ICIC Express Letters
Part B: Applications
Volume **11**, Number **7**, July **2020**

ICIC International ©2020 ISSN 2185-2766
pp. **661–666**

CLASSIFICATIONS OF TABLETS AND PILLS BY THE SHAPE THROUGH UNSUPERVISED LEARNING

Minji Park, Jinhyung Kim and Taezoon Park*

Department of Industrial and Information Systems Engineering
College of Engineering
Soongsil University
369 Sangdo-ro, Dongjak-gu, Seoul 06978, Korea
*Corresponding author: tzpark@ssu.ac.kr

Received January 2020; accepted April 2020

Abstract. *Medication error is one of the most common types of adverse events happening in healthcare. One of the root causes of medication error is that too many drugs share similar characteristics in their names, shapes, and colors. However, the humans' perceptual structure of images is not clearly identified yet. This study tried to apply unsupervised learning techniques to discovering the possible underlying structure from drug images. Totally 1,500 images selected from 15,080 images were analyzed and the result suggested three dimensional structures of brightness, color and arrangement of images. Drug images are allocated into four clusters: big tablet, white circular, dark colored oval, and colored mixture. Further analysis for capturing shape characteristics is needed for better classification.*

Keywords: Medication error, Similar drugs, Visual perception, Unsupervised learning

1. **Introduction.** Medication error is one of the most common adverse events happening in every hospital. American Institute of Medicine's IOM, 2006 reported that about 150,000 people die annually from drug use errors and 7,000 deaths due to medication errors [1]. A study in the United States estimates that 3,170 pairs of drugs are likely to be confused because of similar pronunciations of their phonetic names, resulting in 14 percent of patients who have had adverse drug reactions due to improperly prescribed medication. The biggest problem with drug substitution is that there are too many types of drugs of similar shape, and they are often placed close together. Moreover, there are no standards regulating the shape of drugs nor specific warning systems for similar drugs produced by different pharmaceutical companies. Numerous pharmaceutical companies in the world produce lots of drugs. Even though a company wants to differentiate the shape of drugs on their own, it is very difficult to achieve because there is no identified structure covering all drugs manufactured by other companies. In this sense, identifying the similarity structure of drug shapes is a starting point to understand the confusion in perception.

This study tries to identify the underlying perceptual structure showing how people perceive similar and different drugs. The challenges are that there are too many drugs to identify structure empirically, and there are limitations on human's perception and working memory. Human's limitation on working memory makes it difficult to conduct comparisons of many things together, which makes it infeasible to build a database to explain human confusion empirically. Instead, exploring the overall classification scheme by artificial intelligence technique could give a direction for an in-depth investigation in the future. Recently, there was a big progress in image processing and classifications by using deep learning algorithms. This study adopted unsupervised learning technique to identify the underlying structure of drug perception. Since there is no learning data set available,

DOI: 10.24507/icicelb.11.07.661

it is impractical to apply supervised learning or reinforced learning techniques. We used principal component analysis to visualize the aspects of the images coordinates in a pair of features. As projected images were visualized, we adopted the vector quantization for clustering images. Subject matter experts decided the name of clusters and axis by Delphi method.

2. Background.

2.1. **Medication errors.** Errors happening in the course of medication administration are very complex since it is involved with several steps from prescription, documentation, transcription, dispensing, and administration. One of the most common types of error is confusion of drugs because of their unnecessary similarity in name, shape, color, etc. [3]. Similar name causes confusion mostly in the prescription stage since physicians usually write prescriptions based on either the generic or brand name. On the other hand, similarly looking drugs cause confusion on dispensing and administrating stage. The shapes of drugs are mostly designed for the effective delivery of core substance, but the external characteristics, such as, color and shape, are not of great concern. Some company applies specific color and shape to building a brand image, but most drug manufacturers try to reduce the manufacturing cost by not changing the external shape of the drugs. For these reasons, there is a tendency that external shape of the drugs is similar one another. To prevent confusion several healthcare institutions have adopted automated drug dispenser, which actually helped reduce medication errors, but it is difficult to deny the potential threat of similarly looking drugs even for the over the counter drugs.

2.2. **Similarity & discriminations.** The limitation of human perception causes confusions and errors when differentiating similarly looking drugs. This type of confusion may happen not only for the tablets and pills, but also many other applications. Similarity between two objects is defined as the degree how much commonalities are observed between them [4]. By calculating quantifiable distances between observations, similarity distribution shows which observations are similar to others. The shared nearest neighbors (SNN) uses the extent to which data points share the nearest neighbor. In particular, the two data points shared if they are in the same category in each K cluster [5]. Since the type and range of features depend on the method of measuring similarity, the common way is to calculate the difference between the two features. Euclidean distance is a metric which measures the distance between each feature geometrically. In this study, we used the Euclidean distance to measure the similarity distance of each pill image.

2.3. **Unsupervised learning.** Unsupervised learning is a type of self-organized learning process that helps find previously unknown patterns in data set, which is contrasted against supervised learning or reinforcement learning. As compared to supervised learning, it is known as self-organization and allows modeling probability densities of given inputs [6]. As a hybrid method, semi-supervised learning uses supervised and unsupervised techniques together. A central application of unsupervised learning is in the field of density estimation in statistics [3], though unsupervised learning encompasses many other domains involving summarizing and explaining data features. Unsupervised learning is different from supervised learning in a sense that unsupervised learning intends to infer an a priori probability distribution whereas supervised learning intends to infer a conditional probability distribution conditioned on the label of input data.

Two of the main methods used in unsupervised learning are principal component and cluster analysis. Cluster analysis in unsupervised learning is to group, or segment, data sets with shared attributes in order to extrapolate algorithmic relationships. Cluster analysis is a branch of machine learning that groups the data that has not been labelled, classified or categorized. Instead of responding to feedback, cluster analysis identifies

commonalities in the data and reacts based on the presence or absence of such commonalities in each new piece of data. This approach helps detect anomalous data points that do not fit into either group.

3. **Method.** In order to discover the latent structure of image perception, unsupervised learning algorithm was used. The tablet images used in this study are from the online medical library provided by the Ministry of Food and Drug Safety. The library provides drug images which are used in South Korea. Among various types of drug images tablets, pills and capsules to be consumed by mouth are selected for this study. Because the data set includes several irregularities, preprocessing steps were necessary to get a better image. In the preprocessing of the image files, the size of each image was cut to be 1,179 $\times$ 473 pixels with 24 bit colors. Unnecessary letters or image noises were cleaned up and the background color was set to bright blue to show the image of tablets clearly. Through the preprocessing process totally 15,080 images were included as the total set of analysis data. Figure 1 shows sample images of the analyzed data, which includes common white/colored circular tablet, capsules with single or mixed color, oval tablets, coated pills, etc. Because some tablets have different marks on front or back face, two images showing both sides are captured.

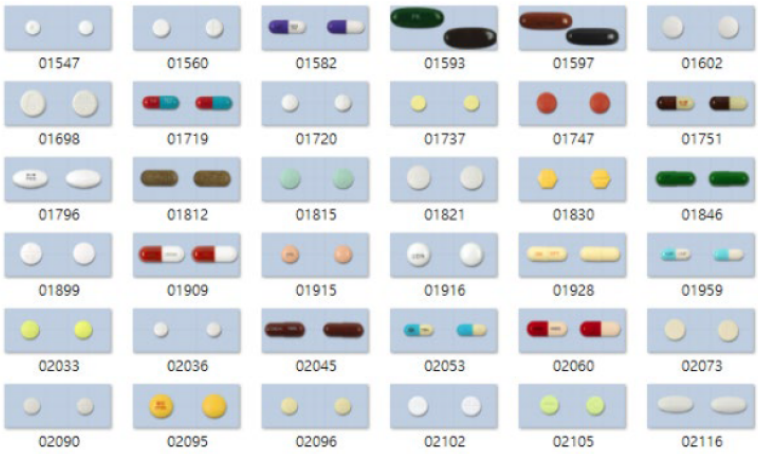


FIGURE 1. Sample images of tablets and pills

Analysis. Among various unsupervised learning methods, vector quantization was selected for this study. Vector quantization is similar to typical k-means, but k-means is not maximizing likelihood. Instead, it can be treated as a greedy algorithm for approximately minimizing a loss function related to data compression. The basic idea of vector quantization is to replace each real-valued vector $x_i \in R^D$ with a discrete symbol $z_i \in \{1, \ldots, K\}$, which is an index into a codebook of K prototypes, $\mu_k \in R^D$. Each data vector is encoded by using the index of the most similar prototype, where similarity is measured in terms of Euclidean distance.

For the analysis, 1,500 images are randomly selected from the whole image set. As the first step, load the image into the memory and flatten the array of the images. The images were serialized by extracting the three color features (R, G, B) and feature vectors. The array of the images was created into pickle file for serializing python objects' structure. Then, the flattened features were extracted by principal component analysis. Principal component analysis requires choosing proper number of principal components by the eigenvalues. From the main principal components identified, the drug images are classified based on the vector quantization and allocated to the closest cluster. The dimensions of principal components were named through Delphi method by domain experts.

4. **Results.** The first step of the analysis is finding an appropriate number of principal components. Among several ways to determine the number of principal components, we used scree plot. Figure 2(a) indicates that three-component structure can explain the data structure fairly well. Similarly, the number of clusters is obtained through elbow method. The kink point in Figure 2(b) shows that four cluster is good enough to separate tablet images.

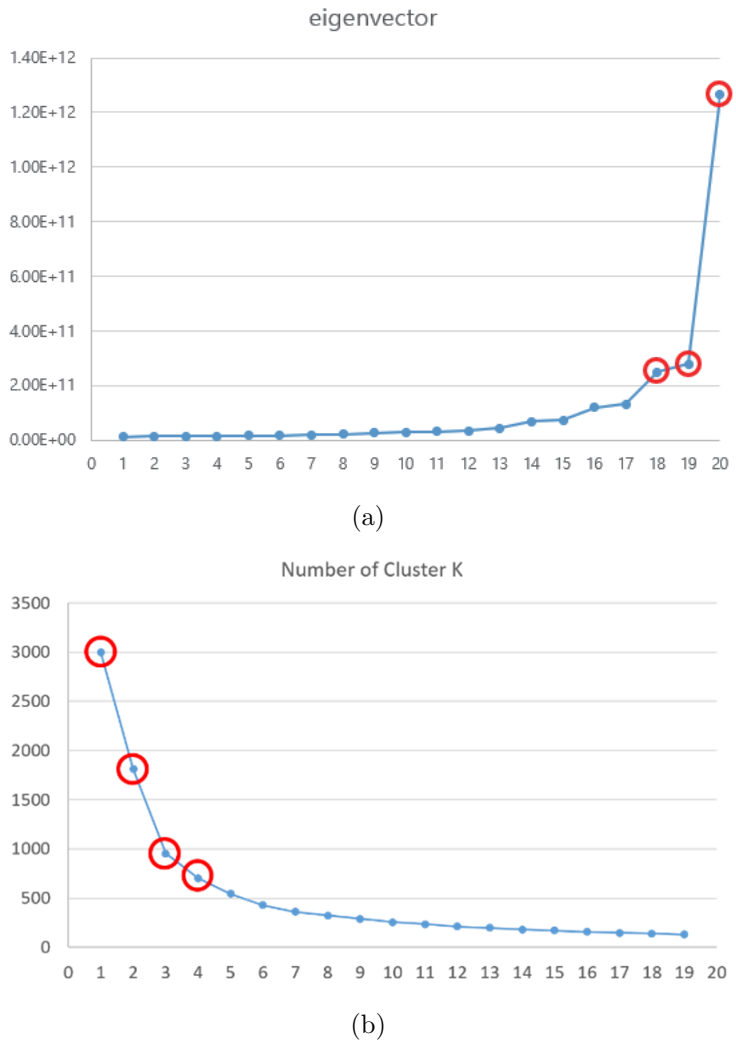
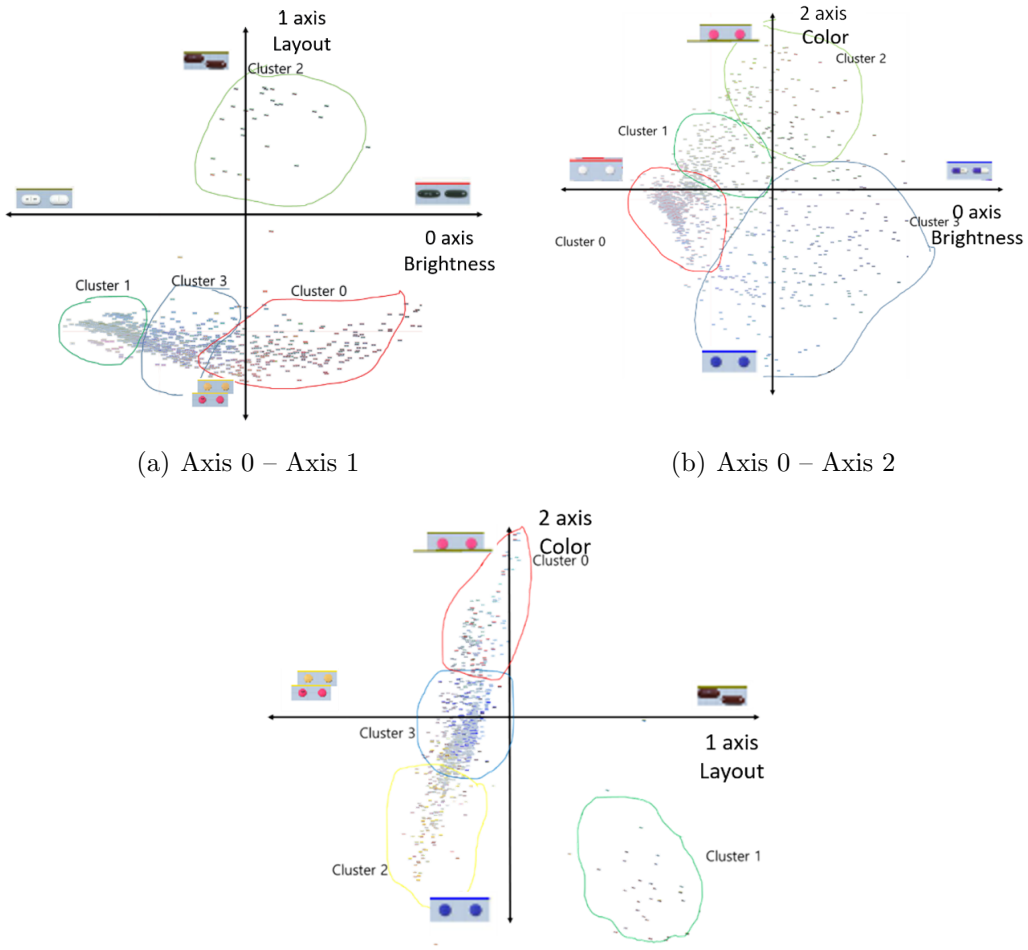


FIGURE 2. Scree plot for principal components and clusters

Cluster analysis result revealed three-dimensional structure: the first dimension is brightness of color, the second dimension is layout of the tablets in the image, and the third dimension is red-blue colors. Tablets are arranged from light to dark color along the first axis. The second axis is found to be the arrangement of tablet images. Some big tablet images are overlapping whereas small tables are displayed in parallel. This difference in arrangement was depicted by the principal component analysis. Pills or capsules with different colors are arranged on the third axis from blue to red colors. Since the color space is too big, there are several outliers on the axis, but there is a notable trend along the axis.

The identified clusters are four. Cluster 0 is located lower right quarter, which contains mostly dark images. A closer look revealed a mixture of dark tablets and capsules. Cluster 1 is located on the lower left corner of Figure 3(a). It includes bright color images on the left and shows oval shape of yellow and orange pills on the right. Cluster 2 is in the upper center of Figure 3(a). The characteristics of Cluster 2 are not from the tablet but



(a) Axis 0 – Axis 1

(b) Axis 0 – Axis 2

(c) Axis 1 – Axis 2

FIGURE 3. Axis structure and identified clusters

the arrangement of images. Because the capture image is real size showing on both sides, bigger tablets cannot fit in the frame; thus two tablet images cannot be aligned on the center. The commonality of Cluster 2 therefore is big sizes. Cluster 3 is located in between Cluster 0 and Cluster 2. Tablets and pills in Cluster 3 show therefore the characteristics of Clusters 1 and 0, but as compared to Cluster 0, Cluster 3 has blue colored tablets more.

5. **Discussion.** Experimental results showed that both tablet characteristics and image characteristics influence the classification result. Especially, the unparalleled arrangement of the big tablets that does not fit in the frame influences the classifications. Three dimensions identified by principal component analysis suggest that color and arrangements are important factors differentiating tablets and pills, which is matching with human's perception of objects by the shape and color. The color differentiation was two folds: one for the brightness of the color and the other for the blue-red differentiation. Different from the expectation, the shape of the tablets is not obviously identified as a separate dimension. It could be because of the selection of features used in the unsupervised learning. The characteristics of vector quantization algorithm are highly dependent on the identified principal component. Over the quantization process, shape features might be dropped which hides the effects of shapes. Since the image is bitmap composed of red, green, and blue and the color depth is decreased over the quantization. Since the shape is detected by the edges where the color changes abruptly, edge line is mangled through the process. Proper preprocessing may be necessary to depict the shape characteristics.

Several computer vision based approaches have been suggested to accurately recognize pills. Caban et al. [8] proposed the method that detected the contours of the pill and calculated the distance vector. Yu et al. [9] focused on imprint of the pill images with modified stroke width transform. Wang et al. [10] adopted the GoogLeNet Inception Network [11] for automatic recognition of pill images with data augmentation. Color and shape are the main features for pill identification. As seeing the result of the unsupervised learning, we expect to be able to classify the entire pill image data with deep learning algorithms.

6. **Conclusion.** The findings of this study suggest that the underlying structure of drug images could be brightness and color of the drugs. Because of large amount of drugs and their features, identifying perceptual structures by human subject experiment is not feasible. Deep learning techniques could provide guidelines or directions to reduce the number of experiments. This study tried unsupervised learning for the drug images, but the result needs also to be verified by human subject experiment.

Medication errors are the most common type of adverse events happening in hospitals. Medication errors are typical types of a systemic problem. Errors in the system may be viewed as the end result and not the cause. Thus, rather than focusing on changing the behavior of every healthcare worker, hospitals are now trying to understand how the system failed. This approach is designed to introduce barriers and safeguards at every level so that a mistake can be caught before the drug is given to the patient. In this sense, understanding human's perception of drugs could be a good starting point to prevent errors caused by confusion.

Acknowledgment. This study is supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government No. 2017R1D1A1B03032632.

REFERENCES

[1] P. Aspden, J. Wolcott, J. L. Bootman and L. R. Cronenwett, *Preventing Medication Errors*, Institute of Medicine, National Academies Press, Washington, D.C., 2007.
[2] T. L. Rodziewicz and J. E. Hipskind, *Medical Error Prevention*, Stat Pearls Publishing, Treasure Island (FL), 2018.
[3] E. Annasaro and A. Hema, Color and shape feature extraction and matching in pill identification systems, *Int. J. Comput. Sci. Inf. Technol.*, vol.5, no.2, pp.1011-1015, 2014.
[4] A. Tversky, *Preference, Belief, and Similarity: Selected Writings*, MIT Press, 2003.
[5] R. A. Jarvis and E. A. Patrick, Clustering using a similarity measure based on shared near neighbors, *IEEE Trans. Computers*, vol.100, no.11, pp.1025-1034, 1973.
[6] J. Hinton and T. Sejnowski, *Unsupervised Learning: Foundations of Neural Computation*, MIT Press, 1999.
[7] K. P. Murphy, *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012.
[8] J. J. Caban, P. Rheingans and T. Yoo, Automatic identification of prescription drugs using shape distribution models, *IEEE International Conference on Image Processing (ICIP)*, 2012.
[9] J. Yu, Z. Chen and S.-I. Kamata, Pill recognition using imprint information by two-step sampling distance sets, *International Conference on Pattern Recognition*, pp.3156-3161, 2014.
[10] Y. Wang, J. Ribera, C. Liu et al., Pill recognition using minimal labeled data, *IEEE Conference on Multimedia Big Data*, 2017.
[11] C. Szegedy, W. Liu, Y. Jia et al., Going deeper with convolutions, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.