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Research Note

Machine Learning Approaches to Text Segmentation

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Two machine learning approaches are introduced for text segmentation. The first approach is based on inductive learning in the form of a decision tree and the second uses the Naive Bayes technique. A set of training data is generated from a wide category of compound text image documents for learning both the decision tree and the Naive Bayes Classifier (NBC). The compound documents used for generating the training data include both machine printed and handwritten texts with different fonts and sizes. The 18-Discrete Cosine Transform (DCT) coefficients are used as the main feature to distinguish texts from images. The trained decision tree and the Naive Bayes are tested with unseen documents and very promising results are obtained, although the later method is more accurate and computationally faster. Finally, the results obtained from the proposed approaches are compared and contrasted with one wavelet based approach and it is illustrated that both methods presented in this paper are more effective.

INTRODUCTION

The segmentation and separation of text from images is an important part of document image analysis, compression and recognition [1]. Due to widespread applications, many various methods have been proposed [2,3]. These techniques include methods based on pixel values in the spatial domain that utilize the inherent differences between text and image properties. This group of block based methods relies on the 8-by-8 image block and uses criteria such as range, variance, absolute-deviation and edge maps to distinguish different regions [4,5]. Other methods are based on image transformation, such as DCT coefficient, Fourier power and wavelet [6-9]. DCT based algorithms have been more popular, since segmentation is based on examination of the appropriate set of DCT coefficients, which represent the difference between texts and images. Since energy is distributed differently on the range of DCT coefficients, the various properties of these coefficients may be used as criterion for segmentation purposes. Techniques based on DCT energy, absolute-sum, DCT-18 absolute-sum and DCT bit rate have been developed [10]. Methods based on wavelet coefficients and wavelet domain hidden Markove models have also been reported [11,12].

This paper introduces two new techniques based on machine learning. The first method is based on inductive inference in the form of a decision tree [13,14]. A decision tree is a widely used machine learning technique for approximating discrete-value functions, in which the learned function is represented by a decision tree or, alternatively, by a set of rules for improved readability. One advantage of using a decision tree for segmentation is its inherent robustness against noisy data and the capability of learning disjunctive expressions.

The second proposed method is based on the Naive Bayes classifier, which is a probabilistic learning technique and has been successfully used for the practical problem of classifying text documents [14]. Although the Naive Bayes technique is based on the simplifying assumption that attribute values are conditionally independent, given the target value [15], it is shown in this paper that surprisingly excellent results can be obtained in an efficient computational framework. Both techniques require training data, which can easily be obtained from a range of compound images.

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DECISION TREE

A general decision tree consists of nodes, including non-leaf and leaf nodes [14]. Each leaf node denotes a class. The input data consists of the values of the different attributes. Initially, all these values are put inside the root node. By asking questions about the attributes, the decision tree splits the values into different nodes. Constructing a decision tree needs both splitting and stopping rules. Once the decision tree is constructed, it can be used to evaluate other values to decide which classes they belong to. Each node in the tree specifies a test of some attribute of instances and each branch descending from a node represents one of these values for this attribute. A constructed decision tree represents the disjunction of a conjunction of constraints on the attribute values of instances. The criteria used for selecting which attribute to test at each node in the tree should be such that the likelihood of classifying the examples is maximized. Several such criteria exist and the most common one is statistical property, called information gains. Information gain is simply the expected reduction in entropy caused by splitting the instances according to the attribute. The Information gain, $G(D, A)$, of attribute A relative to data set D is defined as:

$$G(D,A)\square E(D) \qquad \sum_{q\in \mathrm{Values}(A)} \frac{|D_q|}{|D|} E(D_q), \tag{1}$$

where $E(.)$ represents entropy and is given by:

$$E(D)\square \quad p^{+}\log_2 p^{+} \quad p \quad \log_2 p \quad , \tag{2}$$

P^{+} and P represent the positive and negative instances in D, respectively, Values (A) is the set of all possible values of attribute A and D_q is the subset of D, in which attribute A has value q.

The attribute values are taken as a set of DCT coefficients. The questions are some properties of pixels contained in an 8-by-8 block of image. Each node in the tree contains the DCT-18 feature, and there is a likelihood of these features generating the observation. According to the answers to the question, the text and image can be separated into the left or right child node. For each child node, there is a new likelihood to generate. The sum of these two child likelihoods should not be equal to the parent likelihood.

The decision tree splitting rule is to minimize the expected entropy or maximize the likelihood increase after splitting. The stopping rules are dictated by the biases associated with the decision tree, which is the shortest tree, and the criteria is a threshold on the further reduction of expected entropy.

There are several algorithms used in order to train a decision tree by constructing them top-down. ID3 algorithms and variants, such as C4.5 and C5 [13,14], are most widely used.

NAIVE BAYES CLASSIFIER

The Naive Bayes Classifier (NBC) is applicable to learning tasks where each instance, x, is described by a conjunction of attribute values and the target function, $f(x)$, may take any value from some finite set, V. A set of training examples of the target function is provided; a new instance, which is described by the attribute value $\langle a_1, a_2, \cdots, a_n\rangle$, is then presented. The learner is asked to predict the target value or the classification. The Bayesian approach to classifying the new instance is to assign the most probable, which is the Maximum A Posteriori (MAP) hypothesis, given the attribute values that describe the instance [14].

$$\nu_{\mathrm{MAP}} = \underset{\nu_j \in V}{\arg\max}\, P(\nu_j | a_1, a_2, \cdots, a_n), \tag{3}$$

where ν_{MAP} is the most probable target value. Using Bayes theorem, Equation 3 can be written as follows:

$$\nu_{\mathrm{MAP}} = \underset{\nu_j \in V}{\arg\max}\, \frac{P(a_1, a_2, \cdots, a_n|\nu_j)P(\nu_j)}{P(a_1, a_2, \cdots, a_n)}. \tag{4}$$

Since $P(a_1, a_2, \cdots, a_n)$ is constant and independent of V, Equation 4 can be rewritten as:

$$\nu_{\mathrm{MAP}} = \underset{\nu_j \in V}{\arg\max}\, P(a_1, a_2, \cdots, a_n|\nu_j)P(\nu_j). \tag{5}$$

Using the training data, the two terms in Equation 5 must be calculated. It is very easy to estimate each $P(\nu_j)$ by counting the frequency of occurrence of each target value, ν_j, in the training data. However, estimating different $P(a_1, a_2, \cdots, a_n|\nu_j)$ terms in this way is not possible unless a huge set of training data is available. In order to make the Naive Bayes classifier more practical and computationally efficient, the simplifying assumption that the attribute values are conditionally independent, given the target value, is made. This assumption implies that:

$$P(a_1, a_2, \cdots, a_n|\nu_j) = \prod_i P(a_i|\nu_i). \tag{6}$$

Substituting Equation 6 into Equation 5 results in the approach used by the Naive Bayes classifier, given by the following equation:

$$\nu_{\mathrm{NB}} = \underset{\nu_j \in V}{\arg\max}\, P(\nu_j)\prod_i P(a_i|\nu_i), \tag{7}$$

where ν_{NB} denotes the target value output given by the Naive Bayes classifier.

Despite the fact that the assumption of independence is often violated, in practice, NBC has presented itself as a serious competitor for the more

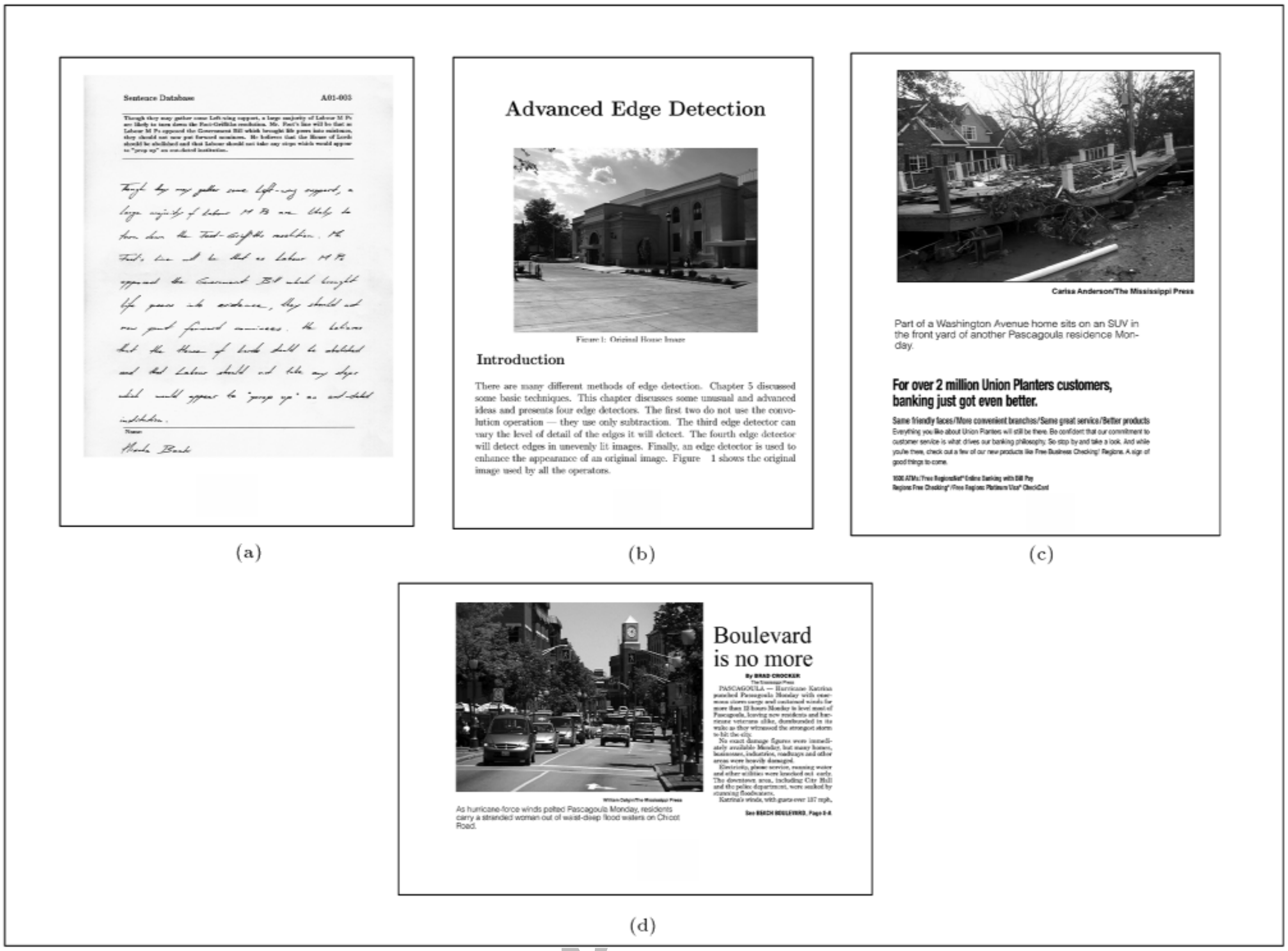


Figure 1. Set of images for generating training data.

sophisticated classifiers. This classifier is shown to be very effective in many practical domains, such as text categorization and medical diagnosis [16,17]. NBC has several distinctive features, which make it suitable for the text segmentation task. First, it is a probabilistic classifier, i.e. it outputs posterior probability distribution over the classes. In this work, text segmentation is treated as a two-class classification task; thus, a probabilistic classifier is appropriate, since it assigns a score to each instance expressing the degree to which that instance is thought to be positive. The second advantage of NBC is that the learning task is not sensitive to the relative number of training instances in positive (text) and negative (non-text) classes. It is only important that all probability estimates in Equation 5 are non-zero. Finally, in Naive Bayes methods, learning time is short and actually linear in the number of training examples, which makes it appropriate for real-time learning. From Equation 5, it is obvious that Naive Bayes learning is simply done through counting the frequency of various data combinations within the training examples.

GENERATION OF TRAINING DATA

In the following, the generation of training data for a text segmentation problem is described. A large training set facilitates the task of learning, tuning and comparing various classifiers. The set of images shown in Figure 1 are selected from a wide category for generating the training data. Note that the images contain both machine-printed and handwritten texts with different fonts and sizes.

For the target value, IsText concept, the integer 1 is assigned to a text block and 0 to a non-text block. The mask images are generated for each of the above training images manually; these are shown in Figure 2 for the four images of Figure 1.

The typical 8-by-8 blocks are used and, for each block, the DCT coefficients are computed as an 8-by-8 matrix. The DCT-18 features are selected, since they capture the difference between the text and the non-text blocks effectively. These are the following elements taken from the matrix of coefficients: 4, 5, 6, 12, 13, 14, 20, 21, 22, 44, 45, 46, 52, 53, 54, 60, 61 and 62, counting from element 1 and going line after line.

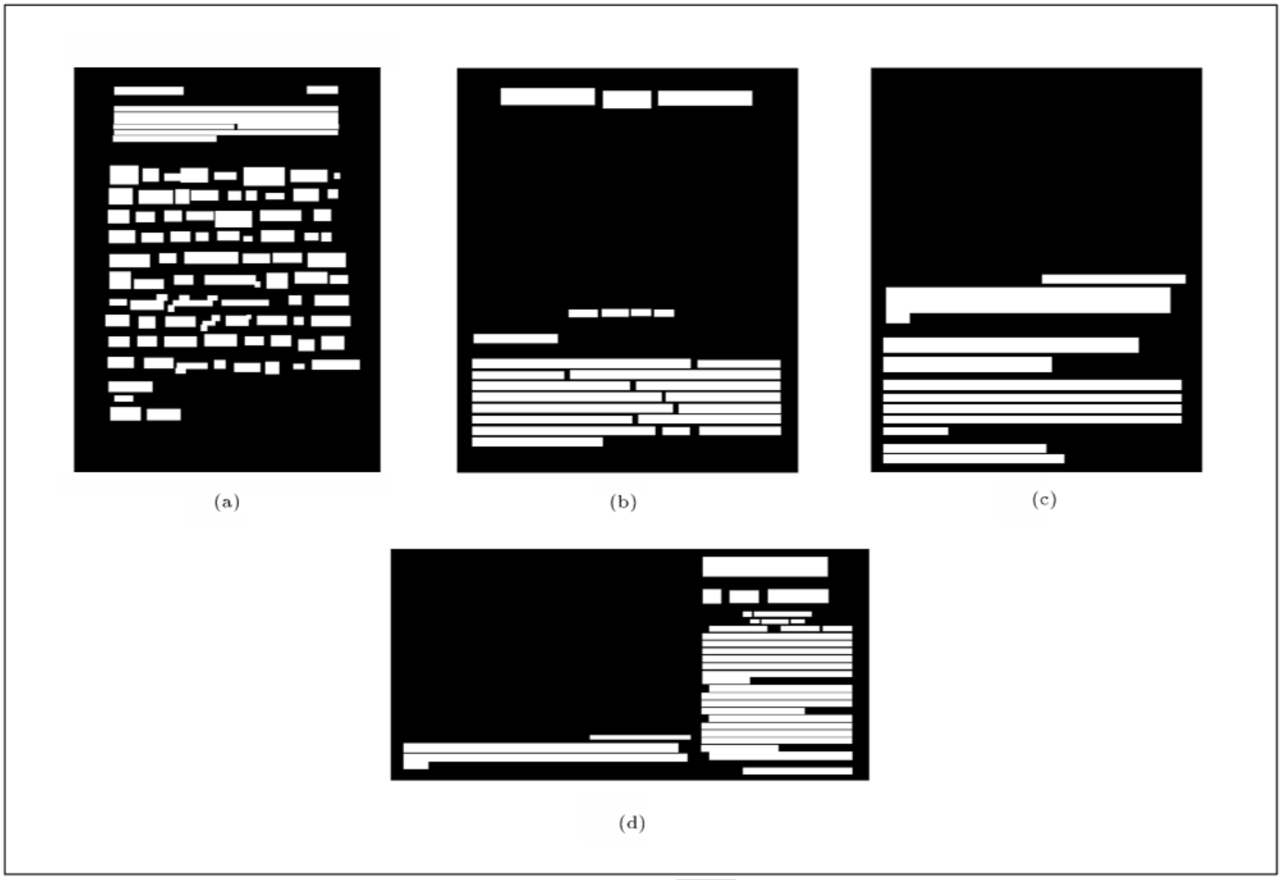


Figure 2. The mask images of Figure 1.

Now, if a block has more than 32 white pixels in its corresponding block of the mask image, it is considered as text (target value is 1) otherwise as non-text. A Matlab program is written for this purpose. By executing this program, a text file is generated; the first line of the file contains attribute names followed by the name of the target concept and each proceeding line represents one training data. Each line (each training data), consists of the 18-DCT coefficients as floating numbers, taken as attribute values and the last number, which is 0 or 1, is the target value. These attribute values are initially continuous real variables and are not suitable for learning algorithms, such as ID3 [14] or Naive Bayes Classifiers [14]. For this reason, a C4.5 [13] algorithm may be used instead of ID3 for learning a decision tree. Further, the training set is converted to a discrete form for the purpose of applying the decision tree and the following set of rules is used to convert the continuous-valued variable, x, into a discrete form:

replace $250 <= x <$ 150 by 'S2', very small,

replace $150 <= x <$ 50 by 'S1', small,

replace $50 <= x < 50$ by 'CE', center,

replace $50 <= x < 150$ by 'B1', big,

replace $150 <= x < 250$ by 'B2', very big.

TEXT SEGMENTATION USING DECISION TREES

A decision tree is used to separate text from non-text blocks in an input document image. The training data generated by the procedure described above is used to learn a decision tree for the text segmentation problem. Once the decision tree is constructed, it is tested with unseen data and some experimental results are presented and compared with the method described in [8].

First, a decision tree is trained using the C4.5 algorithm and the continuous data. Using the procedure described above, 100,000 training examples were generated using the four images. However, in the initial stages of the learning procedure, it was observed that by presenting only 1000 samples of training data, the stopping criterion was satisfied. Therefore, a training set of size 1000 is selected randomly from the whole set and used to train the decision tree. It is shown that the trained decision tree has a good generalization power, even with 1000 training samples. Segmentation of the gray scale input image is carried out by the following procedure:

1. Segment the gray-scale input image to non-overlapping 8-by-8 blocks;
2. Apply DCT to each block and select the 18 coefficients described previously, as the feature vector;
3. Show this vector to the classifier. If the classifier's output is Yes or above 0.5, label this block as text otherwise as non-text;
4. Post-process the output image to reduce noise effect and improve segmentation accuracy.

A Matlab program is written to carry out steps 1 to 4 above. In the post-processing step, a rule based smoothing procedure, in conjunction with morphological operations, is adapted to reduce the noise effect. The most successful smoothing scheme used is shown below:

$$\begin{array}{|c|c|c|}\hline 0&0&0\\ \hline 0&1&0\\ \hline 0&0&0\\ \hline\end{array} \xrightarrow{\text{Isolated text becomes graph}} \begin{array}{|c|c|c|}\hline 0&0&0\\ \hline 0&0&0\\ \hline 0&0&0\\ \hline\end{array}$$

$$\begin{array}{|c|c|c|}\hline 1&1&1\\ \hline 1&0&1\\ \hline 1&1&1\\ \hline\end{array} \xrightarrow{\text{Isolated graph becomes text}} \begin{array}{|c|c|c|}\hline 1&1&1\\ \hline 1&1&1\\ \hline 1&1&1\\ \hline\end{array}$$

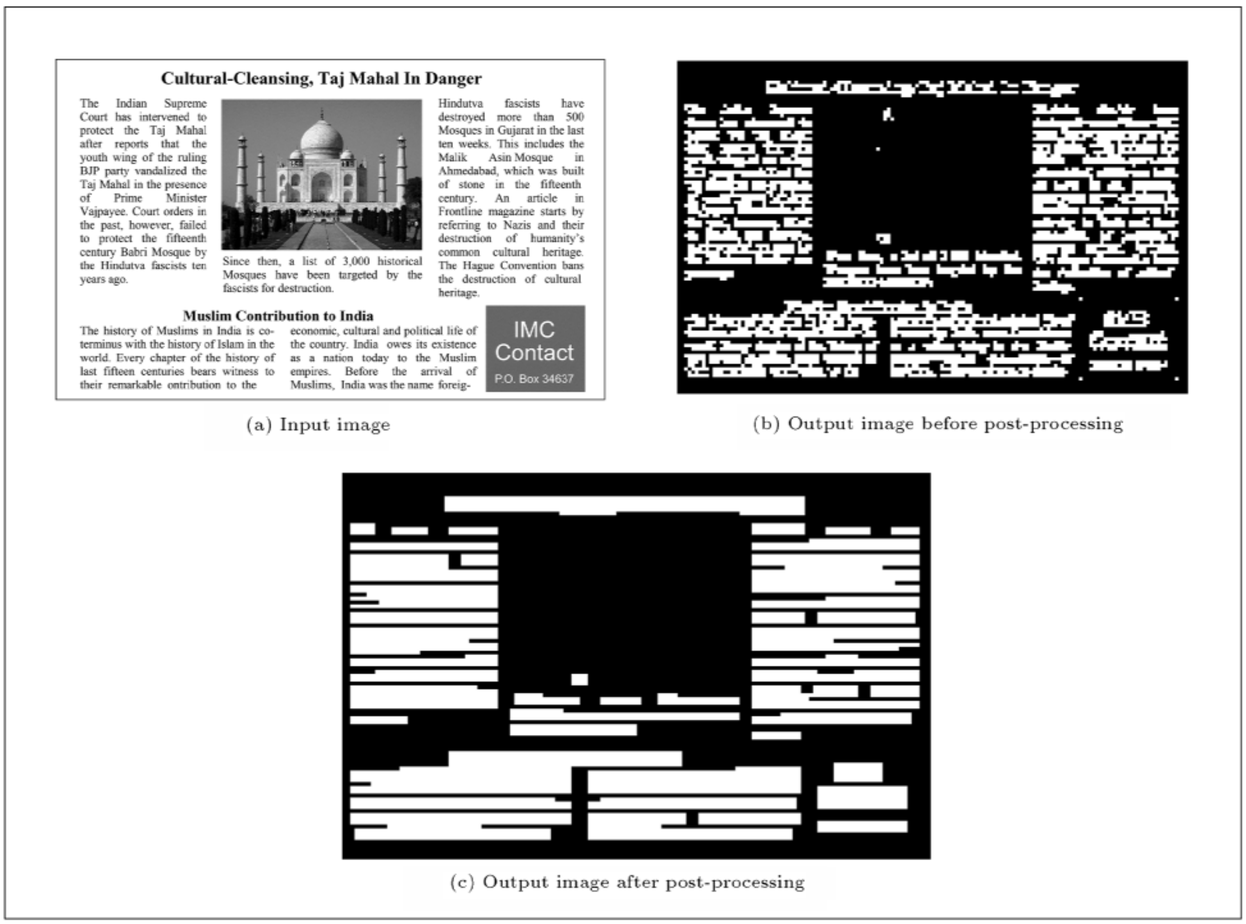
$$\begin{array}{|c|c|}\hline 0&1\\ \hline 1&1\\ \hline\end{array} \rightarrow \begin{array}{|c|c|}\hline 1&1\\ \hline 1&1\\ \hline\end{array} \qquad \begin{array}{|c|c|}\hline 1&0\\ \hline 1&1\\ \hline\end{array} \rightarrow \begin{array}{|c|c|}\hline 1&1\\ \hline 1&1\\ \hline\end{array}$$

$$\begin{array}{|c|c|}\hline 1&1\\ \hline 0&1\\ \hline\end{array} \rightarrow \begin{array}{|c|c|}\hline 1&1\\ \hline 1&1\\ \hline\end{array} \qquad \begin{array}{|c|c|}\hline 1&1\\ \hline 1&0\\ \hline\end{array} \rightarrow \begin{array}{|c|c|}\hline 1&1\\ \hline 1&1\\ \hline\end{array}$$

Semi-rectangular text regions become rectangular

These rules are implemented in C++ for faster computation. The executable computer program accepts the input file name on its first command line as an argument, the output file name as the second, smoothing type as the third and the number of repetitions as the last argument. The input file is assumed to be black and white (bi-level) in BMP format.

The unseen image of Figure 3a is presented to the trained decision tree; the output without post-processing is shown in Figure 3b; and the after post-processing (final output) is shown in Figure 3c.

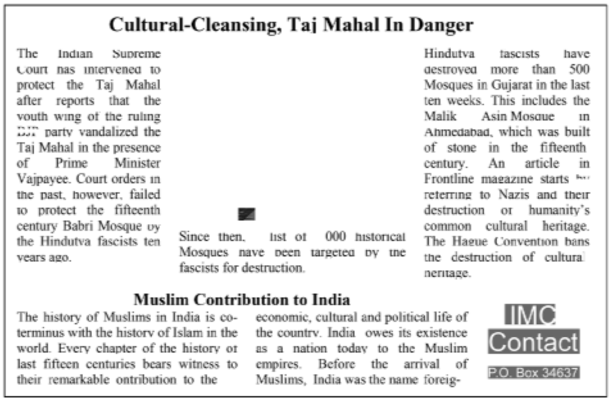


(a) Input image

(b) Output image before post-processing

(c) Output image after post-processing

Figure 3. The test image presented to the constructed decision tree.



Cultural-Cleansing, Taj Mahal In Danger

The Indian Supreme Court has intervened to protect the Taj Mahal after reports that the youth wing of the ruling BJP party vandalized the Taj Mahal in the presence of Prime Minister Vajpayee. Court orders in the past, however, failed to protect the fifteenth century Babri Mosque by the Hindutva fascists ten years ago.

Since then, list of 3000 historical Mosques have been targeted by the fascists for destruction.

Hindutva fascists have destroyed more than 500 Mosques in Gujarat in the last ten weeks. This includes the Malik Asin Mosque in Ahmedabad, which was built of stone in the fifteenth century. An article in Frontline magazine starts by referring to Nazis and their destruction of humanity's common cultural heritage. The Hague Convention bans the destruction of cultural heritage.

Muslim Contribution to India

The history of Muslims in India is co-terminus with the history of Islam in the world. Every chapter of the history of last fifteen centuries bears witness to their remarkable contribution to the economic, cultural and political life of the country. India owes its existence as a nation today to the Muslim empires. Before the arrival of Muslims, India was the name foreig-

IMC Contact P.O. Box 34637

Figure 4. The segmented image.

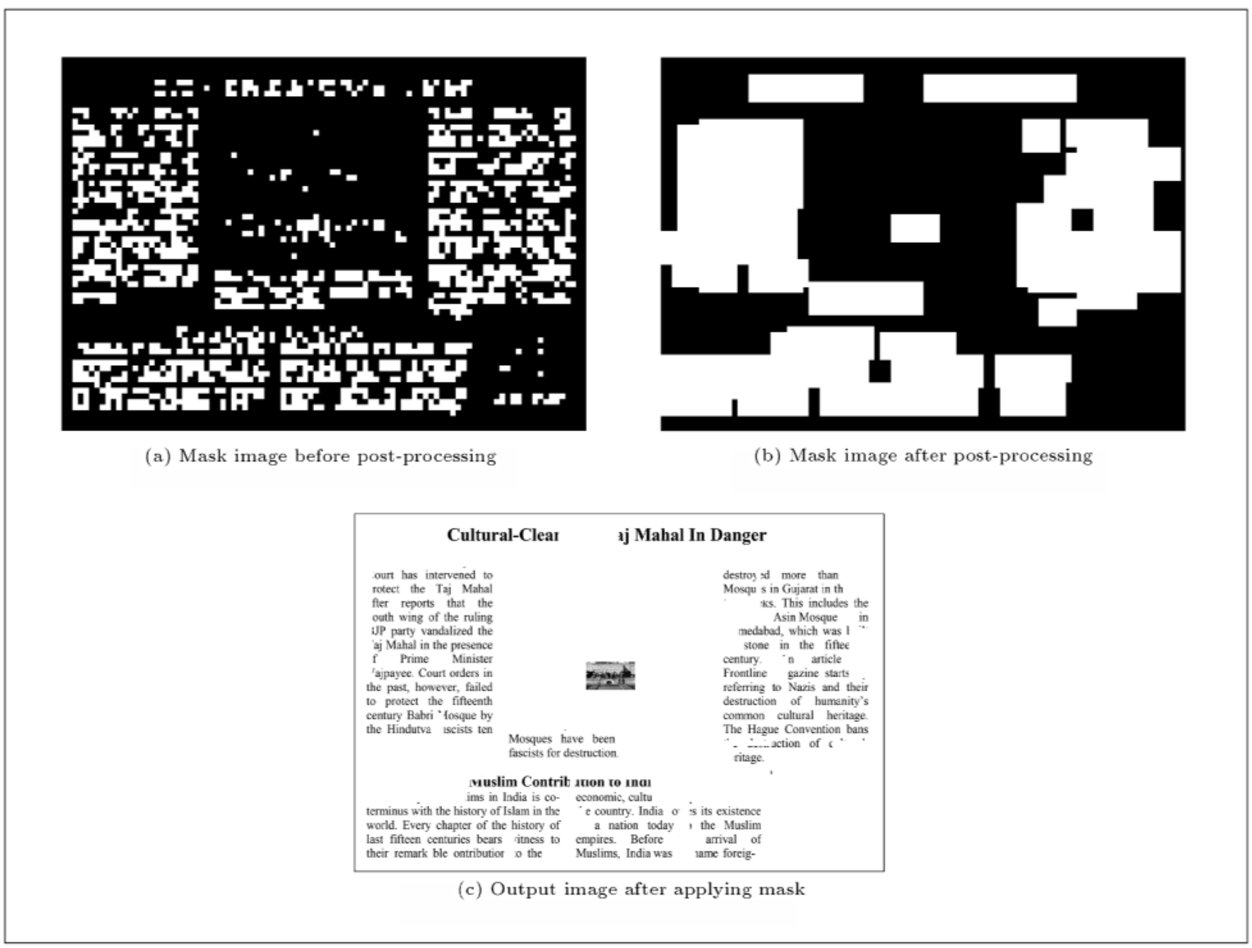
Applying the mask to the image of Figure 3c, the image of Figure 4 is obtained.

In order to compare the results with another technique, the method described in [8], which is based on high frequency wavelet coefficients, was implemented. This method is also tested on the same image of Figure 3a. Figure 5 shows segmentation before and after per-processing and the masked image, respectively.

Generally, it is observed that the decision tree technique presented above gives promising results for the text segmentation problem. It is also observed that the performance of the decision tree is slightly degraded when confronted with segments of text with font sizes considerably different from the sizes in the training data; this is even more significant with the wavelet based method. However, a small fraction of the generated data was selected randomly from the whole set as training data to learn the decision tree. When a large data set is available, classification accuracy can be considerably improved by constructing several decision trees (at least three) trained by several randomly selected sets of the original data and then using majority voting to find the classification result.

TEXT SEGMENTATION USING NAIVE BAYES CLASSIFIERS

In this section, the application of the Naive Bayes classifier to separate text from non-text blocks in a document image is described. First, a set of discrete



(a) Mask image before post-processing

(b) Mask image after post-processing

(c) Output image after applying mask

Figure 5. Segmentation based on high frequency wavelet coefficients.

Table 1. Rules used for discretization of the data.

	Continuous	Discrete		Continuous	Discrete		Continuous	Discrete
A1	(-inf, -15.8]	S2	A2	(-inf, -13.1]	S2	A3	(-inf, -9.5]	S2
	(-15.8, -0.7]	S1		(-13.1, -0.4]	S1		(-9.5, -0.3]	S1
	(-0.7, 0.8]	CE		(-0.4, 0.3]	CE		(-0.3, 0.4]	CE
	(0.8, 16.1]	B1		(0.3, 11.3]	B1		(0.4, 11.4]	B1
	(16.1,inf)	B2		(11.3, inf)	B2		(11.4, inf)	B2
A4	(-inf, -11.5]	S2	A5	(-inf, -10]	S2	A6	(-inf, -6.3]	S2
	(-11.5, -0.5]	S1		(-10, -0.3]	S1		(-6.3, -0.3]	S1
	(-0.5, 0.4]	CE		(-0.3, 0.2]	CE		(-0.3, 0.2]	CE
	(0.4, 11.3]	B1		(0.2, 9.4]	B1		(0.2, 6.6]	B1
	(11.3, inf)	B2		(9.4, inf)	B2		(6.6, inf)	B2
A7	(-inf, -10.6]	S2	A8	(-inf, -7.3]	S2	A9	(-inf, -5.2]	S2
	(-10.6, -0.4]	S1		(-7.3, -0.2]	S1		(-5.2, -0.2]	S1
	(-0.4, 0.3]	CE		(-0.2, 0.2]	CE		(-0.2, 0.2]	CE
	(0.3, 8.5]	B1		(0.2, 6.2]	B1		(0.2, 4.8]	B1
	(8.5, inf)	B2		(6.2, inf)	B2		(4.8, inf)	B2
A10	(-inf, -4.6]	S2	A11	(-inf, -3.3]	S2	A12	(-inf, -3.4]	S2
	(-4.6, -0.2]	S1		(-3.3, -0.1]	S1		(-3.4, -0.2]	S1
	(-0.2, 0.2]	CE		(-0.1, 0.2]	CE		(-0.2, 0.2]	CE
	(0.2, 4.3]	B1		(0.2, 3.7]	B1		(0.2, 2.9]	B1
	(4.3, inf)	B2		(3.7, inf)	B2		(2.9, inf)	B2
A13	(-inf, -3.4]	S2	A14	(-inf, -2]	S2	A15	(-inf, -2]	S2
	(-3.4, -0.1]	S1		(-2, -0.1]	S1		(-2, -0.1]	S1
	(-0.1, 0.1]	CE		(-0.1, 0.1]	CE		(-0.1, 0.1]	CE
	(0.1, 3.3]	B1		(0.1, 2]	B1		(0.1, 2]	B1
	(3.3, inf)	B2		(2, inf)	B2		(2, inf)	B2
A16	(-inf, -2]	S2	A17	(-inf, -2.3]	S2	A18	(-inf, -2.2]	S2
	(-2, -0.2]	S1		(-2.3, -0.1]	S1		(-2.2, -0.1]	S1
	(-0.2, 0.2]	CE		(-0.1, 0.1]	CE		(-0.1, 0.2]	CE
	(0.2, 3]	B1		(0.1, 2.4]	B1		(0.2, 2.3]	B1
	(3, inf)	B2		(2.4, inf)	B2		(2.3, inf)	B2

training instances from the real dataset is generated, as described in the previous section.

For the purpose of learning the NBC, a set of 10,000 training data is selected randomly and each attribute value is converted to discrete form to make it appropriate for the Naive Bayes learner. Each continuous real attribute value is converted to only five discrete values, 'S2', 'S1', 'CE', 'B1' or 'B2', where 'S2' means very small, 'S1' small, 'CE' center, 'B1' big and 'B2' very big. These provide approximately 2000 instances in each of the 5 bins for each attribute value. Different sets of rules for each of the 18 attributes are used. These rules are given in Table 1.

For the "Is Text?" concept, let $V1$ = 'Yes' and $V2$ = 'No'. Evaluation of the two terms required by the Naive Bayes (Equation 7) is carried out. However, for the evaluation of $j = 1, 2$, the m-estimate algorithm [14,18] with $m = 1$ and $p = 0.2$ is applied to avoid zero conditional probabilities. The results for the 18-DCT coefficients are given in Table 2.

No prior information about the source image is assumed, hence, $P(\nu_1) = P(\nu_2) = 0.5$ and a new instance is classified as follows:

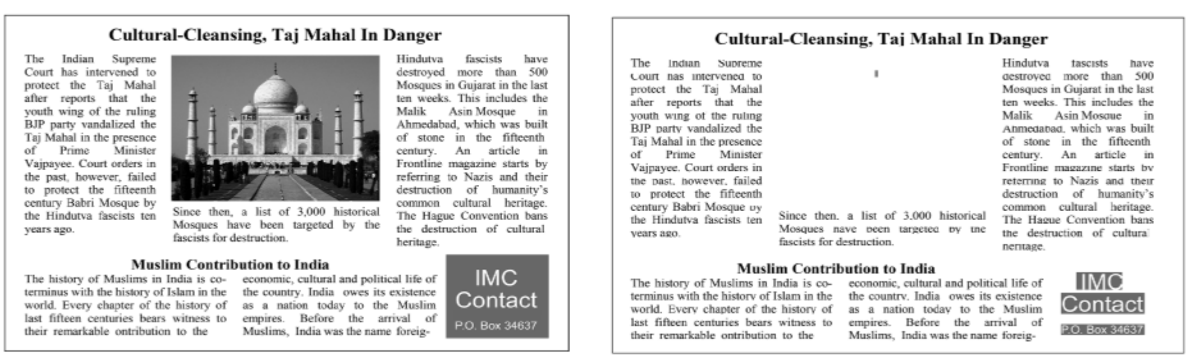
$$\text{If } P(a_1|\nu_1)P(a_2|\nu_1)\cdots P(a_{18}|\nu_1) > P(a_1 > \nu_2)P(a_2|\nu_2)\cdots P(a_{18}|\nu_2), \tag{8}$$

the input is a text block, otherwise it is a non-text block. The same set of rule-based smoothing filters, as described in previous section, is used for post processing. The Naive Bayes classifier is implemented and the same test image is presented. The segmentation result is shown in Figure 6.

Other test images were also presented; it was observed that the proposed NBC method is more accurate, computationally faster than the decision tree technique and much less sensitive to different font sizes. By using the 10-fold cross-validation technique [14], estimation for a classification accuracy of 85% was obtained. Initially, it was thought that if the original continuous training data were used, the classification accuracy would be further improved. The version of

Table 2. Conditional probabilities.

		V				V				V	
$P(A1\|Vj)$		Yes	No	$P(A2\|Vj)$		Yes	No	$P(A3\|Vj)$		Yes	No
A	S2	0.3199	0.0938	A	S2	0.3116	0.0821	A	S2	0.3228	0.1018
	S1	0.1496	0.2496		S1	0.1656	0.2458		S1	0.1513	0.2661
	CE	0.0687	0.3212		CE	0.0490	0.3475		CE	0.0566	0.3112
	B1	0.1369	0.2462		B1	0.1428	0.2274		B1	0.1654	0.2329
	B2	0.3250	0.0893		B2	0.3309	0.0972		B2	0.3038	0.0881
$P(A4\|Vj)$		Yes	No	$P(A5\|Vj)$		Yes	No	$P(A6\|Vj)$		Yes	No
A	S2	0.3454	0.0635	A	S2	0.3459	0.0684	A	S2	0.3323	0.0771
	S1	0.1384	0.2568		S1	0.1344	0.2390		S1	0.1386	0.2522
	CE	0.0442	0.3333		CE	0.0416	0.3576		CE	0.0448	0.3191
	B1	0.1291	0.2869		B1	0.1304	0.2674		B1	0.1403	0.2822
	B2	0.3429	0.0595		B2	0.3478	0.0677		B2	0.3440	0.0694
$P(A7\|Vj)$		Yes	No	$P(A8\|Vj)$		Yes	No	$P(A9\|Vj)$		Yes	No
A	S2	0.3342	0.0584	A	S2	0.3387	0.0572	A	S2	0.3412	0.0578
	S1	0.1359	0.2464		S1	0.1367	0.2585		S1	0.1318	0.2795
	CE	0.0473	0.3578		CE	0.0395	0.3655		CE	0.0452	0.3174
	B1	0.1166	0.2666		B1	0.1209	0.2515		B1	0.1314	0.2733
	B2	0.3659	0.0709		B2	0.3643	0.0673		B2	0.3503	0.0720
$P(A10\|Vj)$		Yes	No	$P(A11\|Vj)$		Yes	No	$P(A12\|Vj)$		Yes	No
A	S2	0.3537	0.0610	A	S2	0.3697	0.0553	A	S2	0.3473	0.0623
	S1	0.1359	0.2941		S1	0.1287	0.3015		S1	0.1285	0.2623
	CE	0.0450	0.3212		CE	0.0404	0.3358		CE	0.0570	0.3667
	B1	0.1221	0.2608		B1	0.1192	0.2505		B1	0.1206	0.2445
	B2	0.3433	0.0629		B2	0.3421	0.0569		B2	0.3465	0.0642
$P(A13\|Vj)$		Yes	No	$P(A14\|Vj)$		Yes	No	$P(A15\|Vj)$		Yes	No
A	S2	0.3543	0.0618	A	S2	0.3609	0.0457	A	S2	0.3571	0.0584
	S1	0.1295	0.3151		S1	0.1177	0.2782		S1	0.1105	0.2994
	CE	0.0334	0.2672		CE	0.0385	0.3523		CE	0.0408	0.2738
	B1	0.1380	0.2952		B1	0.1143	0.2738		B1	0.1280	0.3047
	B2	0.3448	0.0606		B2	0.3687	0.0500		B2	0.3636	0.0637
$P(A16\|Vj)$		Yes	No	$P(A17\|Vj)$		Yes	No	$P(A18\|Vj)$		Yes	No
A	S2	0.3719	0.0853	A	S2	0.3495	0.0661	A	S2	0.3355	0.0669
	S1	0.0968	0.2168		S1	0.1280	0.2894		S1	0.1361	0.3142
	CE	0.0570	0.3597		CE	0.0427	0.3057		CE	0.0488	0.3324
	B1	0.1344	0.2714		B1	0.1346	0.2818		B1	0.1354	0.2265
	B2	0.3400	0.0669		B2	0.3452	0.0570		B2	0.3442	0.0601



(a) Input image (b) Segmented image using Naive Bayes classifier

Figure 6. Result from the Naive Bayes segmentation method for test image 1.

the Naive Bayes that estimates the probabilities, based on analysis of the continuous training data [15], was implemented and tested. Surprisingly, the accuracy of the classification was reduced to 82%.

CONCLUSION

Two different machine learning techniques are presented for text segmentation. One method is based on inductive learning in the form of a decision tree and the other uses statistical learning in the form of Naive Bayes. A set of training data is generated from a wide category of compound text/image documents with different column layouts and different font sizes. The training set includes both handwritten and machine printed documents. Both the decision tree and the Naive Bayes learner are trained using a portion of the randomly selected subset of the training data. Both techniques are tested using benchmark documents. Although the decision tree is easier and faster to train, the Naive Bayes method gives better results. In order to illustrate the effectiveness of the proposed approaches, both techniques are compared with one wavelet based method and it is concluded that the presented methods are greatly superior in terms of accuracy.

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