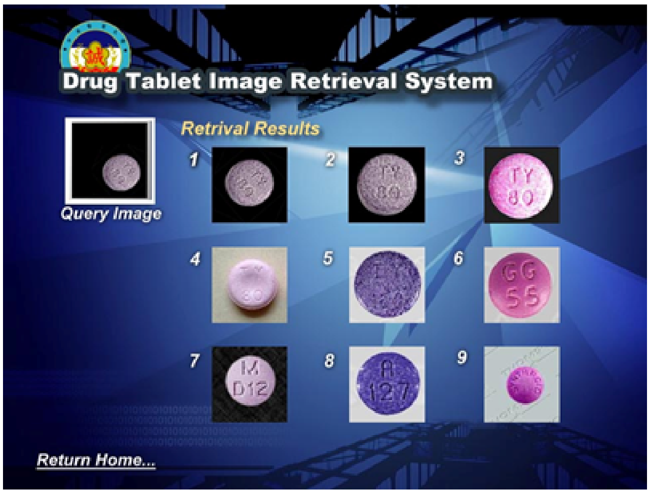


FIGURE 13. Retrieval results of the query image with translation

Figure 14. Retrieval results of different light conditions

Figure 15. A drug tablet with the morphology of a drug tablet is damaged

Our method is based on the morphology of a drug tablet. As a result, identification accuracy is affected while the morphology of a drug tablet is damaged. Figure 15 shows an example. In this case, the proposed method fails in the identification task.

4. Conclusions.

In this paper, we have developed an online drug tablet image retrieval system based on the content-based image retrieval method to assist law enforcement officers in drug tablet identification. The proposed method focuses on the identification of the drug tablet without surface damage. In addition, the system is a powerful, time-efficient and easy to use tool for officers. We use the signature feature and Gabor features to represent the shape and imprint mark of a drug tablet image, respectively. The Gabor feature spaces are especially useful in the scaling, rotation, translation and side-light invariant recognition of objects. Furthermore, the experimental results show the proposed system is a practical and rapid tool for laws enforcement officers to identify the drug tablets by the morphology.

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