Detection and Classification of Interesting Parts in Scanned Documents by Means of AdaBoost Classification and Low-Level Features Verification

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Abstract. This paper presents a novel approach to detection and identification of selected document's parts (stamps, logos, printed text blocks, signatures and tables) on digital images obtained through paper document scanning. This task is realized in two main steps. The first one includes element detection, which is done by means of AdaBoost cascade of weak classifiers. Resulting image blocks are, in the second step, subjected to verification process. Eight feature vectors based on recently proposed descriptors were selected and combined with six different classifiers that represent numerous approaches to the task of data classification. Experiments performed on large set of paper document images gathered from Internet gave encouraging results.

1 Introduction

Paper documents are one of the basic means of human communication. Each of them contains much information in different languages, structures, forms and carries information of different value. Regardless of those features there are common elements such as stamps, signatures, tables, logos, blocks of text and background. In order to prevent the process of document accumulation most of valuable pieces are digitally scanned and kept as digital copies on computers. Storing data this way makes process of document organizing, accessing and exchange easier but, even then without a managing system it is difficult to keep things in order. As stated in [1] a system that is able to recognize digital image of paper document can be used to transform a document into its digital, hierarchical representation in terms of structure and content, which would allow to exchange, edit, browse, index, fill and retrieve much easier.

Developed algorithm can be a part of document managing system, whose main purpose is to determine parts of the document that should be processed further (text [2]), be subjected to enhancement and denoising process (graphics, pictures, charts etc.) [3]. It could be integral part of any content-based image retrieval system, or simply a filter that would select only documents containing

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specific elements [4], segregate them in terms of importance (colored documents containing stamps and signatures are more valuable than monochromatic ones, which suggest a copy [5]) etc. Our approach is document type independent, hence can be applied to formal documents, newspapers, envelopes, bank checks etc.

The rest of the paper is organized as follows: first we provide a review of related works and point out their characteristic features, then we present an algorithm consisting of two stages and present the experimental results. We conclude the paper with a discussion on the results.

2 Previous Works

Document segmentation can be performed using global (multi-class detection and classification) and individual (class-specific detection and classification) methods. Global approaches can be divided in three categories of methods [6]: top-up, bottom-up and heuristic-based. Top-down methods could be useful when it comes to documents of previously known structure. Bottom-up strategy starts with pixel-level analysis, and then pixels of common properties are grouped into bigger structures. Heuristic-based procedures attempt to combine robustness of top-down approach and accuracy of bottom-up methods.

Bottom-up strategy is used in [7], where documents are segmented into 3 classes (background, graphics and text). A sliding window technique is used to segment input image into blocks. Each block is subjected to feature extraction stage and, based on a number of rules, is classified. Reported accuracy of text detection is 99%. Result for other classes were not provided. Very similar approach is presented in [8], but it uses different set of features, that are calculated from GLCM (Gray-Level Coocurrence Matrix), as well as k-means algorithm for grouping. Mean accuracy equals to 94%.

Top-down strategies rely on run-length analysis performed on binarized, skew-corrected documents [6]. Vertical and horizontal profiles are examined in terms of valley occurrence, which represent white space between blocks. Other solutions include usage of Gaussian pyramid in combination with low-level features or Gabor-filtered pixel clustering. Heuristic methods combine bottom-up and top-down strategies are especially useful while processing documents of high complexity [1]. Zone classification issue as a multi-class discrimination problem was investigated i.e. in [3]. It provides a comparative analysis of commonly used features for 8 classes. Tamura's histogram achieved highest accuracy, but due to it's computation complexity was discarded in favor of more simple features vector. Reported error rate is equal to 2.1%, but 72.7% of logos and 31.4% tables were misclassified. Wang et al. [1] proposed a 69-element feature vector, which was reduced to 25 elements in feature selection stage, which allowed to achieve mean accuracy of 98.45%, however 84.64% logos and 72.73% 'other' elements were misclassified.

The problem of class-specific detection and classification is widely represented in literature. In our previous works [5,9–11] a problem of stamp detection and recognition was addressed. Our observation is that logo detection is very similar problem and can be solved with little tweak to our previously presented solution. Others use keypoint analyzing algorithms i.e. SIFT, SURF and FAST or ART.

Text block detection can be realized by means of statistical analysis [12], edge information [13], texture analysis [13,14], stroke filters [15–17], cosinus transform [18] and LBP algorithm [19].

Tabular objects are hard to detect and classify, since they feature high intra-class variance. A simplification of this problem includes the assumption about one column of text with easily separable, non-overlapping lines [20].

The same high intra-class variance influences the accuracy of signature detection. That is why keypoint-based algorithms are widely-applicable. In [21] Zhu et al. proposed algorithm consisting of extensive pre-processing, multi-scale signature saliency measure calculation for each connected component and component connecting based on proximity and curvilinear constraints. High accuracy (92.8%) was achived on popular *Tobacco-800* database. In [22] SUFR algorithm was used to determine keypoint location on images containing results of connected component analysis. Again, connected component analysis is crucial part of [23]. The paper provides a comparative analysis of HOG, SIFT, gradient, TBP and low-level features. Classification is performed by SVM classifier. Experiments performed on *Tobacco-800* database proved that for the set containing gradient and low-level features the accuracy reached 95%.

The analysis of the literature shows, that most of algorithms use some pre-processing (e.g. document rectification), restrict forms of analysed documents (e.g. to cheques) and employ sophisticated features and multi-tier approaches.

In the proposed solution, we do not pre-process images of scanned documents and employ very efficient AdaBoost cascade which is implemented using integral image, hence giving very high processing speed. It is worth noticing, that we analyse probably all possible object types that can be found in documents, which is, surprisingly, not so popular in other works.

3 Algorithm Description

Presented algorithm consists of two subsequent elements. The first one is devoted to rough detection, while the second one is applied for verification of found candidates. The assumption is that the cascade results in rather high number of false positives, so they are subject to verification using additional set of more complex features.

3.1 Cascade Training and Detection

Detection process is performed by a set of AdaBoosted cascades of weak classifiers [24,25]. It means, that we trained 5 separate cascades for specific type of objects, namely: stamps, logos/ornaments, texts and signatures. Example objects selected from all classes are presented in Tab. 1. Background blocks, being an additional class, are taken further as negative examples for training other cascades. The detection was performed using 24×24 block on a pyramid

Table 1. Exemplary training images

Class	Images
stamps	
logos	
text	
signatures	
tables	
backgrounds	

of scales where in each iteration we downscale an input image by 10%. The training procedure was performed in two iterations. The first, preliminary training, was to initialize the classifier. For this stage we used 150 positive and 740 negative samples for each class, taken from Internet and from SigComp2009 [26].

In order to increase the detection accuracy we performed a second iteration, in which we extended training database with objects resulted from the first iteration. The positive results were added to the positive samples while the negative, to negative ones, respectively.

3.2 Verification Stage

Detected objects are verified using a set of eight following low-level features. The classification is performed using several popular classifiers. The initial training set, upon which reference features were calculated, consist of 219 logos, 452 text blocks, 251 signatures, 1590 stamps, 140 tables, and 719 background areas. As in case of detection, background block were used as negative examples and we do not evaluate background detection accuracy. After the fist iteration, we identified problems and solved them by extending the training database.

First Order Statistics (FOS) - a vector of six, direct, low-level features calculated from histogram of pixel intensities. The features are: mean pixel intensity, second (variance), third (skewness), fourth (kurtosis) central moment and entropy. They provide information about global characteristic of input image.

Gray-Level Run Length Statistics (GLRLS) - a vector of eleven features calculated from run-length matrix: short run emphasis, long run emphasis, gray-level nonuniformity, run length nonuniformity, run length nonuniformity, run percentage, low gray-level run emphasis, high gray-level run emphasis, short run low gray-level emphasis, short run high gray-level emphasis, long run low gray-level emphasis, long run high gray-level emphasis. Those features provide information about texture coarseness and/or fineness. Algorithm for GLRLM matrix calculation along with respective equations are in [27–29].

Haralick's Statistics (HS) is a set of 22 features calculated from Gray-Level Co-occurence matrix. Appropriate algorithms are available in [30–32]. List of features used consist of: autocorrelation, contrast, correlation, cluster shade, cluster prominence, dissimilarity, energy, entropy, homogeneity, maximum probability, sum of squares: variance, sum average, sum variance, sum entropy, difference variance, difference entropy, information measures of correlation, inverse difference, inverse difference normalized, inverse difference moment normalized.

Neighboring Gray-Level Dependence Statistics (NGLDS) is a 5-element vector of features (small number emphasis, large number emphasis, number nonuniformity, second moment, entropy) derived from NGLDM matrix. Element and their value distribution inside NGLDM matrix provides information about the level of texture coarseness. Algorithm for matrix calculations and respective equations are in [33].

Low-Level Features (LLF) is a vector of eleven features developed for our previous research on stamp recognition [5,11]. This approach shares common features with measures proposed by Haralic et al. Contrast, correlation, energy and homogenity are calculated in the same way with use of GLCM matrix. Other features include: average pixel intensity, standard deviation of intensity, median intensity, contrast, mean intensity to contrast ratio, intensity of edges, mean intensity to edges intensity ratio.

Histograms of Oriented Gradients (HOG) is a method proposed by Dalal and Triggs in [34] and proved to be an effective method for human detection in digital images and later on in video sequences, but as mentioned in the paper algorithm is also capable of determining between objects of different type. Feature vector of HOG descriptor is 256-elements long.

Local Binary Patterns LBP were introduced in [35] as universal, fine-scale texture descriptor [36]. Similarly to HOG the output vector consist of 256 elements. In our case, Local Binary Patterns come in two, different variants. The first one is calculated on monochromatic image, for the second binarized image was supplied (LBPB).

4 Experiments

In the experimental evaluation the detection stage is performed first. In next step all generated examples were divided into two categories: positive and negative detections. This allowed us to calculate confusion matrices for each combination of classifier and feature set. The details of document images database we used in experiments are provided in [5]. Exemplary documents are shown in Fig. 1.

Fig. 1. Exemplary documents used in the experimental part

4.1 Detection Stage

The decision whether the result should be considered positive or negative was made based on its bounding box area. Objects that are covered by approximately 75% of resulting bounding box were classified positively. The results for both iterations are provided in Tab. 2. The mean accuracy after first iteration of detection was equal to 54% (with highest 80% for text and lowest 14% for signatures). Observed low accuracy is caused by high resemblance between classes, e.g. many logos were classified as stamps, large number of tables (which according to [6] should be considered as graphics) as printed text. The low accuracy for signatures comes from the lack of signatures in input documents, hence we included the samples from SigComp2009, which are quite different in character. Examples of difficult to detect objects are presented in Fig. 4.1.

Fig. 2. Ambiguous objects: overlapped signatures and tables containing text

Lowest accuracy of signature detector results from different characteristics of examples used to train cascade (high resolution, light and noise-free background, clear strokes, contrast ink) and the ones that are actually located on scanned documents (varying background and ink colour, often overlapping with other elements). Those observations were taken into account when preparing data for the second learning iteration.

Analysing the results in Tab. 2 one can see a significant increase in detection accuracy after second iteration of training procedure. After this iteration, there is a significantly lower number of false detections, yet also slightly lower number of positive detections. A clearly visible significant increase in signatures detection rate is still far from ideal. It is caused by the fact, that in most cases signatures are overlapped with other elements, such as stamps, text and signature lines.

Table 2. Detection results

Class	1st iteration			2nd iteration		
	TP	FP	Acc. [%]	TP	FP	Acc. [%]
Stamps	174	281	42.54	235	187	60.04
Logos	444	394	65.29	236	75	84.01
Texts	557	919	80.38	136	84	91.63
Signatures	75	38	13.99	461	92	29.23
Tables	1133	1209	67.48	546	67	94.75

4.2 Verification Stage

Experiments described below were aimed at determining a combination of classifier and feature set (presented above) that gives the highest verification rate. The set of classifiers we investigated consist of: 1-Nearest Neighbour (1NN), Naïve Bayes (NBayes), Binary Decision Tree (CTree), Support Vector Machine (SVM), General Linear Model Regression (GLM) and Classification and Regression Trees (CART). There were two iterations of processing. The first one was performed on an initial features calculated for manually selected samples (see Sec. 3.2). The second iteration of training was performed on a set with certain extra samples, derived from the first iteration output.

In Tables 3 - 7 verification accuracy for each class is presented (there are two columns of results for each classifier, each for subsequent iterations, respectively). The highest accuracy in the first iteration is underlined, while the highest accuracy in the second iteration is double underlined, respectively. Sometimes, more that one accuracy is the highest, hence more results are underlined.

Table 3. Stamps verification accuracy [%]

	1NN		NBayes		CTree		SVM		GLM		CART	
FOS	52.57	53.42	48.66	41.24	61.86	64.96	41.56	39.96	39.85	52.99	64.30	55.77
GLRLS	45.48	48.93	44.01	35.26	52.57	60.04	48.66	40.81	52.32	40.81	58.68	38.89
HS	58.19	60.68	55.75	50.21	74.57	63.25	79.46	71.37	81.17	71.79	73.35	35.47
HOG	73.84	79.06	73.84	69.44	60.39	63.46	65.53	51.07	69.44	66.45	69.19	41.45
LBP	55.01	61.54	48.17	36.97	55.99	56.84	73.84	43.38	73.35	38.46	54.77	39.53
LBPB	56.97	63.46	69.93	39.96	69.44	64.74	76.77	62.39	78.24	65.17	64.30	42.52
LLF	63.81	60.47	62.35	63.89	71.15	67.95	57.46	39.96	64.30	63.46	75.55	68.80
NGLDS	46.94	53.63	52.57	37.82	45.97	53.63	40.10	57.05	37.90	44.02	47.92	39.32

Table 4. Logos verification accuracy [%]

	1NN		NBayes		CTree		SVM		GLM		CART	
FOS	40.44	23.03	42.35	19.19	49.12	23.03	34.71	15.99	38.68	16.63	45.88	20.26
GLRLS	42.79	26.44	54.12	39.45	53.97	37.10	67.94	51.60	42.35	19.40	45.88	26.65
HS	42.35	18.98	59.12	32.41	54.12	33.48	61.18	39.23	49.12	23.67	44.26	20.26
HOG	53.82	30.28	55.88	39.23	51.32	35.61	60.74	43.07	58.53	49.12	47.21	31.34
LBP	40.00	18.76	47.65	17.70	37.50	21.54	46.76	22.17	43.24	21.32	38.53	18.76
LBPB	41.47	40.51	61.91	20.04	43.68	32.62	62.06	50.75	48.53	32.84	42.65	30.92
LLF	50.44	25.16	58.82	37.10	61.62	43.07	34.71	15.99	61.18	38.38	40.44	48.83
NGLDS	39.12	18.98	32.21	25.59	51.62	25.37	58.38	34.12	34.71	15.99	59.85	21.96

Table 5. Texts verification accuracy [%]

	1NN		NBayes		CTree		SVM		GLM		CART	
FOS	38.67	33.30	39.11	49.25	43.97	44.27	19.62	08.37	26.84	28.71	31.17	31.70
GLRLS	48.92	38.19	85.71	83.55	66.67	61.02	84.42	08.37	47.76	33.80	49.35	45.26
HS	39.83	36.39	69.70	74.88	67.82	55.83	59.31	86.64	64.79	67.80	38.67	45.36
HOG	71.28	79.56	84.70	87.64	54.69	66.00	55.41	87.04	77.63	85.34	61.76	58.23
LBP	62.91	60.42	77.34	69.69	67.53	68.79	80.52	83.25	72.87	79.36	46.75	47.16
LBPB	49.35	40.68	64.36	72.88	55.56	55.03	73.74	08.37	74.17	77.87	54.40	52.14
LLF	53.82	50.05	59.60	56.33	61.18	62.91	19.62	08.37	43.43	40.28	61.04	57.13
NGLDS	39.39	33.80	42.86	59.82	44.16	42.47	77.20	81.26	30.74	19.44	24.39	19.34

Table 6. Signatures verification accuracy [%]

	1NN		NBayes		CTree		SVM		GLM		CART	
FOS	84.51	69.23	85.45	52.31	85.63	64.62	77.43	70.77	80.97	67.69	84.33	65.38
GLRLS	85.45	71.54	85.82	70.77	86.01	70.77	85.82	57.69	79.85	66.15	85.63	66.92
HS	84.70	70.00	86.01	56.92	85.82	71.54	85.82	71.54	84.70	70.77	81.34	70.00
HOG	80.41	80.00	78.92	73.08	71.08	67.69	79.85	71.54	83.77	64.62	82.84	64.62
LBP	86.01	72.31	86.01	70.77	86.01	70.77	86.01	71.54	86.01	76.15	85.63	69.23
LBPB	86.01	72.31	80.22	63.85	86.01	69.23	86.01	75.38	86.01	75.38	85.82	72.31
LLF	83.96	70.00	85.63	63.08	85.63	70.00	86.01	70.77	82.46	56.92	76.31	66.15
NGLDS	86.01	71.54	86.01	70.77	86.01	70.77	86.01	70.77	86.01	70.77	85.07	72.31

Table 7. Tables verification accuracy [%]

	1NN		NBayes		CTree		SVM		GLM		CART	
FOS	32.70	05.02	31.98	05.09	32.28	05.17	31.63	05.09	32.28	05.25	32.76	05.64
GLRLS	23.47	06.27	31.51	05.02	32.34	05.09	32.04	04.86	32.28	05.09	33.53	05.09
HS	32.46	05.17	32.10	05.25	32.22	05.02	31.21	05.17	32.58	05.17	32.34	06.50
HOG	27.99	05.02	32.28	05.02	29.30	04.78	22.45	04.70	20.49	05.49	29.18	07.68
LBP	24.54	21.87	32.94	06.90	32.88	07.21	29.60	04.86	28.23	08.54	31.80	13.40
LBPB	47.41	33.07	41.16	11.29	32.58	12.77	27.34	04.62	32.04	05.49	41.27	19.91
LLF	58.13	54.78	69.62	57.60	60.21	54.39	32.52	05.25	55.39	50.63	51.58	40.20
NGLDS	27.04	21.94	18.76	12.07	25.25	08.86	23.05	12.07	22.57	05.72	27.34	06.82

4.3 Discussion

As shown in Tab. 4 verification accuracy of logo-detecting cascade had decreased. Large number of detected samples were misclassified as negative instead of positive. This is due quite rigorous character of classifiers used. Taking into account the accuracy of detection process (which is done through classification) a cascade could be assigned a higher decision weight than the best pair of feature set and classifier used in verification to compensate for low precision in verification stage. Similar situation occurs in case of tables - again high detection accuracy is combined with low verification result. This is caused mostly by fuzzy line separating tables containing text and text class.

Average accuracies achieved at both stages of stamps and texts processing mean that equal decision weight could be assigned to both cascade and best combination of feature set and classifier. In both cases high precision of detection is coupled with high verification result. It is important to note that tables filled with text were classified as text. Otherwise, the results would be much lower.

As it was noted, signatures class causes most of the problems. Higher detection accuracy is only a result of much lower FP rate. This is caused by extension of learning set (both in training of cascade and at verification stage). Further increase, especially in case of positive samples number, would be beneficial.

The analysis of presented verification results shows that all of discussed object classes should be considered separately. It is impossible to point out a single pair classifier/features set that wins in all cases. There seems to be no one rule that is behind above results.

In case of stamp class the most accurate pair consist of GLM classifier and HC features set and pair of 1NN classifier and HOG descriptor comes at second. Those pairs alternate between iterations. Analogous observations were made in case of the worst pair. In the first iteration, GLM classifier and NGLDS features were worst and NBayes+GLRS were second worst. Reverse relationship occurred in the second iteration. The average accuracy across all sets is equal to 60.17% and 53.37% in first and second iteration respectively. HS is the most accurate descriptor (average accuracy of 70.42%) in the first iteration and HOG (with 61.82% average accuaracy) in the second. An accuracy of 63.51% places CART classifier as the best in the first iteration and 61.86% places CTree classier at the top in the second iteration. Results for remaining classes were described in similar manner - first percentage value always corresponds to the result achieved in the first iteration and so on.

In both the first and the second iteration of logo verification SVM classifier and GLRLS features set proved to be the best. There were no recurrence in case of the worst pair. Average accuracy is equal to 48.6% and 29.04%. The highest average score was achieved by SVM classifier (53.31%, 34.12%) and HOG descriptor (54.58%, 38.11%).

Bayes-based classifiers, namely NBayes+GLRLS and NBayes+HOG achieved the highest accuracies in the first and the second iteration of text verification process, respectively. Analogous switch in terms of the best and the second best as in case of stamp occurred. Overall accuracy stands at 55.52% and 52.99%. The LBP and HOG descriptors proved to be the most accurate (67.99%, 77.3%). In both cases NBayes was selected as the best (65.42%, 69.26%).

The analysis of signature verification results shown that GLM+LBP achieved high scores in both stages, only to be defeated by 1NN+HOG pair in the second iteration. Overall accuracy equals to 84.02% and 68.94%. In both iterations the same feature set and classifier produced the highest scores: LBP (85.95%, 71.8%) and 1NN (84.63%, 72.12%).

Only in case of tables verification there is significant domination of one classifier and feature set pair (NBayes+LLF) over all other combinations. Although, the average accuracy is low (33.47% and 12.66%), the accuracy achieved by the best pair is satisfactory. NBayes classier paired with LLF feature set reached 69.62% and 54.17% accuracy. Mean result of classification with use of NBayes classifier is equal to 36.29% and 19.14%, and mean accuracy of LLF feature set stands at 54.58%, 43.81% in the first and the second iteration, respectively.

5 Summary

Based on results we obtained, it is justified to say that the idea of using boosted cascade of weak classifiers to solve the task of graphical element detection in digital images of scanned paper documents proved to be valid. High accuracies achieved in extensive analysis performed on large, real document set prove this fact further. Results from the second iteration (see Tab. 2) are particularly encouraging. Although, there is a high similarity between some classes and numerous challenging examples throughout image database (see Fig. 4.1), the detection is successful. The signatures class is an exception and can be put down to the poor representation across databases. Increasing the size of learning set for signatures detection with high degree of probability would boost results as shown in case of the first and the second iteration.

High accuracies for certain classes in particular could lead to dropping the verification stage as it is redundant if cascade looks as like what it really is - a classifier itself. However, as long as there is more than a few of misclassified samples the use of this stage is justified. If we decide to use the verification stage, it is important to examine each class separately, as shown in previous section. It is well illustrated in Tab. 7. While overall accuracy is really low, accuracy for LLF feature set is several times higher than in case of any other feature set.

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