Form Analysis by Neural Classification of Cells

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Abstract: *Our aim in this paper is to present a methodology for linearly combining multi neural classifier for cell analysis of forms. Features used for the classification are relative to the text orientation and to its character morphology. Eight classes are extracted among numeric, alphabetic, vertical, horizontal, capitals, etc. Classifiers are multi-layered perceptrons considering firstly global features and refining the classification at each step by looking for more precise features. The recognition rate of the classifiers for 3. 500 cells issued from 19 forms is about 91 %.*

Keywords: Form Cell, Neural Approach, Cell Classification, Form Analysis

1. Introduction

Form analysis becomes with the success of OCR/ICR techniques a very promising domain with different issues and applications. Several administrations and companies are today faced to a fast treatment of their forms in different domains such as order lecture, revenue form capture or multiple choice question paper analysis. Systems designed this last decade for form analysis are numerous and themes are varied. However, all of these systems are oriented towards a full form recognition without a real separation between the different phases. This makes difficult the reuse of systems and leads sometimes, for a new application, to the complete rewriting of the techniques. So, we have considered that for some classes of forms such as the tax forms, cells are the base of the form analysis and cell classification can constitute a generic part of a form analysis system.

Considering cell detection and extraction, the literature mentions mainly two approaches. The most common one deals with known forms and uses a detailed model for each class of forms [Casey92, Yuan95, Ishitani95, Arai97]. Although the systems are efficient on specific forms, they can be hardly applied to other kind of forms. In opposite, the systems, in the other approach, ignore any *a priori* knowledge on the form and base the analysis mainly on cell analysis [Shimotsiyi96, Hirayama96]. Although they are more general than the first ones and can be applied on a wide range of forms, their performance is limited because of their lack of knowledge.

Our aim in this paper is to propose an intermediate solution for unknown form analysis based on cell classification. Cells are first extracted from the form and classified according to different criteria based more on the content aspect than on its semantic interpretation.

The cell extraction and classification is a very important step in a form analysis process for several reasons:

- The information contained in the form is mainly located in the cells.
- The cell extraction allows to locate the information and to situate it according to the rows and columns. This leads to find at the same time the layout and the logical structure of the form (correspondence between rows and columns, number of dimensions, etc.).
- The exam of the content of each cell can help to the content classification, first by separating cells containing the information from empty ones, second, by analyzing the type of content (text, digits, etc.) in order to apply on it the adequate treatment.
- At last, the cell extraction and content classification can help to the pre-classification of forms with a modest investigation.

The outline of this paper is as follows. After a brief description of the approach used for the cell location in section 2, we present in section 3 the different classes retained for the classification and give in section 4 the classification schema. Details dealing with the main classification steps will be then exposed in this section. So, we show the different features used for the different classes and the hierarchy of neural architectures. At last, before concluding, some experiments and results will be discussed in section 5.

2. Cell Extraction

As mentioned in [Turolla96], cell location and extraction is operated in three steps.

In the first step, lines are detected in the image by applying Hough Transform. This technique was used for its robustness and reliability. It transforms the following line problem in a counting point problem [Risse89]. In order to avoid a multitude of line candidates, voting points are limited to only those belonging either to the contours or to the black or gray areas. A recursive cut of the polar parameter space of lines and a fusion of close cells allow to fast locate the accumulation areas.

In the second step, segments associated to the lines, are extracted from the image. The line following is operated by advantaging the closest black pixels of the Hough lines. The lines detected can be simple, double, continuous or discontinuous, contours of black and gray areas, or vertical alignments of parentheses.

The cells are located at the third step. They are represented by a graph which arcs are the horizontal and vertical segments and which nodes are the intersection points between horizontal and vertical lines. Cells are given by the research for minimum circuits of the graph.

This first part of the system has been tested with success on French tax forms as well as on tables. The line extraction takes about 30” per image.

3. Cell Classes

A detailed study of French tax forms led us to define eight classes for cells described below:

- *DIGI*: it regroups the set of cells containing only digits. These digits generally correspond to amounts and can be preceded by the sign '+' or '-'.
- *GRAY*: it corresponds to gray areas which cannot be filled by any kind of data.
- *HLET* (for horizontal letters): all cells which text is horizontally aligned and which are constituted by alphanumeric chains containing lower-case letters and probably higher-case letters are affected to this class. They correspond essentially to form wordings.
- *VLET* (for vertical letters): it reassembles the same kind of cells within the class *HLET* but with text vertically aligned.
- *HHCL* (for horizontal higher-case letters): cells containing higher-case letters horizontally aligned and some digits or symbols such as parentheses are attributed to this class. These cells often correspond to wordings representing amounts.
- *VHCL* (for vertical higher-case letters): it corresponds to the class *HHCL* but considering only cells which text is vertically aligned.
- *BLAC*: it regroups cells in inverse video (with black foreground). These cells play a particular role in our forms.
- *EMPT* (for empty classes): this class regroups all the cells containing any data.

The choice of these classes depends of course on our application but can be adapted on other kind of forms.

4. System Overview

The cell classification schema can be divided into three steps as shown if fig. 1.

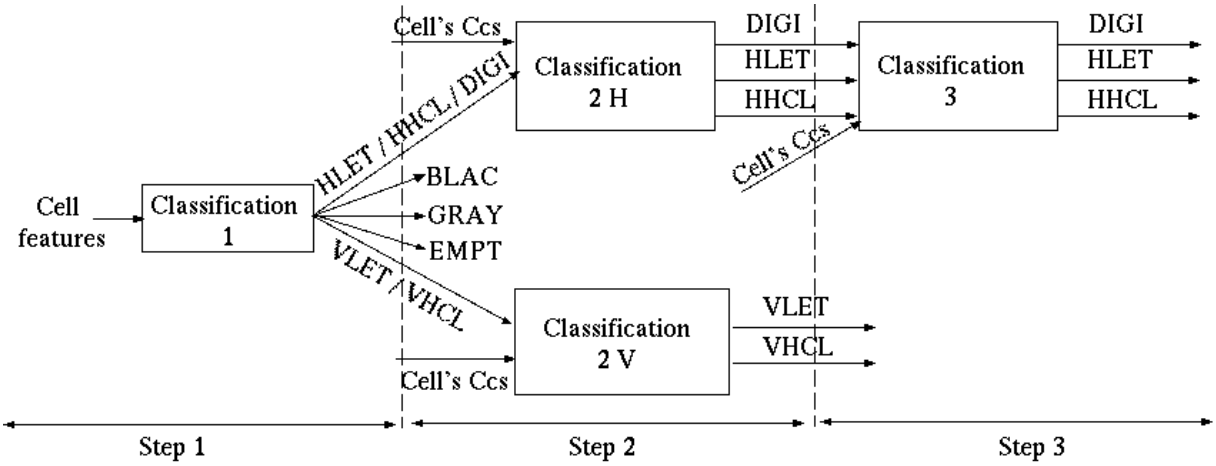


Fig. 1: Cell Classification Steps.

In the first step, the classification is operated on numeric parameters extracted from the cells. These parameters which will be detailed further do not allow to distinguish neither between the classes: *DIGI*, *HLET* and *HHCL* for the text horizontally aligned, nor between the classes *VLET* and *VHCL* for the text vertically aligned. This is du to the bad quality of images and to the variability of fonts and character sizes.

The objective of the second step is to separate the classes *DIGI*, *HLET* and *HHCL* and the classes *VLET* and *VHCL*. The classification is made directly from the image of the CCs of the cell.

In theory, a CC must correspond to one character but this is false in practice because some characters adjoin and some others are cut. This problem is very frequent for the digit ‘0’

which is always cut into two parts. This is an error source for the digit classification and explains the use of the third step which objective is to detect the ‘0’ cut and so to improve the classification into *DIGI*, *HLET* and *HHCL*.

We used neural networks in the three steps of the system, a one-layer perceptron in the first step and a multi-layer perceptron in the second and third steps.

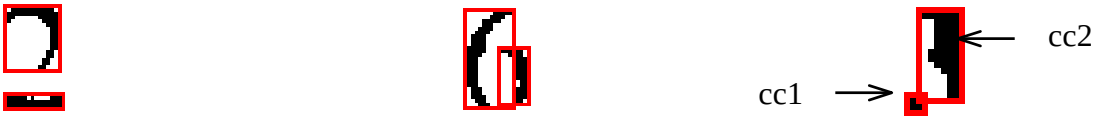
4.1. Classification from CC Parameters

12 simple numerical parameters have been experimentally determined for the classification in the first step.

1. *Number of connected components*: this is related to the number of CCs after a merging step introduced because of the presence of numerous cut characters (cf. fig. 2). The merging is made within a cell, line by line. Two CCs are merged if they respect the following constraints:

   - they belong to the same text line,
   - they are consecutive in the line,
   - they are superposed (cf. fig. 3a) or overlapped with an important intersection area (cf. fig. 3b) or overlapped with a small intersection and where one of the CC is very small compared to the average size of the Cell’s CCs studied.

Fig. 2: Connected Components Before Merging.



(a) : Merging of 2 CCs

(b) : Overlapping of 2 CCs

(c) : The size of CC1 is very small compared to the size of CC2 .

Fig. 3 : Different configurations of Connected Components.

2. *Text alignment*: we have observed in the forms studied that the cells which are more wide than tall, contain text horizontally aligned. In opposite, when the cells are more tall then wide, the text can be aligned horizontally or vertically. An analysis of the text is then necessary in this case. Three cases are considered:

   - the number of horizontal CCs , i.e. those which the height is greater than the width,
   - the homogeneity of the height of the text lines,
   - the height of the greater CCs of each line.

   If the number of horizontal CCs is important, text lines are homogeneous and if there are CCs in each line which height is similar to the line height, the text is considered as horizontally aligned. Otherwise, it is considered as vertically aligned.

3. *Number of text lines*: the text lines are detected by analyzing the histogram obtained by horizontal or vertical projection of the image.

This analysis is performed in three steps:

- In the first step, the black areas of the histogram are delimited. When the text is of a good quality and lines are not overlapped, each black area corresponds to a text line. To avoid to take into account the noise, only black areas are considered with a size experimentally fixed to 3 pixels for the height and 5 pixels for the width. It is important to combine the height and the width in order to avoid to consider as noise, lines containing only one character (cf. fig. 4).

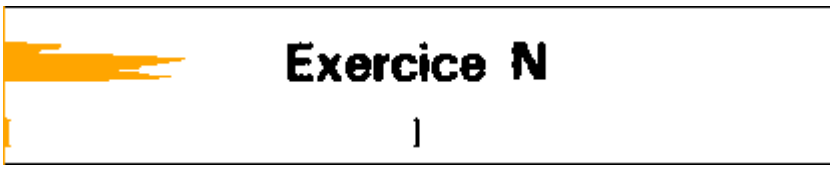


Fig. 4 : Example of a Line containing only one Character.

- In the second step, picks found are merged where they are close (separated with less than 3 pixels). In fact, in some cases, a line can be represented by two picks. This is the case for the line of fig. 5 because the letter 'g' of the word 'outillage' is composed of two CCs.

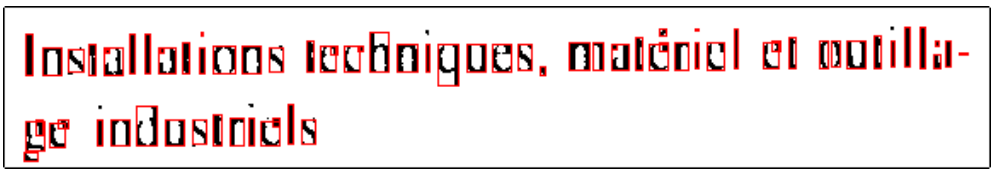


Fig. 5 : Bad Segmented Characters.

- Lines previously found are examined in order to separate couples of consecutive lines connected by the down-strokes of the ones or the stems of the others (cf. fig 6). For this, each black area is analyzed so that picks separated by a valley which height is less than a threshold ‘s’ which value has been fixed at 28% of the biggest height (cf. fig. 7) are extracted. Picks having the deepest valleys are determined. If

the distance between a pair of picks is less than the sum of the width of the two picks, this probably indicates the presence of two close text lines. If the widths of these two potential lines are comparable, then two separated lines are considered. In the other cases, we merge the two picks which forms a single line. When all the picks have been treated by pairs, we compare the size of the lines obtained during this step. If their size is homogeneous, the lines are selected, else only lines extracted in the second step are preserved.

Fig. 6 : Very Close Text Lines.

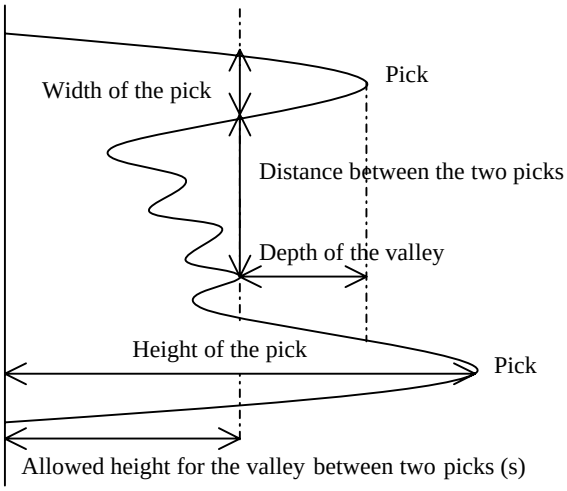


Fig. 7 : Example of two Consecutive Picks Used for Line Detection.

4. *Number of classes of CC heights*. It is obtained from the analysis of height histogram of the CCs.

A pick is indicated by a high value of the histogram. The class searching is determined as follows:

Begin

- Create a class with the biggest pick.
- Examine the others picks in a decreasing order.
- Let *Pc* be the current pick,
  search *Pg* a bigger pick than *Pc* and the closest of *Pc*.
- **If** *Pc* is enough close to *Pg*
  then *Pc* belongs to the same class than *Pg*
  else create a new class containing *Pc*.

End

5. *Number of CC width classes*.
6. *Number of width classes of the spaces between CCs*.
7. *Average number of black segments per line in a CC.*
8. *Average density of black pixels per CC.*
9. *Density of black pixels in a cell.*
10. *Average height of CCs.*
11. *Number of CCs deleted*: this value is determined during the CC extraction step; it corresponds to the number of CCs assimilated to the noise.
12. *Ratio between the number of CCs deleted and the total number of CCs*.

The choice of these 12 parameters results from a series of observations and tests realized on a database built up for this problem and from which we have verified the contribution of each one of these parameters in the classification process.

The classifier uses a mono-layer perceptron with 12 neurons on the entry layer (for the 12 parameters) and 5 neurons on the exit layer (for the 5 classes retained).

4.2. Classification from Cell CCs

This phase including the steps 2 and 3 of the classification process, tends to classify cells containing text into three classes: *DIGI*, *HLET* and *HHCL* for cells with horizontal alignment or into two classes: *VLET* and *VHCL* for cells with vertical alignment. In the tax forms, there was not amounts vertically aligned. This explains the class difference in relation with the alignment.

In the second step, the entry data of the classifier is the size normalized image of a CC. The classifier retained is a perceptron with a hidden layer. It contains 64 neurons on the entry layer (the 64 pixels of the normalized image of a CC), 12 neurons on the hidden layer and 2 or 3 neurons on the output layer according to the alignment of the studied cell. A value is associated to each output. For every output, we compute the product of the values of each CC of the considered cell. The output having the higher product is attributed to the cell.

The results obtained at the end of this step are satisfactory except for the *DIGI* class. Errors come essentially from the '0' often bad segmented and cut in two parts. So, cells containing a majority of '0' are bad classified. The solution for this problem is given in the third step.

In this step, CCs presented to the classifier are normalized and grouped by pairs. This treatment is realized for cells which number of height class of CCs is 1 or 2. The classifier used is a perceptron having 128 neurons on the entry layer (the 128 pixels of the image normalized and merged into 2 CCs), 18 neurons on the hidden layer and 2 neurons on the output layer: one for the '0' class and one for the other characters.

These results are compared with those of the step 2 and a decision is taken for the belonging or not of the cell to the classes *DIGI*, *HLET* or *HHCL*.

A score is determined for each one of the three classes and we retain the one which score is the highest. Let notice

ScDIGI: the score of the class DIGI for the cell considered,

ScHLET: the one of HLET,

ScHHCL: the one of HHCL,

SjC2Hcci: the output value j of the classifier 2H for the CC i,

SjC3cci: the output value j of the classifier 3 for the CC i merged with the CC i+1.

The computations are made as follows:

```
Begin
        ScDIGI, ScHLET, ScHHCL = 1
        i = 1
        For every CC i of the current cell do
            If S1C3cc i < S2C3cc i then
                ScDIGI = ScDIGI * S1C2Hcci
                ScHLET = ScHLET * S2C2Hcci
                ScHHCL = ScHHCL * S3C2Hcci
                i = i +1
            Else
                ScDIGI = ScDIGI * S1C3cci
                ScHLET = ScHLET * S2C2Hcci * S2C2Hcci + 1
                ScHHCL = ScHHCL * S2C2Hcci * S2C2Hcci + 1
                i = i +2
            Endif
        Endfor
End
```

5. Results and Discussion

The classification process was tested on 19 French tax forms belonging to the General Direction of French Revenue. The classification time for one form is about 1’45’’ on a SUN Ultra Spark station, model 140 MHz.

The results obtained are detailed in the table of the figure 8 and the classification rates are presented in fig. 9. A classification example of a form is given in fig. 10. The color attributed to each cell indicates the class found (cf. fig 11). A classification error is materialized by the presence of a little square on the bottom left. It has the color of the wanted class.

classes obtained / classes desired	DIGI	HLET	HHCL	VLET	VHCL	GRAY	BLAC	EMPT	Total Number Of Cells
DIGI	638	9	6	0	0	0	0	0	653
HLET	5	587	233	0	0	4	0	0	829
HHCL	4	22	308	4	2	2	0	0	342
VLET	0	0	0	23	0	0	0	0	23
VHCL	0	0	0	0	72	0	0	0	72
GRAY	0	0	1	0	0	23	1	0	25
BLAC	0	0	0	0	0	0	72	0	72
EMPT	0	0	2	0	0	7	0	1479	1488

Fig. 8 : Form Classification Results.

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DIGI	HLET	HHCL	VLET	VHCL	GRAY	BLAC	EMPT	Total
97.70 %	70.81 %	90.06 %	100.00 %	100.00 %	92.00 %	100.00 %	99.40 %	91.38 %

Fig. 9 : Classification Rates.

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(1) **BILAN - ACTIF**

Formulaire obligatoire (article 53 A du code general des impôts)

Désignation de l'entreprise *FINAL* — Durée de l'exercice exprimée en nombre de mois* 12

Adresse de l'entreprise *20 rue de la Convention - 91164 LONGJUMEAU* — Durée de l'exercice précédent* 12

Numéro SIRET* — Code APE — Exercice précédent (N-1) clos le :

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Exercice N, clos le : 31 12 N N

			Brut 1	Amortissements, provisions 2	Net 3	Net 4
	Capital souscrit non appelé (0)	AA				
ACTIF IMMOBILISE* — IMMOBILISATIONS INCORPORELLES	Frais d'établissement*	AB	50 000	AC 50 000		
	Frais de recherche et développement*	AD	38 000	AE 15 200	22 800	
	Concessions, brevets et droits similaires	AF	4 000	AG 701	3 299	
	Fonds commercial (1)	AH	194 000	AI 0	194 000	
	Autres immobilisations incorporelles	AJ		AK		
	Avances et acomptes sur immobilisations incorporelles	AL		AM		
IMMOBILISATIONS CORPORELLES	Terrains	AN	142 000	AO	142 000	
	Constructions	AP		AQ		
	Installations techniques, matériel et outillage industriels	AR	270 000	AS 147 407	122 593	
	Autres immobilisations corporelles	AT	412 618	AU 226 313	186 305	
	Immobilisations en cours	AV		AW		
	Avances et acomptes	AX		AY		
IMMOBILISATIONS FINANCIERES (2)	Participations évaluées selon la méthode de mise en équivalence	CS		CT		
	Autres participations	CU		CV		
	Créances rattachées à des participations	BB		BC		
	Autres titres immobilisés	BD	62 419	BE 0	62 419	
	Prêts	BF		BG		
	Autres immobilisations financières*	BH	12 600	BI 0	12 600	
	TOTAL (I)	BJ	1 185 637	BK 439 621	746 016	
ACTIF CIRCULANT — STOCKS*	Matières premières, approvisionnements	BL	97 450	BM 0	97 450	
	En cours de production de biens	BN		BO		
	En cours de production de services	BP		BQ		
	Produits intermédiaires et finis	BR	135 240	BS 3 800	131 440	
	Marchandises	BT		BU		
	Avances et acomptes versés sur commandes	BV		BW		
CREANCES	Clients et comptes rattachés (3)*	BX	240 598	BY 12 963	227 635	
	Autres créances (3)	BZ	107 236	CA 0	107 236	
	Capital souscrit et appelé, non versé	CB		CC		
DIVERS	Valeurs mobilières de placement (dont actions propres : .....)	CD	56 000	CE 1 750	54 250	
	Disponibilités	CF	15 236	CG	15 236	
Comptes de régularisation	Charges constatées d'avance (3)*	CH	16 500	CI	16 500	
	TOTAL (II)	CJ	668 262	CK 18 513	649 749	
	Charges à répartir sur plusieurs exercices* (III)	CL	57 280		57 280	
	Primes de remboursement des obligations (IV)	CM				
	Écarts de conversion actif* (V)	CN	330		330	
	TOTAL GENERAL (0 a V)	CC	1 911 509	A 458 134	1 453 375	

Renvois : (1) Dont droit au bail : — (2) Part à moins d'un an des immobilisations financières nettes CP — (3) Part à plus d'un an CR

Clause de reserve de propriété : * — Immobilisations — Stocks : — Créances :

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Fig. 10 : An Example of a Form Cell Classification.

Class	Color
DIGI	red
HLET	brown
HHCL	orange
VLET	clear green
VHCL	dark green
GRAY	cyan
BLAC	yellow
EMPT	mauve

Fig. 11 : Colors of the eight Cell Classes.

We can remark that the scores are very good for the classes *DIGI*, *VLET*, *VHCL*, *GRAY*, *BLAC* and *EMPT*, but are less good for the classes *HLET* and *HHCL*. There are several reasons explaining the confusions:

- The bad quality of images can produce an over-segmentation (cf. fig. 12) or a under-segmentation (cf. fig 13) .
- Some characters have the same morphology in lower-case and higher-case and cannot be differentiated after normalization. It is the case of characters as ‘c’, ‘o’, ‘s’, ‘u’, ‘v’, ‘x’ and ‘z’.

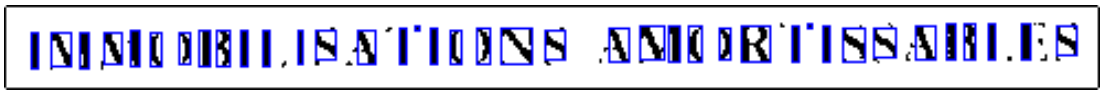

Fig. 12 : A Cell with over-segmented Characters.

Fig. 13 : A Cell with under-segmented Characters.

Several solutions can be considered in order to resolve these problems:

- creation of a reject class for cells for which it is difficult to make a choice between the classes *HLET* and *HHCL*,
- fusion of the classes *HLET* and *HHCL*: this fusion gives a general classification rate equal to 98,32 %,
- the consideration of the CC height before normalization.

6. Conclusion

This paper outlines a feasibility study for the classification of form cells into eight classes depending on the presence of information or not, on the text alignment: horizontal or vertical and the character modes higher-case or lower-case.

Few systems have been developed in this sense. Most of the classification methods developed try to differentiate between text and non text areas.

We used a perceptron for the classification. It is mono-layer for the first step which realizes a pre-classification by using numerical parameters. It contains one hidden layer for the steps 2 and 3 which analyze the text areas from normalized images of CCs. The results obtained are acceptable. Improvements and adaptations remain are possible.

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