Image to text

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1 Abstract

Character recognition is one of the most interesting areas of pattern recognition and artificial intelligence. Image to character recognition extracts the relevant information and automatically enters it into electronic database instead of the conventional way of manually retyping the text. it is a vast field with a number of varied applications such as social networking, legal industry, banking, health care industry etc. Image to text conversion can be used to catagorize,analyse big data without any human correction or human effort, Automatic number plate recognition and Handwritten Recognition. It contributes immensely to the advancement of an automation process and can improve the interface between man and machine in numerous applications. Several research works have been focusing on new techniques and methods that would reduce the processing time while providing higher recognition accuracy. Now it is possible to scan documents as an image and to make it editable and searchable for further information processing.

2 Introduction

Aim is to create an Android application which can recognize text from image taken using camera and convert it to a human editable form *ex word,pdf etc.* Artificial intelligence and image recognition are the key principle behind working of this application.

2.1 Edge Detection

A set of connected pixels that forms a boundary between two disjoint regions is known as an edge. The task of segmenting an image into regions of discontinuity is done using edge detection. Edges usually occur on the boundary of two different boundaries in an image. Edge detection helps to clearly identify the changes in region of an image where gray scale and texture change in the regions of an image. There are many available edge detection techniques for extracting edges from images such as Robert, Prewitt and Sobel which were not much efficient. Then in 1986 John. F. Canny developed an algorithm which provided high probability of edge detection and error rate.

2.2 Canny Algorithm

This algorithm focuses mainly on three main aims of low error rate, minimize distance between real edge and detected edge and minimum response i.e. one detector response per edge to detect the edges in an image.

2.3 Image Segmentation

Image segmentation is another important aspect necessarily required to divide an image into regions or categories which then helps to identify correctly the object in an image. Segmentation functions on the properties shown by the pixels in an image, every pixel which belongs to same category has similar gray scale value whereas pixels of different categories have dissimilar values. Segmentation is often one of the critical steps in analyzing the images because additional overhead of moving to each new pixel of an image while working with object in an image. Once image segmentation is done successfully, the other stages in image analysis are much easier. While considering a fully automatic conversion algorithm, the success of image segmentation is partial and sometimes requires manual intervention. Segmentation mainly has two main objectives: 1) divide or decompose the image into parts for further processing, 2) perform change in organizing the pixels of image into higher-level units so that the objects become more meaningful.

3 Related works

3.1 Image Parsing to Text Description

Benjamin Z. Yao, Xiong Yang,
Liang Lin, Mun Wai Lee and Song-Chun Zhu

Fast growth of public photo and video sharing websites, such as “Flickr” and “YouTube”, provides a huge corpus of unstructured image and video data over the Internet. Searching and retrieving visual information from the Web, however, has been mostly limited to the use of meta-data, user-annotated tags, captions and surrounding text (e.g. the image search engine used by Google [1]). In this paper, we present an image parsing to text description (I2T) framework that generates text descriptions in natural language based on understanding of image and video content. Fig. 1 illustrates two major tasks of this framework, namely image parsing and text description. By analogy to natural language understanding, image parsing computes a parse graph of the most probable interpretation of an input image. This parse graph includes a tree structured decomposition for the contents of the scene, from scene labels, to objects, to parts and primitives, so that all pixels are explained. It also has a number of spatial and functional relations between nodes for context at all levels of the hierarchy. The parse graph is similar in spirit to the parsing trees used in speech and natural language understanding [2] except that it can include horizontal connections (see the dashed curves in Fig. 1 (a)) for specifying relationships and boundary sharing between different visual patterns. From a given parse graph, the task of text description is to generate semantically meaningful, human readable and query-able text reports

1) **An image parsing engine** that parses input images into parse graphs. For specific domains such as the two case study systems presented in section 7, the image/video frame parse is automatic. For parsing general images from the Internet for the purpose of building a large-scale image dataset, an interactive image parser.
2) An And-or Graph (AoG) visual knowledge representation that embodies vocabularies of visual elements including primitives, parts, objects and scenes as well as a stochastic image grammar that specifies syntactic (compositional) relations and semantic relations (e.g. categorical, spatial, temporal and functional relations) between these visual elements. The categorical relationships are inherited from WordNet, a lexical semantic network of English [3]. The AoG not only guides the image parsing engine with top-down hypotheses but also serves as an ontology for mapping parse graphs into semantic representation (formal and unambiguous knowledge representation [4]).

3) **A Semantic Web** [5] that interconnects different domain specific ontologies

with semantic representation of parse graphs. This step helps to enrich parse graphs derived purely from visual cues with other sources of semantic information. For example, the input picture in Fig. 2 has a text tag "Oven's mouth river". With the help of a GIS database embedded in the Semantic Web, we are able to relate this picture to a geo-location: "Oven's mouth preserve of Maine state". Another benefit of using Semantic Web technology is that end users not only can access the semantic information of an image by reading the natural language text report but can also query the Semantic Web using standard semantic querying languages.

4) **A text generation engine** that converts semantic representations into human readable and query-able natural language descriptions. We will come back to discuss these components in more detail in sections 1.3, 1.4, 1.5. As simple as the I2T task in Fig. 1 may seem to be for a human, it is by no means an easy task for any computer vision system today - especially when input images are of great diversity in contents (i.e. number and category of objects) and structures (i.e. spatial layout of objects), which is certainly the case for images from the Internet. But given certain controlled domains, for example the two case study systems presented in section 7, automatic image parsing is practical. For this reason, our objective in this paper is twofold: (a) We use a semi-automatic method (interactive) to parse general images from the Internet in order to build a large-scale ground truth image dataset. Then we learn the AoG from this dataset for visual knowledge representation. Our goal is to make the parsing process more and more automatic using the learned AoG models. (b) We use automatic methods to parse images/videos in specific domains. For example, in the surveillance system presented in section 7.1, the camera is static, so we only need to parse the background (interactively) once at the beginning, and all other components are done automatically. In the automatic driving scene parsing system discussed in section 7.2, the camera is forward looking at roads and streets. Although the image parsing algorithm may produce some errors, it is fully automatic.

3.2 Recognizing Actions Across Cameras by Exploring the Correlated Subspace

Chun-Hao Huang, Yi-Ren Yeh, and Yu-Chiang Frank Wang

Action recognition has been an active research topic for researchers in the areas of computer vision and image processing. However, in practical scenarios, one typically needs to deal with multiple cameras with different lighting, depression angle, etc. conditions. Moreover, actions of interest might not be seen by a particular camera in advance, and thus no training data for that action is available. Therefore, it is expected that most existing single-view action recognition approaches cannot be easily extended for cross-view action recognition due to poor generalization [1]. While some researchers proposed to extract view-invariant representations for cross camera action recognition (e.g., [2, 3]), transfer learning [4] has recently been applied to address this problem [5, 6]. The purpose of transfer learning is to transfer the knowledge observed from one or few source domains to the target domain, so that the task in the target domain (e.g., predicting the action of interest captured by a new camera) can be solved accordingly. Based on canonical correlation analysis (CCA) [7], we present a transfer learning based approach (via CCA) for cross camera action recognition. Our method aims at determining a correlation subspace as a shared representation of action models captured by different cameras. However, the correlation between the projected source and target view data will be different in each dimension of this subspace, depending on the corresponding correlation coefficient. Therefore, we need to take such domain transfer ability into consideration when designing the classifier in this joint subspace. We propose a novel SVM formulation, which incorporates such ability into classification in the joint subspace, so that the unseen actions at the target view can be projected and recognized accordingly.

1) **Learning Correlation Subspace via CCA** The idea of applying transfer learning for cross-view action recognition is to determine a common representation (e.g., a joint subspace) for features extracted from source and target views, so that the model trained from the source-view data can be applied to recognize test data observed at the target view. Among existing methods [15, 5, 16, 6], canonical correlation analysis (CCA) is a very effective technique. It aims at maximizing the correlation between two variable sets [15, 16] and thus fits the goal of this work.

2) **Domain Transfer Ability of CCA** unseen test at the target view can be first projected onto the CCA correlation subspace Xc and thus the model learned from the Recognizing Actions Across Cameras by Exploring the Correlated Subspace 5 source view data at this subspace can be applied for recognition. It is worth repeating that each dimension v

3)**The Proposed SVM Formulation** generally, if the ith feature attribute exhibits better discrimination ability, the standard SVM would produce a larger magnitude for the corresponding model. As discussed earlier, transfer leaning via CCA does not take the domain transfer ability into account when learning the classifiers in the 6 Chun-Hao Huang, Yi-Ren Yeh, and Yu-Chiang Frank Wang correlation subspace and thus degrades the recognition performance. To address this problem, we introduce a correlation regularizer and propose a novel SVM formulation which integrates the domain transfer ability and class discrimination in a unified framework. Due to the introduction of such ability, the generalization of our SVM for transfer leaning will be significantly improved.

3.3 An Automatic Approach for Translating Simple Images into Text Descriptions and Speech for Visually Impaired People

Mrunmayee Patil,Ramesh Kagalkar

1) **Pre-processing** : Pre-processing of images involves mainly of removal of low-frequency background noise, removing reflections and masking portions of images. Pre-processing technique enhances data images in order to do further computational processing. Some common methods of preprocessing are:

- Smoothing: Spatial smoothing of images.
- Background Subtraction: Removal of unwanted background.
- Close (Dilate+Erode): Perform dilation followed by erosion on a binary image.
- Dilate: Perform dilation on a binary image.
- Erode: Perform erosion on a binary image.
- Max: Maximum value over neighboring pixels.
- Median: Median value over neighboring pixels.
- Mean: Mean value over neighboring pixels.
- Min: Min value over neighboring pixels.
- Open (Erode+Dilate): Perform erosion followed by dilation on a binary image.

2) **Gray scaling**: In gray scaling each pixel value of an image is represented using shades of gray. These kind of images are also known as black and white images. Each pixel intensity is expressed within the range of minimum and maximum where range is 0(black) and 1(white), any fractional value is in between.

3) **Edge Detection**: Edge detection is the technique used to identify the fine edges in digital images. It identifies the points in the image at which the brightness of image changes very sharply. Point at which the image brightness changes are organized into set of curved line segments known as edges. Edge detection is mainly an important tool in the field of image processing for detection of features and feature extraction. Approaches of edge detectionTwo main methods of edge detection are search based and zero crossing based. Search based method detects edges by computing the edge strength. The zero crossing based method searches for the zero crossing second-order derivative expression computed form images in order to find edges.

4) **Segmentation**: The aim of segmentation is converting an image into more meaningful and easy to analyze portions. Segmentation does the job of partitioning an image into multiple segments which help to locate the objects and boundaries (curves, arcs, lines, etc.) in an image. With the help of image segmentation we can assign a label to each pixel which then same labels share the certain characteristics. We can characterize the pixels in a region with respect to the characteristics such as color, intensity or texture.

5) **Feature extraction**: In the fields of machine learning, pattern recognition and image processing, feature extraction plays an important role of building derived values which are known to be the features. These features are intended to be informative, nonredundant, facilitating the subsequent and generalized steps. Extracted features should contain relevant data from input data. This technique plays an important task in our proposed system. Feature Extraction is the key concept in CBIR. A certain number of features for each image are extracted, describing its high level content information. Then, according to the similarity of these vectors, we can compare two specific images to each other. This class uses different techniques to extract features related to a single or the group of images. There are two methods in this class which extracts the features: - extractSingleImage : which extracts the features for a single image. It is used to extract the features of the input image.

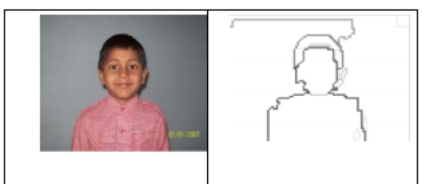
6) **Speech Synthesis**: It is the process of artificially producing the human speech. Systems used for such purpose are called speech synthesizer which can be a software or hardware product. Concatenations of several pieces of recorded speech are stored in database and then synthesized speech is created. A text -to-speech conversion system is used in our work to convert the generated text of images into speech output.

3.4 Synergy between Object Recognition and Image Segmentation

Y.Ramadevi, B.Kalyani, T.Sridevi

Image segmentation is the foundation of object recognition and computer vision. In general, image noise should be eliminated through image preprocessing. And there is some specifically-given work (such as region extraction and image marking) to do after the main operation of image segmentation for the sake of getting better visual effect. Two major computer vision problems, image segmentation and object recognition, have been traditionally dealt with using a strict, bottom-up ordering.
Image segmentation is to partition an image into meaningful regions with respect to a particular application. The segmentation is based on measurements taken from the image and might be grey level, colour, texture, depth or motion. The result of image segmentation is a set of segments that collectively cover the entire image.
Object recognition is the task of finding a given object in an image or video sequence. For any object in an image, there are many 'features' which are interesting points on the object that can be extracted to provide a "feature" description of the object. This description extracted from a training image can then be used to identify the object when attempting to locate the object in a test image containing many other objects.

1)**Segmentation** Edge-based segmentation partitions an image based on abrupt changes in intensity near the edges whereas region-based segmentation partitions an image into regions that are similar according to a set of predefined criteria. Region-based segmentation looks for uniformity within a sub-region, based on a desired property, e.g. intensity, color, and texture as shown figure



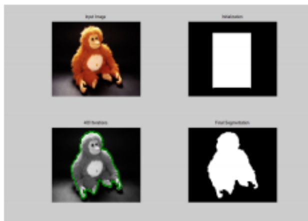
Original Image | Region Based Segmentation

Figure 1. Region based Segmentation

Table 1. Differences Between Region-Based Segmentation And Edge-Based Segmentation

Region-based segmentation	**Edge based segmentation**
Closed boundaries	Boundaries formed not necessarily closed
Multi-spectral images improve segmentation	No significant improvement for multi-spectral images
Computation based on similarity	Computation based on difference

2)**Active contours** are popular technique for image segmentation. An advantage of active contours as image segmentation methods is that they partition an image into sub-regions with continuous boundaries. There are two kinds of active contour models according to the force evolving the contours: edge- and region-based. Edgebased active contours use an edge detector, usually based on the image gradient, to find the boundaries of subregions and to attract the contours to the detected boundaries. Region-based active contours use the statistical information of image intensity within each subset instead of searching geometrical boundaries as shown in figure.



3)**Image Segmentation** the generative models are used to decide which part of the image a model should occupy. Active Appearance Model (AAMs) is used as generative models and addresses the problem of jointly detecting and segmenting objects in images. Regarding recognition, each object hypothesis is validated based on the image area assigned to the object, as well as the estimated model parameters, which indicate the familiarity of the object appearance. On one hand, knowing the area occupied by an object is needed for the estimation of the model parameters and, on the other hand, the model synthesis is used to assign observations to the model. Since neither is known in advance, we cannot address each problem separately. We view this problem as an instance of the broader problem of parameter estimation with missing data: In our case, the missing data are the assignments of observations to models. A well-known tool for addressing such problems is the EM algorithm.

4)**Expectation-Maximization** (EM) algorithm is used for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved latent variables. In order to find maximum likelihood estimate we have to find probability density function and loglikelihood.
The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) estimate in the presence of missing or hidden data. Each iteration of the EM algorithm consists of two processes: The E-step, and the M-step. In the expectation, or E-step, the missing data are estimated given the observed data and current estimate of the model parameters. This is achieved using the conditional expectation, explaining the choice of terminology. In the M-step, the likelihood function is maximized under the assumption that the missing data are known. The estimates of the missing data from the E-step are used in lieu of the actual missing data. The EM algorithm seeks to find the MLE by iteratively applying the following two steps:

- Expectation step: Calculate the expected value of the log likelihood function, with respect to the conditional distribution of z given x under the current estimate of the parameters $\theta(t)$.
- Maximization step: Find the parameter which maximizes this quantity.

5)**Image segmentation using OTSU** ,OTSU algorithm is based on the point of image segmentation in the global threshold selection. This method of its calculation is simple, stable and effective, has been widely used still image processing toolbox MATLAB gray image as the threshold value automatically select a single standard algorithm. The OTSU method is one of the applied methods of image segmentation in selecting threshold automatically for its simple calculation and good adaptation. In image processing, OTSU's thresholding method is used for automatic binarization level decision, based on the shape of the histogram. The algorithm assumes that the image is composed of two basic classes: Foreground and Background. It then computes an optimal threshold value that minimizes the weighted within class variances of these two classes. It is mathematically proven that minimizing the within class variance is same as maximizing the between class variance. The thresholding techniques are categorized into six groups as:

a. Histogram shape-based methods, where histogram of image is viewed as a mixture of two Gaussian distributions associated to object and background classes, such as convex hull

b. Clustering-based methods, where gray-level pixels are clustered in two classes as either background and foreground objects or alternately modeled as mixture of two Gaussians, such as iterative thresholding, clustering thresholding, minimum error thresholding and fuzzy clustering thresholding.

c. Entropy-based methods use difference in entropy between foreground and background regions, such as, entropy thresholding.

d. Object attribute-based methods; find measure of similarity (fuzzy shape similarity, edge coincidence, etc) between gray-level and binarized images, such as edge field matching thresholding and topological stable-state thresholding.

e. Spatial methods, use higher-order probability distribution and/or correlation between pixels, such as higher order entropy thresholding.

f. Local methods, calculate threshold value at each pixel based on local image characteristics, such as local contrast method and surface-fitting threshold.

g. The major problem with thresholding is that we consider only the intensity, not any relationships between the pixels. There is no guarantee that the pixes

6)**Image segmentation** using Genetic Algorithm Genetic Algorithms (GAs) can be seen as a software tool that tries to find structure in data that might seem random, or to make a seemingly unsolvable problem more or less 'solvable'. GAs can be applied to domains about which there is insufficient knowledge or the size and/or complexity is too high for analytic solution. Basically, a genetic algorithm consists of three major operations: selection, crossover, and mutation. The selection evaluates each individual and keeps only the fittest ones in the population. In addition to those fittest individuals, some less fit ones could be selected according to a small probability. The others are removed from the current population. The crossover recombines two individuals to have new ones which might be better. The mutation operator induces changes in a small number of chromosomes units. Its purpose is to maintain the population diversified enough during the optimization process