Brazilian Bank Check Handwritten Legal Amount Recognition

CINTHIA OBLADEN DE ALMENDRA FREITAS[1], ABDENAIM EL YACOUBI[1], FLÁVIO BORTOLOZZI[1], ROBERT SABOURIN[2]

[1]PUCPR – Pontifícia Universidade Católica do Paraná, R: Imaculada Conceição, 1155, Prado Velho, 80215-901Curitiba, PR, Brasil
{cinthia, yacoubi, fborto}@ppgia.pucpbr.br

[2]ETS - Ecole de Technologie Supérieure, 1100,rue Notre-Dame Ouest, Montréal(Québec), H3C 1K3 Canada
sabourin@etsmtl.gpa.ca

Abstract. This paper presents a system that is being developed for the recognition of the handwritten legal amount in Brazilian bank checks. Our strategy used to approach the handwritten legal amount recognition problem puts on evidence the key-words: "mil", "reais/real", "centavos/centavo" which are almost always present in each amount. The recognizer, based on Hidden Markov Models, does a global word analysis, therefore, it doesn't carry out an explicit segmentation of words into characters or pseudo-characters. In this context, each word image is transformed into a sequence of observations using pre-processing and feature extraction stages. Our system, when tested on our database simulating Brazilian bank checks, shows the viability of our approach.

1 Introduction

Usually, to approach the Handwritten Word Recognition - HWR problem, two main approaches are considered: local or analytical approach held at the character level [4,8,10] and global approach held at the word level [3,5,9].

In the first approach, the system is faced with the necessity of word segmentation into characters/letters or pseudo-letters. This approach is known for the difficulty it shows when defining a boundary between the characters. Therefore, the recognition system will also depend on the success of the segmentation process. In this manner, the systems will be made up of distinct stages, one for segmentation and one for recognition, or even associating segmentation and recognition in a unique stage.

On the other hand, the global approach permits the word segmentation stage to be avoided by extracting global features from the words, therefore not needing their explicit segmentation. This approach seeks to explore the information from the word context, allowing aspects based on psychological models to be inserted [3,5]. However, this approach is restricted to applications with small lexicon.

The two approaches, local and global, may be combined to allow the possibility of working with a hybrid approach [2]. In this manner, it is possible to combine the advantages and to reduce the disadvantages of these two approaches.

Considering the possible approaches to the problem, the feature extraction stage is characterized by being an important task in the success of the handwritten word recognition system. The main role, of a selected set of features, is to reduce the intra-class variability and increase the inter-class discrimination. Many different types of features can be combined when trying to obtain more robust systems from a small set of features, yet maintaining a high discrimination among the classes considered [16,18].

The bank check image recognition arouses great interest in researches, since there is a high level of ambiguity and complexity in such a kind of images, as seen in Figure 1. The challenges faced are due to practical applications in the bank check compensation systems, since it is well known that the manual process demands both time and elevated cost, besides not being efficient in given situations.

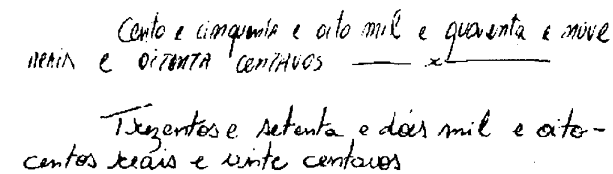

Figure 1 Examples of writing styles.

The purpose of this work is to recognize handwritten words in the legal amount, therefore, the complexity of the problem can be seen in the following factors: different styles of handwriting, handwriting context, the size of the lexicon of possible words and the number of writers. The recognition of legal amounts in checks is an example of a an omni-scriptor recognition task, with no restrictions in

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the writing style, and involving a small and static lexicon. The handwritten legal amount recognition works with a small lexicon and, therefore, most of the works held use a global approach. Typically, the legal amount is segmented into words (many hypotheses can be proposed), the global features are extracted and the isolated word recognition is held by using structural or statistic methods. At the end of the recognition process, a parsing module is applied to generate the hypothesis at the legal amount level.

The present work presents a system that is being developed for the handwritten legal amount recognition of Brazilian bank checks using a global approach not requiring an explicit segmentation and using Hidden Markov Models (HMM).

The objective of the work is to seek for a contextual reduction of the lexicon related to the recognition process. This strategy is different from the majority of the other approaches because it does not apply all the models (associated with the considered classes) to the isolated words by considering the words evenly balanced. It also explores the capacity of legal amount decomposition in small parts, that is, word sub-sets from the lexicon.

The proposal strategy puts on evidence at the first level the recognition of key-words: "mil", "real/reais", "centavo/centavos", and at the second level the others words of the lexicon.

This approach is motivated by the fact that the legal amount almost always contains the 3 key-words: "mil", "real/reais", "centavo/centavos". Thus, it is possible to apply an approach that takes into first level the key-words and does not consider all the segmented words in the legal amount image as equi-important words in the legal amount. Also, as the key-words are almost always present, their frequency is much higher and training much reliable accordingly, thus justifying their prior use in the recognition process.

This article is organized into 6 sections. Section 2 presents the state of the art, describing works developed that have the same aim. Section 3 explains the proposed approach. Section 4 presents the feature extraction phase. Section 5 describes the recognition methodology, and the algorithms used in the training, validation and test phases. Section 6 shows the experiments and finally Section 7 presents some conclusions and future works to be considered.

2 State of the Art

Generally, bank check recognition systems can be treated using two approaches: a) *Global approach*: consider the word as a whole by defining a different model for each possible word [3,5] and b) *Local or analytical approach*: works at the letter or pseudo letter level, using an explicit segmentation [4,8,10].

The Guillevic [5] system for handwritten legal amount recognition adopts a global approach, by considering a model per word. The legal amount images are submitted to the pre-processing stages: the mending of small breaks between the character traces in the word images, the slant correction, the image smoothing and the noise removal. The next stage is the segmentation of the legal amount into isolated words. During this phase a Bayesian classifier is used to remove the strokes, put by writers, at the beginning and end of the legal amount. In case this strategy fails, the notion of character is used to identify the first and last characters of the word. Eventually, if these two options aren't enough, a traditional character level recognition is done. The chosen features are: ascenders, descenders, loops in the body of the word, word length, vertical, horizontal and diagonal strokes. The probability of each feature, given the test class, is computed applying a Bayesian estimate of the features in the training database. The final score of matching between the image and its class is given by the combination of the features probabilities pondered by optimized weights. A parsing module is applied, at the end of the recognition process, to obtain, from the list of the most probable legal amounts, the ones that are also syntactically and semantically correct.

Côte [3] only works with isolated words, having as main goal to favor the use of the perception principles and the reading models, considering that the studies on human beings can help improve the performance of the automatic reading system. The Percepto system works with a set of four types of features: primary, secondary or conditional, concave, convex and the number of transitions in the words. The set of features so called primary, is used to help allow the key-letters definition: the ascenders (t, l, b), the descenders (p, q, g), the ascenders-descenders (f, gh) and the loops in the body of the words (o, e). The second set of features is called conditional, because of its dependence on the existence of one feature from the primary set, for example: the stroke of a "t" and the loops associated to the ascender or descender primary features such as, a "d" or a "p". The concavities and convexities are extracted with the aim of representing the regularities of the cursive word. And finally, the number of black-white transitions obtained over the average of the word body height is used to represent seven different classes of the words, with variation between three and nine letters. The recognition phase uses a connexionist model.

Avila [1] treats the legal amount as a whole, using an approach with global features (ascender, descender and empty) and local features based on an alphabet of 12 strokes. The global features are used for the validation of the segmentation of the legal amount into words. The local features are used to generate grapheme sequences for the word modeling process through HMM. Pre-processing is applied to the whole legal amount line, and only after this stage the latter is segmented into words. The proposed strategy for the generation of the legal amount list, based on recognized words, is made by generating hypotheses for each word, taking into consideration different legal amount segmentation hypotheses. By using the generated lists, a syntax verifier is applied to generate the best recognized legal amount hypothesis.

Consequently, it is possible to verify that different methods are used to recognize handwritten legal amounts from bank checks. The difference between the proposed systems lies mainly in the employed features sets and in the selected classifiers.

However, the common point between these systems is that they try to recognize the legal amount like a conventional reading process, that is, read what is written in the writing direction, from left to right by applying recognition methods for isolated words. So, this process is sequential and all the models are tested equally for any word that is being recognized. At the end of the process, a list of candidate words is established and validated through the parsing module to hold a syntax analysis of the recognized legal amount.

The difference between the present work from the others is the proposal of a solution that brings the possibility of a reduction of the models of words to be tested, considering the models not equi-important for the recognition task.

3 Problem Proposal Approach Strategy

The legal amount corresponds to a numeric value to which is applied a known grammar at the moment of the handwriting of the value. Therefore, from the numeric value it is possible to define two characteristics of the problem: the key-words and their internal blocks formed by words that represent the numeric value, as shown in Figure 2.

The three key-words are understood as being the three words that identify 3 main blocks in the check's legal amount. Considering that the databases were formed to comprise values between R$ 0,01 ("um centavo") and R$ 999.999,99 ("novecentos e noventa e nove mil, novecentos e noventa e nove reais e noventa e nove centavos"), the key-words are the ones that correspond to the lexicon indicating **mil** at the comma, the period indicating the value of the whole part in **reais/real** and to the terminal indicating the decimal value in **centavos/centavo**.

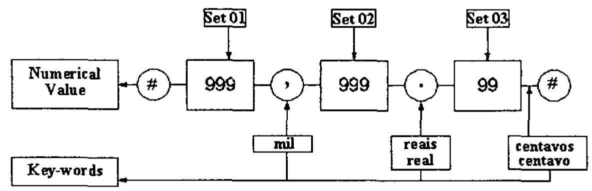


Figure 2 Outlining of the numeric value in a bank check and the relationship with the key-words.

It is understood that the block is the group of graphed handwritten words used to represent the quantity in the numeric value of the check. In this manner, the analysis of the blocks allows the identification of the internal of each one using words from the lexicon. Blocks 1 and 2, as shown in Figure 2, are identical. These blocks have as grammar endings the same group of words. On the other hand, block 3, that represents the numeric value that refers to the "centavo/centavos" part, has the characteristic of not presenting a subgroup of words "entos". Figure 3 shows the representation of words sub-sets of the lexicon.

The division of the problem into differentiated levels for the recognition based on the characteristics described earlier, allows the establishment of a hierarchical approach to the recognition process.

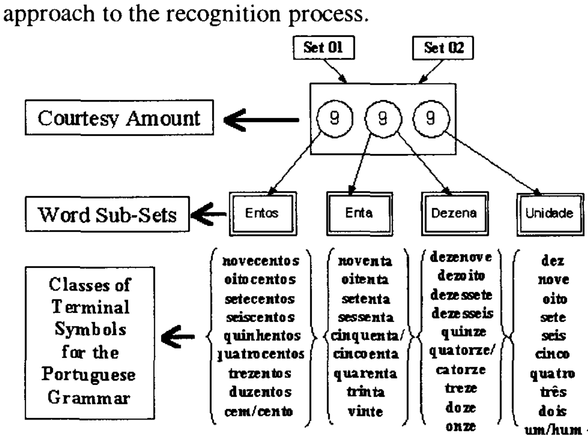


Figure 3 Sub-sets and lexicon.

In this manner the proposed strategy considers the following levels of approaches:

- Level 01 - Key-words: defined models for the words "mil", "reais/real" and "centavos/centavo", this aims at identifying the three main blocks of handwritten words;

- Level 02 - Isolated words: defined models for each of the 39 isolated lexicon words.

Knowing the grammar and contextual information of isolated words in the legal amount context, it is possible to establish an list of probable legal amounts.

The present work intends to explore these legal amount characteristics, seeking to help in the reduction of the word groups to be used during the recognition process. Two facts motivate this approach:

- The databases used count on legal amounts that have on the great majority the three key-words. Therefore, the proportion of these words as far as the others from the lexicon are concerned, is of 5 to 1. Approximately, 1200 images are available for each key-word while only 230 images in average is available for each remaining word class. In this manner, it is possible to apply an approach that considers on first hand the key-words and does not consider all the lexicon models as equiprobable words in the legal amount. In such case, the key-words training and recognition will be more expressive than the others words,
- Exploration of the contextual information of the check for the application of the recognition models.

The present methodology serves as support in the choosing of the features and helps in the definition of the handwritten word recognition process based on the HMM application.

4 Pre-processing and Feature Extraction

In the present work the pre-processing level is being used to minimize the effect of the writing variability related to the different writing styles, the writer's particular writing characteristics and the word slant. The feature extraction follows a global approach, without explicit segmentation.

4.1 Image Pre-processing

As a pre-processing the slant correction and smoothing phases are applied. No kind of correction of the baseline is being used, taking into consideration that the legal amount in checks has as indicators 2 printed guidelines in the regular check pattern.

Many techniques can be applied for slant correction, for example the technique presented by Yacoubi [17] based on projection histograms with different inclination and Guillevic [5] that deals with the slant correction applying 29 projection histograms for angle varying from –70° to +70°, by steps of 5°. Both of the techniques make a global estimation of the inclination of the character, presenting as disadvantages the processing time [17] and the influence on the determination of the inclination angle for the long horizontal strokes with an inclination different from 0° [5].

Therefore, we implemented a simple yet fast algorithm presented by Yacoubi [18] that only uses the external contour of the words to estimate the average inclination of the characters.

The smoothing of the word image is held after the slant correction. The aim of this module is to regulate the continuous contour of the word, eliminating small noises in the image. The algorithm that we adopted in our case is the one described by Strathy [15]. Figure 4 shows the results obtained with an application of the pre-processing stages.

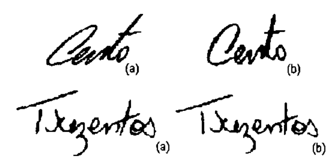


Figure 4 Word pre-processing; a) original images and b) slant correction and smoothing.

4.2 Features Extraction

Feature extraction is known as one of the most important steps in the success of a handwriting recognition system. It is from the features or from the characteristics of the word chosen to be extracted that it is possible to obtain the robustness of the system. In this context, an optimal group of non-varying features was sought for, that is, ones that would remain constant to one style of handwriting. And still, each feature of the group should be independent, in other words, not be related to the others. Each feature has its own identity and expresses the meaning of elements that are familiar to the recognition.

As mentioned earlier, the present work consider a global approach for word recognition, with no explicit segmentation, that is, treating each word as a unit for its recognition.

Two questions are important in the feature selection: What are the relevant features (*perceptual features*) in the handwritten recognition process? and how to represent cursive words without the presence of perceptual features? The answer is in joining the relevant aspects of the writing and reading processes as described in the works of Madhvanath [11] and Schomaker and Segers [14]. Madhvanath provides a definition of the perceptual features that are the most used characteristics in the word form representation, especially in the cases where small lexicon applies, such as is the legal amount recognition task. Perceptual features are known as: ascenders, descenders and loops, represented by symbols and positions.

The perceptual features are presented in the great majority of the lexicon word classes in question. However, when carefully analyzing the vocabulary used in the Brazilian bank checks, we can find a sub-group of words that do not have this kind of characteristic ("um", "cinco", "seis", "nove", "cem", "reais") or that are short words ("dois", "três", "sete", "oito"). Therefore, we propose a second and complementary set of features so as our models become able to adequately model every word in the lexicon. This set of features is based on the representation of *concavities* and *convexities* that exist in the body word.

In this manner, a set of features called Set 1 – PF has as its base the extraction of perceptual features as seen in Figure 5-a. The following features were defined: ascenders, descenders and loops in one of the three word zones. The features selected contain information about the feature type, the size and positional information (related with x axis and related with the word zones).

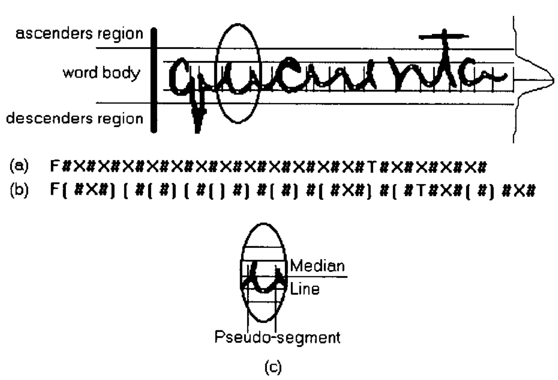


Figure 5 Features sets: a) perceptual features (PF) and b) perceptual features, concavities and convexities (PFCC).

The words are analyzed according to the following 3 zones: upper, body and lower. These zones are determined based on the horizontal transition histogram. The body of the word is the area located between ±70% from the maximum value of this histogram.

The ascenders, descenders and loops features in the body of the words are differentiated according to their size as large or small. The large features are those that show a height that is larger than 50% the height of the word body, otherwise they are called small features. The lower and upper loops do not have a size indication, in this case the size of the ascender or descender that corresponds to the extracted loop, is valid. These empiric thresholds were the best of all the various thresholds tested by error analysis on the validation set.

A Set 2 of features – PFCC was selected to complement the representation of the cursive word through its ligatures, as well as, its strokes. Concavities and convexities in the word body area are extracted in addition to the perceptual features previously described, as shown in Figure 5-b.

The features are extracted over the word images and a segmentation process is applied to obtain a sequence of corresponding observations, as seen in Figure 05-c. Between two black-white transitions over the maximum peak of the horizontal transition histogram, called the median line, a segment is delimited and a corresponding symbol is designated to represent the extracted set of features, making up a grapheme. Only the transitions that aren't found inside the loops of the body of the word are considered. In case no features can been extracted in the analyzed segment, an empty symbol is emitted.

The symbol alphabet was defined based on the occurrence of the basic feature types, as well as, on the occurrence of the combination of these features in a same pseudo-segment. Table 1 presents the basic feature alphabet retained to represent the possible features in each zone. The entire and definitive alphabet (obtained by possible combinations of the elements of the basic feature alphabet) is composed of 22 different symbols, for example: large or small loop in the body associated with a large ascender (oT or OT), small or large loop in the body associated with the large descender (oF or OF).

Table1 Basic feature alphabet

Item	Feature	Symbol
01	Large and small ascender	T, t
02	Large and small descender	F, f
03	Superior loop	l
04	Large and small loop in word body	O, o
05	Inferior loop	j
06	Concave	(
07	Convex	)
08	Empty	X

5 Recognition using HMM

Our modeling approach applies the Hidden Markov Models – HMM to capture the information obtained from the employed structural features. The advantage of these models is that they offer a probabilistic model for the structural features and allow an automatic learning of the parameters to be estimated. This method requires an elevated number of training examples, so that a more correct learning process can be obtained. This strategy allows a profit to be taken, at the same time, from the feature extraction advantages and from the applied statistics [1,2,18]. The theoretic formulation of HMMs is beyond the scope of this paper. An excellent introduction to HMMs can be found in Rabiner [13].

The interest in the HMM lies in its ability to efficiently model different knowledge sources. Its strong side lies first in the fact that it correctly integrates different modeling levels (morphological, lexical, syntactical), and second, in the existence of efficient algorithms that determine an optimum value of the models parameters.

5.1 Modeling

The HMM we have chosen is discrete, with a left-to-right topology (Bakis Topology), where each state can skip at most one state, as seen in Figure 6. The lexicon size is of a small dimension, 39 words; this permits the development of models for each class in each of the proposed strategy levels.

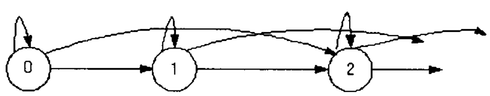


Figure 6 Topology of the isolated word models.

The modeling, training and recognition stages take into account two groups of models. Group 1 is made up of all the isolated words from the lexicon, 39 models, using the topology presented in Figure 6. The word models are independent of the handwriting style or the orthography for the same word, for example: 1 – "um" and "hum", 14 - "quatorze" and "catorze", 50 – "cinquenta" and "cincoenta", the two possibilities in each case being correct.

Group 2 is made up of the key-word models, "mil", "reais/real", "centavos/centavo" and of the model that involves all the other lexicon words, called "all".

In the current system, a unique model for the pair "reais" and "real", and a unique model for the pair "centavos" and "centavo" are being used because the words "real" and "centavo" are not frequent in real financial applications and are just found in the case of a numeric values equal to "R$ 1,00 – um real" or "R$ XX,01 – um centavo", respectively.

The topology in Figure 6 was adopted for the key-words. For the "all" model a topology that permits all left-right transitions was adopted. The adoption of this different topology for the "all" model is due to the huge variability of the observation sequence lengths. Indeed, this model characterizes all the no key-words from the smallest sequences for the word "um", to the largest for the word "quatrocentos".

5.2 Training

The model training is based on the Baum-Welch Algorithm[13], and the Cross-Validation process. The objective of the Cross-Validation process is to monitor the general outcome during the training process of the model.

The cross-validation process is done over two sets of data: training data and validation data. After each iteration of the Baum-Welch Algorithm applied on the training data, the likelihood of the validation data is computed using the Forward Algorithm [13]. In this manner, the training process evaluates the training and validation likelihoods at each iteration of the model re-estimation and stops when the likelihood of the training data falls below a given threshold. The final model, the one that will be retained and stored, is the one that corresponds to the iteration yielding the maximum likelihood on the validation set.

To define the adequate number of states for each one of the words, the Cross-Validation process was applied using a variable number of states i, with $1 \leq i \leq$ *average of the observation sequence lengths - 2*. With this, it is possible to find the number of state models that best adapts to the sequence of observations corresponding to each word class.

5.3 Recognition Process

For our experiments, the matching scores between each model and an unknown observation sequence is carried out using the Forward Algorithm.

The goal of experiments made with the Group 01 models is to evaluate the classical system performance as reported in others legal amount recognition systems.

The experiments with the Group 02 models concern the evaluation of our proposed strategy based at the key-word level. The analysis of the obtained results will allow us to confirm the validity of our approach.

6 Experiments

This section describes the characteristics of the used database and presents the results obtained with the experiments held with the Group 01 and 02 models.

6.1 Databases

There exists several international databases [6,7] of handwritten checks. However, these databases do not deal with the Portuguese language. Owing to the difficulties of obtaining databases with real document checks through national bank institutions, the creation of a bank check laboratory database was chosen.

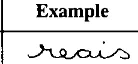
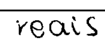
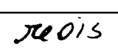
The acquisition of the images was off-line, 300 dpi, 256 grey levels. The images were binarized through the Otsu Method [12]. The database is omni-scriptor (a writer by check) and in unconstrained writing style. The vertical inclination of the existing characters in the images come from the different kinds of writing styles. Our database also involves the presence of different grammatically correct words which correspond to the same word class such as: "1 - um and hum", "14 - catorze and quatorze", "50 - cinquenta and cincoenta". This possibility exists in the Portuguese language and isn't found in the French or English languages for instance.

Our laboratory database has the following properties: minimum value of R$ 0,01 ("um centavo"); maximum value of R$ 999.999,99 ("novecentos e noventa e nove mil, novecentos e noventa e nove reais e noventa e nove centavos"); a guaranteed repetition, of at least 20 times, of the same digit in each possible position for each numeric group value, existence of the words: "real", "reais", "centavo" and "centavos".

The experiments held are using 3 databases, called: Base 1 - Training Base (A); Base 2 - Validation Base (V) and Base 3 - Testing Base (T). The database used in the present work has a total of 11736 isolated words. The composition of the databases is the following: 60% for Training, 20% for Validation, 20% for Tests. The average of examples per word in each database is 174, 60 and 58 respectively.

The cursive writing is the most frequent writing style in the training database as seen in Table 2.

Table 2 Distribution of the writing style at learning base

Writing Style	Example	%
Pure Cursive		72
Upper Case		13
Spaced Discrete		7
Mixed		8

6.2 Results

The obtained results for Group 1 with 39 models, considering Set 1 of features - PF and Set 2 of features - PFCC, are presented in the Table 3.

Table 3 Group 01 - Recognition Experiment

Features Set	Recognition Rate(%)
Set 01 – PF	56.4
Set 02 – PFCC	64.8

A significant increase in the recognition rate is observed with the use of concave and convex features in set 2, showing, as expected, a better word representation especially for the words with an absence of perceptual features.

The key-word models, "mil", "reais", "centavos" and the "all" model form the experiments, related to Group 2, and the results obtained with both sets of features are shown in Table 4. The matrix of confusion is presented in Table 5.

Table 4 Group 2 - Recognition Experiment

Models	Set 01 - PF (%)	Set 02 - PFCC (%)
All	74.41	82.96
Mil	94.16	94.55
Reais	84.25	90.87
Centavos	95.37	93.95

Table 5 Group 2 - Confusion Matrixes

Words	Set 01 of Features - PF			
	Mil	Reais	Centavos	All
Mil	242	5	0	10
Reais	22	214	2	16
Centavos	0	6	206	4
All	174	155	93	1227
	Set 02 of Features - PFCC			
Mil	243	5	0	9
Reais	5	229	3	15
Centavos	0	5	202	8
All	73	149	59	1368

In the confusion matrix presented in Table 5 for the Set 1 - perceptual features, significant confusion can be observed between the model of the words "mil" (or "reais") and the "all" model. With Set 2 - perceptual features + concavities and convexities, the word "mil" is better represented. The inclusion of the concavities and convexities permits a great reduction of the graphemes with no interesting feature which account for an average of 67,3%.

7 Conclusions

This paper presents a new approach for legal amount recognition in the context of Brasilian bank checks, considering that the handwriting of the legal amount has as its base a numeric value. Therefore, it is possible to formulate a solution that considers the reading and writing processes, besides considering the previous knowledge of the problem.

The obtained results motivate the application of the proposed strategy considering that the key-words models show a good performance as opposed to the other lexicon words.

Observing that the proportion between graphemes with concavities and/or convexities in conformity to the remaining features is of about 50,5%, we can conclude that the representation of the concavities and convexities requires a more detailed discrimination in order to make up the graphemes. In this manner, a future work will establish a classification capable of separating graphemes made up of "C", "S", "E" and "Z" or, "u", "n", "r" and "i". By improving the features extraction stage and the models of the isolated words of the lexicon, the process will be improved as a whole, allowing the proposed strategy to be applied with promising perspectives.

Other options will be analyzed to improve the recognition of keywords: different models for upper and lower case letters and different models for words "reais" and "real"; "hum" and "um", etc.

The future works that shall be held can still count on the inclusion of the handwritten grammar aside from the contextual information of the bank checks. Therefore, it will be possible to work with the complete legal amount and evaluate the proposed strategy.

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