Decision Trees Based Image Data Mining and Its Application on Image Segmentation

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Abstract. In this paper, a general mining approach based on decision trees for segmenting image data is proposed. Pixel-wise image features are extracted and transformed into a database-like table that allows existing data mining algorithms to dig out useful information. Each tuple in the table has a feature descriptor consisting of a set of feature values for a given pixel along with its label. With the feature label, we can employ the decision tree to (1) discover relationship between the attributes of pixels and their target labels, (2) build a model for image processing by using the training data set. Both experiments and theoretical analysis are performed in our research. The results show that the proposed model is very efficient and effective for image mining and image segmentation. It can also be used to develop new image processing algorithms, refine existing algorithms, or act as an effective filter.

Keywords: Data mining, decision tree, image segmentation, pixel.

1 Introduction

As the necessity of effective and efficient decision making becomes more and more apparent, many researches have been focused on data mining [4], [6], [7]. The main goal of data mining is to discover previously unknown knowledge from a huge amount of historical data that can help us initiate proper actions. “Knowledge mining from data” is another name for the term “data mining”, which is more appropriate but somewhat too long. Many people treat data mining as a synonym for another popular term, Knowledge Discovery in Databases (KDD) [7]. Although plenty of knowledge can be hidden in image data, very few literatures discuss KDD in this type of data.

We refer the term - knowledge discovery in image databases as image mining. In [2], the authors have classified the issues of image mining into four classes. They were associations, classification, sequential patterns, and time series patterns. However, only the prototype of finding associations has been proposed.

Image segmentation [13] is an important procedure to crop useful information from images. Knowledge can be more easily recognized when presented in the form of images. For example, geophysical and environmental data from satellite photos, Web pages containing images, medical imaging including Computed Tomography (CT),
Magnetic Resonance Imaging (MRI), and Ultrasound Imaging (UI), are sources of useful information used in our daily life. They are conformed to various standard image protocols. Although many image segmentation algorithms have been proposed, only few of them can be applied to image mining.

Mining non-standardized data and multimedia data is the trend in the future [17]. However, most existing data mining techniques have been designed for mining numerical data and are thus not well suited for image mining. In this paper, we solve this problem by presenting a new approach based on decision trees for both of image data mining and segmentation.

Decision tree induction [8], [10], [15] is a well-known methodology used widely on various kinds of domain, such as artificial intelligence, machine learning, data mining, and pattern recognition. A decision tree is a flow-chart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and leaf nodes represent classes or class distributions [7]. An advantage of decision trees over other methodologies, such as neural network, is that it could provide understandable English-like rules or logic statements, for example, “If a pixel’s gray level ranges from 180 to 240 and its local variation is greater than 80 and its slope variation is greater than 0.5, then it is the pixel we wanted.” This basic idea of simple and easily understandable is also the main principle of our approach.

In [3], an image mining method that works at a higher generality level for mining image associations is proposed. In contrast to that, our proposed model works on a relative low generality level for image pixel classification. Pixel-wise image classification is an essential part of many image segmentation methods, for example, determining pixels of an edge (corner) in edge (corner) detection methods [1]; pixels of a particular object in objects segmentation based methods [3], pixels of abnormal tissue of medical image processing [11], and pixel classes in thresholding [14], etc.

The proposed model can be used to mine hidden relationships between an image’s pixel and its class label, and determine the interrelated features. Besides, the created model can be applied to perform pixel-wise segmentation on input images. The rest of the paper is organized as follows. Section 2 gives a brief overview of our approach. The detailed process and the experiments are presented in Section 3. The applications of the mining result are in Section 4. In Section 5, we give theoretical analysis and discussions of the proposed model. Lastly in Section 6, we conclude our paper and discuss the future work.

2 Overview

The general processing flow of the proposed model is depicted in Fig. 1. The data we used for input is formatted as a set of raw and label image pair. Each pixel’s value of the label image is a class label with respect to the pixel in the raw image at the same position. The label of a pixel could indicate the type of a pixel, its frequency, etc. Section 3.1 has more detailed description of the input data. In addition, we propose three kinds of input data source: 1. defined by users, 2. from other algorithms, 3. hybrid, which will be explored further in Section 5.1.
Once a set of interested raw and label image pair has been obtained, they are transformed and stored in a database-like table. Each row of the transformed table represents a given pixel, and each column of such table represents an encoded feature associated with that pixel. More detail of this encoding procedure and the feature selection issues will be discussed in Section 3.1.

After obtaining such a database-like table from the images we are interested in, we can then begin to dig on it. In this paper, we have chosen the decision tree methodology for this purpose. Based on the decision tree technology, our proposed model is able to generalize rules between the label of pixels and their features. This mining process and experiments will be described in Section 3.2. The results of such process could not only help us understand more about image properties as to the real world instance, but also to segment new cases of the same domain. The mining results and their applications are discussed in Section 4, and the segmentation model will be presented in Section 5.

Fig. 1. The general processing flow of the proposed model
3 Image Mining and Segmentation Model

In this section, the kernel of the proposed model including two phases will be discussed. These two phases are: image transformation and image mining.

(1) **Image Transformation Phase**: This relates to how to transform input images into database-like tables and encode the related features.

(2) **Image Mining Phase**: This relates to how to apply data mining algorithms on the transformed table and find useful information from it.

### 3.1 Image Encoding Transformation and Feature Selection

In this subsection, we discuss how to transform the input image data set into a database-like table and encode the related features. As was mentioned before, the input data of the proposed model is formatted as a set of raw and label image pair. A simple example for an atom of such set is shown in Fig. 2. Each pixel value of the raw image represents the gray level of that pixel, whereas each pixel value in the label image represents the class label of that pixel with respect to the pixel in raw image at the same position.

![Fig. 2. An example for an atom of the input image data set](image)

In this example, the raw image contains a capital letter “I” with some degree of blur. Thus, the inside pixels in the raw image are darker and the outside pixels are lighter. Any pixel in the label image with a value of 1 represents that the pixel in the raw image at the same position is a pixel of outside contour. Supposedly, this is an interesting piece of information for us. Note that the value of the label image is not restricted to binary. It could be in any kind of forms.

With a desire to mine relationships between a set of these two kinds of image, we propose a methodology to transfer them into a database-like table and allows any data
mining algorithms to work on top of it. This process is simple and straightforward as shown below. Table 1 shows a part of the result for this transformation process according to the data in Fig. 2. Each row of such database-like table represents a pixel. Hence the cardinality (number of rows) is the same as the total number of pixels in the raw image. Besides, each column of such table represents a feature associated with that pixel.

Table 1. The result of transforming the input data image

<table>
<thead>
<tr>
<th>Pixel</th>
<th>Label</th>
<th>Feature 1</th>
<th>Feature 2</th>
<th>...</th>
<th>Feature m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>7</td>
<td>2</td>
<td>...</td>
<td>Value 1,m</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>9</td>
<td>1.25</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>n</td>
<td>1</td>
<td>7</td>
<td>2</td>
<td>...</td>
<td>Value n,m</td>
</tr>
</tbody>
</table>

The Image Transformation Algorithm

```plaintext
process img2tab (image: raw, label)
begin
set feature_generated_functions(1..n)
set label_generated_function()
initiate table, pixel
while pixel exists do  (pixel scanning procedure)
    begin
        i = location_x(pixel)
        j = location_y(pixel)
        insert into table
        value = label_generated(i,j,label),
        feature_generated(i,j,raw),..., feature_generated(i,j,raw)
        continue to scan on the next pixel
    end
return table
end
```
In the above example, Feature 1 represents gray level for a given pixel, Feature 2 represents local variation, and so on. Other pixel-wise features such as n-neighbors, eigenvalue, eigenvector, gradients, etc, can also be encoded in the table as long as they have something to do with the pixel class.

Moreover, the label image was also encoded as a column in that table. And with the presence of the feature label, we are able to mining the hidden relationships between these two kinds of images.

3.2 The Mining Process and Experiments

After obtaining such a database-like table according to the input image set, mining algorithms can then be used to do the work. We chose a well-known commercial product SAS Enterprise Miner (EM) [16] for our mining process.

First, we demonstrate the image segmentation ability by using synthetic images, which contain alphabets with added noises. Second, we perform image restoration with enhancement by using a blurred image as shown in Fig. 3.

In both experiments, the distorted and original images that contain letters “F” to “Z” and the combination of two letters (e.g., FF, FG... ZY, ZZ) are all used as label and raw image pair for training data sets. The encoded features contain pixel’s gray level, location (spatial coordinates), 24-neighbors and local variations. And the value of the label feature is the same as the gray level in the label image. In order to simplify the demonstration, we didn’t adopt any encoded strategy such as normalization (exp. transform the value between 0 and 1) or generalization (exp. transform the value to high, medium, and low) on the features. If necessary, they can be applied.

![Fig. 3. Top row: original images; middle row: distorted images; third row: result images; where (a) shows the case with noises and (b) is the blurred case.](image)

The result in Fig. 3(a) shows that the main portions of the alphabets were successfully segmented and Fig. 3(b) shows that the blurred images with alphabets were successfully restored or enhanced.

In the case of noisy image, the local variation shows more significant affect on the result than in the case of blurred ones. While the gray level is the most dominant feature, the location is the most irrelevant one in both cases. These two simple experiments also demonstrate the flexibility of the proposed model on various characteristics of image data problems.
4 Mining Results and Their Applications

The mining result of the proposed model is basically a decision-tree classifier. Fig. 4 shows a simple example of the image classifier in action. The result model of decision tree induction could be translated into a set of if-then rules. For example, according to the leaf node in Fig. 4 from left to right, we can obtain the following rules:

- If a pixel’s gray level is less than 8 and its local variation is less than 5, then it is a pixel of outside contour.
- If a pixel’s gray level is less than 8 and its local variation is larger than or equal to 5, then it is not a pixel of outside contour.
- If a pixel’s gray level is larger than or equal to 8 and its local variation is larger than or equal to 5, then it is a pixel of outside contour.

These rules could not only provide us necessary information about the desired image problem, but also segment new images having the same conditions with the training data set. The segmentation functionality and usability of the proposed model are discussed in Section 5.

Moreover, these derived rules could fit in rule induction algorithms for post processing to mine relatively higher level of appearance in order to meet the need of different information granularity requirements.

The other important result is the selection of the crucial features. The feature at the top level for the tree splitting criteria shows more significant influence to the pixel class. The decision tree learning process comprises two processes that are necessary when building image interpretation systems: feature selection and learning the classifier [12]. In the proposed model, these two processes are performed in an intermingled fashion that is not separated independently. Thus, using this objective kind of feature selection procedure can pick up more relevant features than a subjective feature selec-
tion. Here we refer this objective kind of feature selection procedure another name – “feature mining in image data”, or “feature mining” for short.

The selected features could help us understand the property of a pixel class and design or refine other segmentation algorithms. Feature selection is an important issue in many decision support problems.

5 Theoretical Analysis and Discussions

In this section, the input data source, its characteristics, and compatibility of the proposed model will be analyzed and discussed.

5.1 The Input Data Source

First, we explore several important issues for the input data source of the proposed model. As described above, there are three kinds of source for the label image:

1. **User defined.** As we know, there are many image processing problems that require better segmentation methods. Most of these issues are user specific. Users or domain experts could artificially manipulate the label image according to their requirements, and then apply our approach to obtain a model with automatic segmentation capability as required.

   On the other hand, we are also able to mine information and determine the important features for the unknown images. These could let us better understand the image property and design or refine other image processing procedures. The applicable areas include image enhancement, image restoration, and image segmentation, etc.

2. **From other algorithms.** There already exist methods for some special cases of image segmentation problems. In such a case, we could simply use their result as our label image, and let our model to learn from that segmentation method. As a result, the generated model is able to segment the images with similar or better result, and do the job more efficiently than the original method.

   Besides, we could encode all the features that might closely relate to the result in the table and let the decision tree algorithm to make selection on them. Thus, we can find what features are closely related to the result, and the degree of their correlation. These could let us better understand the image property and to refine the original segmentation method.

   The most important advantage is that our model is able to mining, or explaining the decision process of the original method by using the derived rules. This explanation capability is particular helpful when the original method, such as a neural network, is more or less a black box for human.

3. **Hybrid.** The hybrid method could be extremely powerful on image processing. It is done by exploiting other algorithm’s outcome plus human’s manipulation as training data. By this way, the flaw of other algorithms could be
identified more easily. Further more, our expertise could also be embedded in the new model, and thus, making the new model a superior one.

5.2 Efficiency and Effectiveness

It is remarkable that the proposed segmentation model is efficient, and requires only one scan of the data set. It can be used to effectively solve the time-consuming problem of segmentation with neural-networks. Here we suggest two manners to apply our approach in similar situations.

The first one is using our model to substitute the existing method with the strategies mentioned above. The second one is using our model to quickly filter out the images that need advanced examinations. For example, after singling out suspicious mammograms that might contain pixels of cancer [5], one can apply the original method for second segmentation. The first manner is suitable for the case that our segmentation method result is better than the original one or the loss of correctness does not make significant difference [12]. The second one is suitable for the case that the segmentation result is used in a critical manner, and the proposed model is unable to reach that requirement level.

When used for fast filtering, the misclassification cost in our model could be artificially tuned in the decision tree training process to minimize the penalty when the application uses different weights with different output classes. The controllability is a big advantage of decision tree over other algorithms such as a neural network. With this controllability, we can improve the decision process or interactively train our model [16].

5.3 Extensibility and Flexibility

In our experiments, most of the segmentation methods require spatial filters, or masks for image pre-processing. These various kinds of mask can be applied together in our model while performing the pixel scanning procedure in the table encoding process. The resultant gray level after applying a mask can also be encoded as a column in that table. Moreover, the features of a pixel after applying a mask can also be encoded in the table. Thus, we can say that the proposed model is able to mining across different layers of image, and determine important features over disparity of masks.

Besides, the proposed model can easily extend from 2D to 3D image processing without making a revolution and the created model can generate very efficient and compact code [9].

6 Conclusion and Future Works

In this paper, an efficient and effective model for image mining and image segmentation was proposed. It is clear that all evidences show the proposed model is qualified for mining and segmenting image data.
Our model was constrained to that we must acquire the label image first. To make improvements, our future work is to make this model become an unsupervised one that doesn’t need the label image as input. On the other hand, we’re trying to adjust the proposed model to specialize for a particular case. The specialization of the proposed model will involve more widely issues, such as the feature generation of the raw image and the encoding methodologies of the label image. There are many more benefits can be made by extending our proposed model.

References

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