ABSTRACT

Most search engines index the textual content of documents in digital libraries. However, scholarly articles frequently report important findings in figures for visual impact and the contents of these figures are not indexed. These contents are often invaluable to the researcher in various fields, for the purposes of direct comparison with their own work. Therefore, searching for figures and extracting figure data are important problems. To the best of our knowledge, there exists no tool to automatically extract data from figures in digital documents. If we can extract data from these images automatically and store them in a database, an end-user can query and combine data from multiple digital documents simultaneously and efficiently. We propose a framework based on image analysis and machine learning to extract information from 2-D plot images and store them in a database. The proposed algorithm identifies a 2-D plot and extracts the axis labels, legend and the data points from the 2-D plot. We also segregate overlapping shapes that correspond to different data points. We demonstrate performance of individual algorithms, using a combination of generated and real-life images.

Categories and Subject Descriptors

Data Mining/Extraction [Information Systems Applications]:

General Terms
Information Extraction, Machine Learning, Metadata

1. INTRODUCTION

A wide variety of quantitative information is summarized and visually presented using 2-D plots, including scientific results, business performance reports, time series, etc. The embedded information is invaluable in that once extracted, the data can be indexed and the end-user has the ability to query the data, and operate directly on the data. However, in order to extract information from figures without manual intervention, we must identify 2-D plot figures, segment the plots to extract the axes, the legend and the data sections, extract the labels of the axes, separate the data symbols from the text in the legend, identify data points and segregate overlapping data points. Performing all of these tasks automatically with high precision is a challenging problem and we believe that ours is the first attempt to achieve this goal. This paper is devoted to a subset of the overall process, specifically the identification of 2-D plots and disambiguation of overlapping data points. We perform content-based image analysis to identify appropriate features that characterize a 2-D plot from other figure types. Li, et al., [6] have shown that the histogram distribution of the wavelet co-efficients can effectively be utilized as a global image feature for picture and non-picture classification. We adapt these methods by using additional features including line features determined after edge detection and hough transform, and the text surrounding the figure, e.g. the figure caption. Identifying data points from an image is a hard problem especially when multiple data points overlap. Typically, a figure uses common symbols (triangle, square, circle etc.) to designate a series of data points in a two dimensional space. When data points overlap, the resulting irregular shape does not exactly match with any regularly shaped data point. To extract data precisely from figures in digital documents, one must segregate the overlapping shapes and identify the shape and the center of mass of each overlapping data point. We employ simulated annealing, a stochastic optimization method to segregate these shapes and find the method to be fairly accurate.

2. RELATED WORK

The image categorization portion of our work bears a similarity to image understanding, however, we focus on deciding whether a given image contains a 2-D plot. Li et.al. [6] developed wavelet transform, context sensitive algorithms to perform texture based analysis of an image, in separating camera taken pictures from non-pictures. Building on this framework, Lu et.al. [5] developed an automatic categorization image system for digital library documents which categorizes the images into multiple classes within non-picture class e.g. diagram, 2-D figures, 3-D figures, diagrams and other. We find significant improvements in detecting 2-D figures by substituting certain features used in [5]. [7] presents image-processing-based techniques to extract the data represented by lines in 2-D plots. However, [7] does not ex-
3. PRELIMINARY
Our algorithm segments a 2-D figure into three regions: 1) X-axis region containing X-axis labels and numerical units, i.e., area below the horizontal axis in Fig. 1., 2) Y-axis containing labels and numerical units i.e. area to the left of vertical axis in Fig. 1. and, 3) plotting region, which contains legend text, data points, and lines. A 2-D figure depicts a functional distribution of the form \( y_i = f_i(x) \) with conditions \( w_i \), where Y-axis and X-axis labels contain the description for \( y \) and \( x \) data. The legend with textual content provides the particulars for conditions \( w_i \), and the values for these functions are represented by the data points or the lines in the plot.

![Figure 1: A sample 2-D plot displaying experimental results reported in [9]. The areas of interest in the diagram are namely X-axis, Y-axis and plotting region.](image)

4. METHOD

4.1 Overview
The system uses a machine-learning based classifier to identify which figures in the document are 2-D plots. An identified image is then segmented into the previously mentioned three regions. The algorithm performs connected component analysis to label each connected component in the three regions so that its shape and position can be further analyzed. Next, the candidate text components are identified based upon their mutual positioning and spacing information. This identification is based upon the intuition that the two characters appearing in the same string are very likely to be placed next to each other. Also, the spacing between them is roughly the same for any two characters appearing in any other string of text in the figure. In the next stage, we identify the data points in the plotting region. This is achieved by removing the lines from the region in a manner whereby only the data points remain; Fig. 2 depicts the entire process.

4.2 Identification of 2-D Plots

The system uses a machine-learning based classifier to identify which figures in the document are 2-D plots. An identified image is then segmented into the previously mentioned three regions. The algorithm performs connected component analysis to label each connected component in the three regions so that its shape and position can be further analyzed. Next, the candidate text components are identified based upon their mutual positioning and spacing information. This identification is based upon the intuition that the two characters appearing in the same string are very likely to be placed next to each other. Also, the spacing between them is roughly the same for any two characters appearing in any other string of text in the figure. In the next stage, we identify the data points in the plotting region. This is achieved by removing the lines from the region in a manner whereby only the data points remain; Fig. 2 depicts the entire process.

4.3 Data Point Disambiguation
Overlapping data points occur frequently in 2-D plots and identifying each individual data point and its coordinates is a difficult task. We apply simulated annealing (SA) in order to resolve individual data points within a region of overlap. SA

![Figure 2: Process flow of Information extraction from 2-Dimensional Plot](image)
is a stochastic method, based on the Metropolis algorithm, often used in non-convex optimization problems. It bears a close similarity to annealing (i.e. slow cooling) in metallurgical processes. By analogy to its physical counterpart, the optimal configuration (lowest energy \( E_{\text{min}} \)) is approached while the temperature \( T \) is lowered. In accordance with the Metropolis algorithm, occasionally higher energy configurations \( E_f > E_i \) are assumed with probability \( e^{-\frac{(E_f - E_i)}{T}} \).

The specific details of the algorithm are presented below.

We generate an ‘initial configuration’ image, which consists of large numbers of randomly selected candidate shapes, with random positions. Candidates are previously identified shapes extracted from the 2-D plot, using standard shape detection methods \( \text{[10]} \). The target image consists of overlapping data points, extracted from within the plotting region, which has failed to be classified as a particular shape. Hence, we consider two matrices with binary (boolean) values: the generated image and the original overlapping data point image. A Grammian matrix is constructed from the individual data points are ascertained. Carnevali, et al., \( \text{[2]} \), applied simulated annealing to construct an image from known sets of shapes in the presence of noise. However, to the best of our knowledge, application of simulated annealing to disambiguating overlapping shapes is a novel contribution.

### 5. EXPERIMENTS

In this section, we report the results obtained by evaluating the new features for 2-D plot identification and data point disambiguation algorithms. The data set that we used for our experiments is randomly selected publications crawled from the web site of Royal Society of Chemistry www.rsc.org and randomly selected computer science publications from the CiteSeer digital library \( \text{[3]} \) for scientific publications.

#### 5.1 2-D figure Classification

For our classification experiments, we extracted the images from the aforementioned documents and had them manually tagged by two volunteers as 2-D or non-2-D. Our set consists of 2494 images, out of which 734 images are 2-D plots. As mentioned previously, we train a linear SVM (with \( C = 1.0 \)) on this dataset.

**Table 1: Cross-validation accuracies**

| Features | % CV(±3) accuracy |
|----------|-------------------|
| Only IS  | 85.24             |
| Only CT  | 78.3              |
| IS + CA  | 85.85             |
| CT + CA  | 80.67             |
| IS + CT  | 85.85             |
| All      | 88.25             |

**Table 2: Confusion matrix(train set)**

| Class | Non-2-D | 2-D |
|-------|---------|-----|
| Non-2-D | 273    | 27  |
| 2-D    | 66     | 134 |

**Table 3: Confusion matrix(sample test set)**

5.1.1 Feature extraction

Table 1 shows the 3-fold cross-validation accuracies with different combinations of features. We use the following abbreviations: IS for image segmentation, CT for caption text, CA for the coordinate axes. The confusion matrix over a sample test set is shown in Table 3. For comparison purposes, we have also shown the confusion matrix over the training set in Table 2. The libSVM software was used for support vector classification \( \text{[3]} \).
examples of pixel regions containing overlapping data points and the corresponding machine-learned version; table 4 details the experimental parameters and results corresponding to fig. 3.

Figure 3: Examples of overlapping data points (left) and machine learnt versions (right)

| Iterations | Temp. | Type | Offset (orig.) | Offset (calc.) |
|------------|-------|------|---------------|----------------|
| 10k        | 0.4   | A    | (11,39)       | (11,40)        |
|            |       |      | (19,4)        | (20,3)         |
|            |       |      | (21,35)       | (22,35)        |
|            |       |      | (10,18)       | (10,17)        |
| 10k        | 0.3   | A    | (29,24)       | (29,23)        |
|            |       |      | (22,9)        | (21,9)         |
|            |       |      | (23,37)       | (21,39)        |
|            |       |      | (2,39)        | (2,39)         |
|            |       |      | (18,17)       | (18,16)        |

Table 4: Example parameters for simulated annealing applied to the data point disambiguation problem.

Table 5 gives the overall results of these experiments using an annealing constant of 0.4 and 10k iterations. As the annealing schedule is slowed and iterations increased, the recall approaches 100%. A slower annealing schedule than that used here and more iterations are required as the pixel region and number of possible different data points increases. However the results are promising in that data that would traditionally be considered lost is recovered with fairly high accuracy.

| Shape | Total | # Correct | % Recall |
|-------|-------|-----------|----------|
| Diamond | 72    | 64        | 88.9     |
| Triangle | 78    | 71        | 91.0     |

Table 5: Experimental Results for Data-Point Disambiguation

6. CONCLUSIONS AND FURTHER WORK
We have outlined a system that can identify 2-D plots in digital documents and extract data from the identified documents. Overlapping data points present a major challenge in reconstructing data series from within the plotting region, once lines are filtered from 2-D plots. We present an unsupervised machine-learning algorithm to segregate overlapping data points and identify their exact shape and location. The work presented here is currently being integrated into the overall figure extraction system. In addition, attention is being given to improving the quality of extracted textual information, to assist in indexing of figures.

7. REFERENCES
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