AUTOMATIC IDENTIFICATION OF PRESCRIPTION DRUGS USING SHAPE DISTRIBUTION MODELS

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ABSTRACT

Medication errors are one of the safety problems most frequently seen in hospital organizations. It is estimated that 12.2% of all hospitalized patients are involved in some form of adverse drug event (ADE) [1]. A significant amount of ADEs result from handing the incorrect drug to a patient or prescribing the wrong medication.

This paper introduces a simple yet robust classification technique that can be used to automatically identify prescriptions drugs within images. The system uses a modified shape distribution technique to examine the shape, color, and imprint of a pill and create an invariant descriptor that can be used to recognize the same drug under different viewing conditions. The proposed technique has been successfully evaluated with 568 of the most prescribed drugs in the United States and has shown a 91.13% accuracy in automatically identifying the correct medication.

Index Terms— Feature extraction, Image classification, Image retrieval, Object Recognition, Image Processing

1. INTRODUCTION

Patient care and patient safety are the primary goals of any hospital organization or clinic. Adverse drug events (ADEs) such as those resulting from medication errors are a leading source of safety violations that often result in extended hospitalization for patients and higher overall costs of care [2]. It is estimated that 12.2% of all patients that visit a hospital in the United States will experience some form of ADE [1]. Recent studies have demonstrated that most of the medication errors occur during transition of care [3]. Transition of care are defined as the times when a patient is moved to a different department/building, rushed to a different hospital, receiving multiple medication changes over a short period of time, and being discharged from a hospital.

The automatic identification of prescription drugs within images opens new opportunities so clinicians, nurses, and pharmacists can verify the correctness of medications before dispensing them to patients, and patient can verify the drugs before taking them. The correct implementation of such a system promises to have a great impact on patient safety and potentially to reduce the cost associated with healthcare.

2. BACKGROUND

During the last few years, the identification of prescription drugs has been an important topic that has resulted in the development of multiple web-based frameworks and databases. Sites such as Drugs.com [4], NLM Pillbox [5], WebMD [6], and DailyMedPlus [7] offer search features where users can manually describe color, shape, imprint, and size of a pill in an attempt to identify the drug. Manual entry is a time consuming process that is prone to human error and does not fit the dynamic conditions often seen in clinical settings. To be able to create a system that can be used during the transition of care, it must be reliable, easy to use, and fast.

In the United States, every drug has a National Drug Code (NDC) number which works as a unique product identifier. In addition, Structured Product Labeling (SPL) is used to describe all the information associated to any drug approved for consumption [8]. Based on our analysis of 14,085 public SPL records, 46.76% of the approved pills are round, 26.30% are oval, and 21.60% are capsules. In addition, our analysis suggests that 44.29% are white, 12.90% yellow, 9.10% orange, and 9.00% blue. This information demonstrates the complexity of the pill identification task, given that any technique to extract information must be able to capture subtle structural differences and characterize similar color distributions. Figure 1 shows a sample set of some of the images used to design our classification model. Note that the first and last pills in Figure 1 are very similar to demonstrate the challenges of the classification task.

3. APPROACH

In general, there are three characteristics that any technique to automatically identify pills must capture: *shape, imprint*, and *color*. Given the frequency of indistinguishable and subtle differences between pills, current state-of-the-art object recognition techniques that are based on keypoints such as

Fig. 1. Sample set of some of the images used to design our system. The first and last images show different forms of the same pill to highlight the complexity of the problem.

SIFT do not provide a quick alternative to design a classification model [9, 10]. Instead, imaging techniques specific for this problem must be designed. In this section we describe how the shape, imprint, and color of the pills are captured to create a simple and robust system to automatically identify prescription drugs.

3.1. Shape

Effective characterization of shape differences is a fundamental problem that needs to be considered when designing an automatic pill identification system. Inspired by the effectiveness and simplicity of shape distributions models [11], a classification model was designed to capture the shape properties of a pill.

The key idea is to represent the shape of a pill by using a shape distribution model sampled from the centroid of the drug. Given a mask $\mathcal{M}$ describing the location of the pill, the pixel distribution within the area is analyzed and used to estimate the center of mass $\mathcal{C} = \{c_x, c_y\}$. By exploiting the fact that pills are convex objects, $\mathcal{K}$ equally spaced points $P = \{p_1, p_2, p_3, \ldots, p_k\}$ are estimated along the boundaries of the pill. Once the points are obtained, the Euclidean distance $d_i = \sqrt{(c_x - p_{i_x})^2 + (c_y - p_{i_y})^2}$ between the center $\mathcal{C}$ and each $p_i \in P$ is estimated and normalized. From the distance distribution, features such as the minimum, maximum, average, standard deviation, and roundness of the pill are estimated and used to describe shape. Note that such a feature is invariant to rotation, translation, scaling, and illumination changes. Figure 2 (top) shows two pills and some of the lines that were used to estimate the shape distribution model.

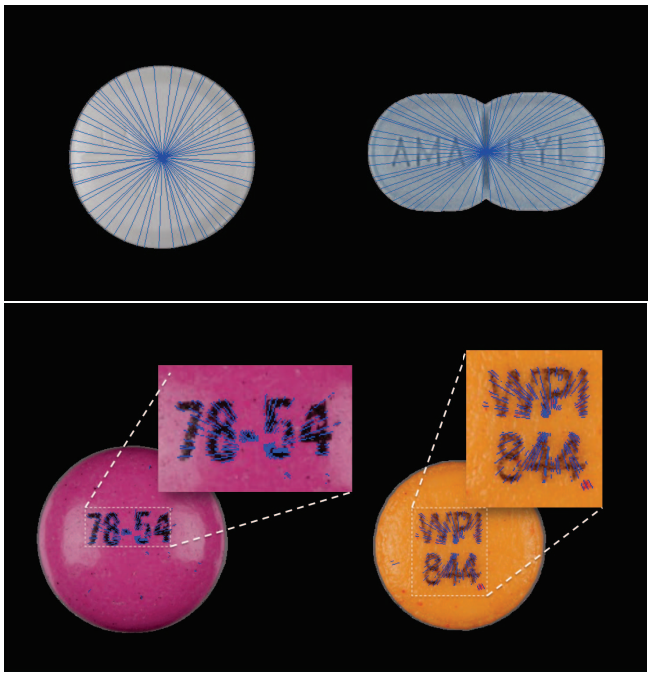

Fig. 2. (top) A shape distribution model sampled from the centroid of the pill is used to capture shape properties. (bottom) An extension of shape distribution models is used to describe imprint by only considering edge points.

3.2. Imprint

A key motivation for our design was simplicity and efficiency. In particular, we wanted a technique where the different features could be extracted in parallel and using minimum computational resources. The simplicity and efficiency requirements will make it easy to port the proposed algorithm to mobile devices, tablets, and thin clients.

The general concept of the shape distribution model is also used to create a rotationally invariant feature to describe the imprint of a pill. Given a mask $\mathcal{M}$ describing the location of the pill, morphological operations are used to estimate $\mathcal{M}'$, a reduced version of the original mask where $\mathcal{M}' \ll \mathcal{M}$. This step is done to reduce the high frequency signals often observed within the boundaries of an object. An edge map is estimated for the pill and masked by $\mathcal{M}'$. Then, following the same steps as before, the center of mass $\mathcal{C}$ is estimated and $\mathcal{K}$ points along the boundaries of a pill are computed. For each $p_i \in P = \{p_1, p_2, p_3, \ldots, p_k\}$, the (C, p_i) line is traversed and a set $E = \{e_1, e_2, \ldots, e_k\}$ is estimated with the number of edge points found along each path. The number of edge points will correspond to the frequency of finding text, imprints, symbols, and engraves between the center and boundaries of the pill. Once E is normalized, features such as average, standard deviation, minimum, and maximum are used to describe the imprints of a drug in a scale and rotationally invariant approach. The advantage of our imprint de-

scriptor is that the sampling frequency around the centroid of the pill (where imprints are usually located) is higher than around the outer areas, thus augmenting the emphasis of imprint edge points. Figure 2 (bottom) shows a pill with blue stripes within the imprint representing the areas of the $(\mathcal{C}, p_i)$ lines that were included in the set E.

3.3. Color

Color is one of the most important characteristics of a pill. In our effort to design a simple approach that could be used in dynamic settings such as those often seen in hospitals, the shape distribution technique was also extended to capture color. Just as before, given a mask $\mathcal{M}$ describing the position of the pill, the center of mass $\mathcal{C}$ is estimated and $\mathcal{K}$ points along the boundaries are computed. The pill image is converted to HSV to more effectively capture color changes. For each $p_i \in P = \{p_1, p_2, p_3, \ldots, p_k\}$, the $(\mathcal{C}, p_i)$ line is traversed and each pixel value along the path (in the Hue and Saturation channels) are added to a list from where two 20-bin histograms are estimated.

To also capture color differences within the pill such as those caused by text and imprints, a second hue histogram is estimated for approximately one third of the pill closest to the center of mass. A mask $\mathcal{M}' \ll \mathcal{M}$ was used to define the internal region of a pill to be considered for the imprint hue histogram.

The individual features are combined into a single feature vector of color, imprint, and shape, and used to classify and identify prescription drugs.

4. RESULTS

To test our classification technique, images for 568 of the most prescribed pills were obtained from the National Library of Medicine. The images were captured under the same conditions, using the same camera sensor, lights, and camera resolution. To test the accuracy of the proposed method, query images were generated by randomly translating, rotating, and scaling the images, in addition to randomly changing the brightness and contrast of the images by $\pm 40\%$.

First, we explored the effectiveness of our image descriptor by comparing each feature vector with the rest of the pills. Figure 3 shows a matrix with some of our results. From the results we can see that our simple feature descriptor is effective at capturing the subtle differences between individual pills and always the minimum weight of a pill is with itself, thus forming a diagonal line.

Our second experiment was to measure how the classification model performs with increasingly harder query images. For this experiment eight query images were generated for every image in our dataset. Figure 4 shows a heat map with the weights between 40 images of five different pills.

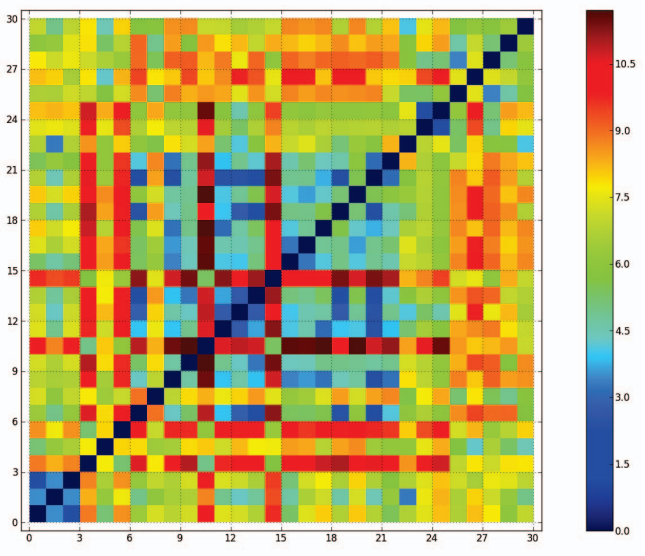

Fig. 3. Heatmap showing the Euclidean distance between 30 random pills. The diagonal likes shows that the minimum distance of every pill is with itself, demonstrating the our technique can capture the subtle differences between some of the pills.

From the results we can see that, after sorting the query images by their NDC numbers, the weights between the eight query images belonging to the same drug are often the lowest values, thus forming a diagonal line with 8×8 blocks. As expected, the distance between the pills increase as the noise and luminance of the images is changed. However, the results demonstrate that even when the image is rotated, translated, and intensities changed more than 40%, our shape distribution-based image descriptor can still be used to successfully identify the correct pill.

Our third experiment was designed to measure the accuracy of our technique. It is important to understand that multiple pills can share the same front face image given that the only difference between them could be the imprint in the back face containing the doses information (e.g. 50mg vs 25mg). Since the primary motivation of our approach was to create a classification technique that could quickly return the top matches of a given pill from a single image, a successful identification was defined as the correct pill being among the top 5 matches.

Four experiments with 1000 query images demonstrated that our system can return the correct pill within the top 5 matches with $91.13\% \pm 1.52$ accuracy. These results demonstrate that our technique is robust under translation, scaling, rotation, and luminance changes. In addition, our results demonstrate the potential of using such a classification system within clinical settings.

Regarding performance, given a 1200x800 image, the

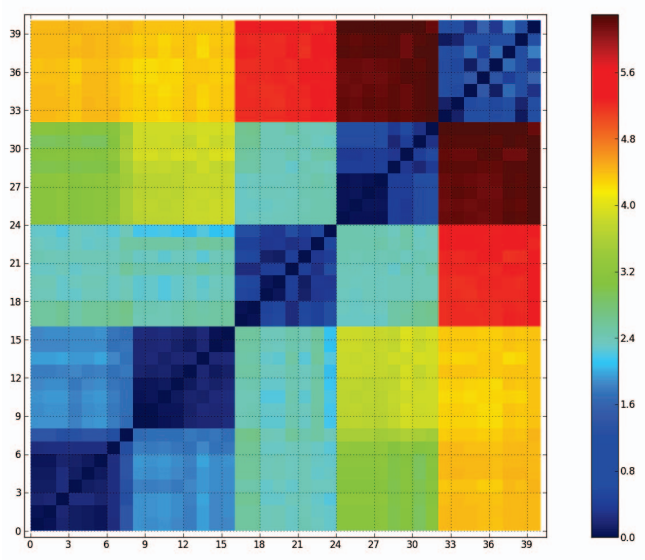

Fig. 4. Heatmap showing the Euclidean distance between 40 query images representing five different pills.

non-optimized and non-parallel feature extraction step on average takes 0.322 ± 0.032 seconds to extract the complete feature descriptor in an Intel Core i5 2.4GHz and 0.410 seconds to return the top matches. That is, our techniques can receive an image, extract shape, imprint, and color features, and return the top matches of a given pill in less than 1 second. These results show that the proposed technique has the potential to be used in the dynamic and rapidly changing clinical environments.

5. CONCLUSION

This paper introduces a simple and robust classification technique that can be used to automatically identify prescriptions drugs. The system uses a modified shape distribution technique to examine the shape, color, and imprint of a pill and create an invariant descriptor that can be used to recognize the same drug under different conditions. The proposed technique has been successfully tested with 568 of the most prescribed drugs in the United States and has shown a 91.13% accuracy in automatically identifying the correct drug, where a successful identification was defined as the correct pill being among the top 5 matches.

The proposed identification technique assumes that the image contains a top view/birds-eye-view of the pill and complete view of the pills so that the full contour of the pill can be extracted. In future work we plan to extend our system to accept views of the back of a pill as a method to refine the results. Furthermore, our current system uses uniform weights for the color, imprint, and shape features. In the future we plan to explore assigning different weights to individual feature sets.

6. REFERENCES

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