CHARACTER RECOGNITION BY SIGNATURE APPROXIMATION

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This paper describes a new method for character recognition of typewritten text. The proposed approach is based on the approximation of character signatures by rational functions. Specifically, after the preprocessing operation, a separation procedure is applied to each character and its one-dimensional signatures are derived. These signatures are then approximated by rational functions via a linear programming technique and according to the minimax criterion. The values of the approximation errors for each signature are specified as character features. Through this technique only six powerful features are derived for each character. The classification technique employed is simple, adapted to the features selected and is based on features' similarities in combination with the minimum Euclidean distance classifier.

Keywords: Optical character recognition, features, thresholding, classification, rational approximation.

1. INTRODUCTION

Processing of typewritten texts is of great interest in office automation. Optical Character Recognition (OCR) techniques are used to translate human readable characters to machine readable codes. In OCR techniques, the choice of appropriate features is of course of the utmost importance. Until now, several OCR techniques based on statistical, matching, transform and shape features have been proposed with varying degrees of success.[1–7] An excellent survey on OCR is given by S. Impedovo *et al.*[8] On the other hand it is well known that a set of "good" features generally embody four characteristics:

(a) Discrimination. Features should take on significantly different values for characters belonging to different classes.
(b) Reliability. Features should take on similar values for characters belonging to the same class.
(c) Independence. Features should be uncorrelated with each other.
(d) Small feature space. The number of features used should be small to make classification simple and fast.

Additionally, the features must satisfy other desirable requirements such as low computational cost and low complexity of the feature extraction techniques. For these reasons, simple and powerful features cannot be found easily.

The subject of the proposed paper is to define a new set of features for OCR that satisfy the above characteristics. These features can be easily extracted by a novel linear rational approximation (LRA) technique.[9,11] Specifically, after pre-

International Journal of Pattern Recognition and Artificial Intelligence Vol. 8 No. 5 (1994) 1171–1187

processing, a separation procedure is applied for each typewritten character, from which the one-dimensional signatures of the characters are derived. Each signature is then approximated by a rational function via the solution of a linear programming problem. The result of this procedure is a set of only six powerful features for each character. There is no restriction about the type of characters that can be recognized. The only requirement is to have differences in the signatures of the characters. It is important to note that the proposed methodology for feature extraction can have extended applications in the fields of image processing and recognition. Specifically, using similar approaches, it is possible to approximate the one-dimensional signatures of any digital object by the LRA technique.

The classification technique employed is simple: it is adapted to the features selected and consists of two steps. First, the number of similar features is determined between the input and the prototype characters. In this step if the character is not recognized, then a second step using the minimum Euclidean distance classifier is applied.

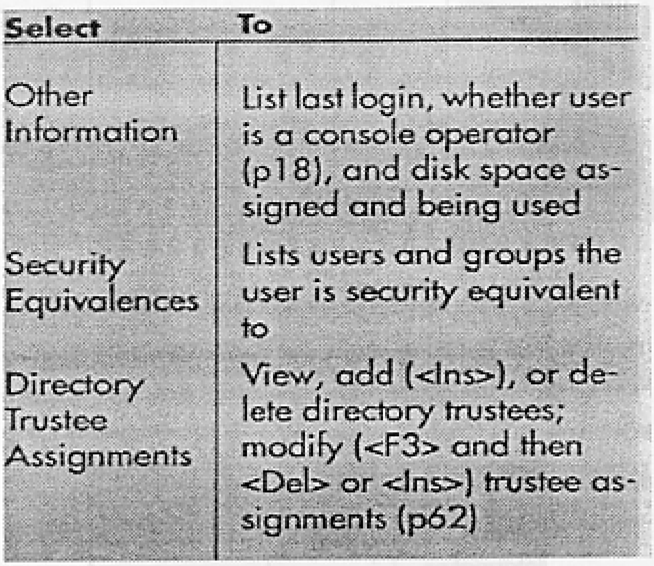
The proposed OCR method is independent from the type or the size of the typewritten characters, and yields high recognition rates and low error rates. Of course, the recognition rate depends if we have characters of the same type. The performance of the OCR method increases if we consider characters of similar type with the prototypes, and under these normal conditions the recognition rate is greater than 98%.

2. PREPROCESSING

Starting with a digitized document, a preprocessing scheme is necessary. This preprocessing operation includes the following main procedures:

- An optimal threshold selection technique to obtain a binary image from a digitized gray level image. To implement this procedure a new global threshold selection technique has been developed that consists of three main steps. The first step is based on the hill-clustering method proposed by D. Tsai and Y. Chen.[12] According to this method the locations of the histogram peaks can be approximately determined by an iterative procedure. For a digitized document, this procedure gives the locations of the two main histogram peaks. In the second step, the histogram between the peaks (the histogram valley) is fitted by a rational polynomial and according to the LRA algorithm. Afterward, the Golden search technique[13,14] is applied to find the optimal threshold value. This technique is simple and leads to a satisfactory binary image as it can be seen in Figs. 1, 2 and 3 for a badly illuminated document.
- Rotation of the document to remove some orientation and skewing variation.[15] After this step all symbols have approximately the same orientation.
- Image filtering to minimize the noise of the image and to achieve optimal boundary extraction. As a final filtering process, morphological filters are applied to suppress small islands and sharps caps of the characters.[16,17]
- Segmentation techniques to separate the characters from the background.

– Normalization. The normalization technique being used is based on scaling each character by a coefficient so that the character is tangential to the lower left corner of a 64×64 pixel rectangular. Obviously, the value of the scaling coefficient depends on the size of each character. This technique does not change the relative positions of the character pixels even if there are some noise pixels.



Select	To
Other Information	List last login, whether user is a console operator (p18), and disk space assigned and being used
Security Equivalences	Lists users and groups the user is security equivalent to
Directory Trustee Assignments	View, add (<Ins>), or delete directory trustees; modify (<F3> and then <Del> or <Ins>) trustee assignments (p62)

Fig. 1. Text image with 256 gray levels.

3. SIGNATURES EXTRACTION AND APPROXIMATION BY RATIONAL FUNCTIONS

The next recognition step is the feature extraction of each character. The selection of "good" features is critical to the performance of the character classification. It is well known that a set of "good" features generally embodies discrimination, reliability and independence. Additionally, the number of features used should be small to make the classification simple and fast. In the proposed approach, the features of the characters are extracted from their signatures. We can say that a character signature is a one-dimensional functional representation of its boundary.[18] In the proposed approach the two-dimensional character representation is transformed to a one-dimensional signature. The signatures of the characters are identified by specifying the correspondence between the character pixels with a pair of values (w_k, R_k) where w_k is the angle and R_k the distance of each pixel from the origin. In our approach the 64×64 scaled character is divided into four segments as illustrated for the character in Fig. 4. It must be noted that for calculation accuracy, it is necessary to normalize the amplitude of each pixel between -1 and 1. With this

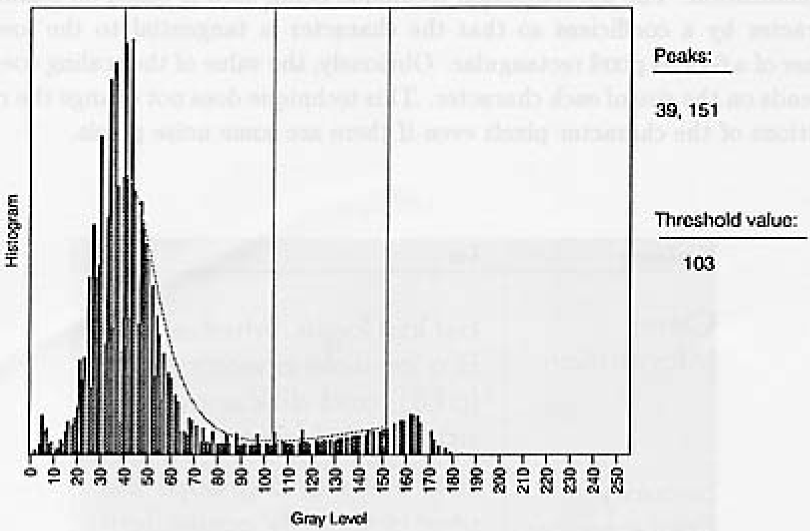
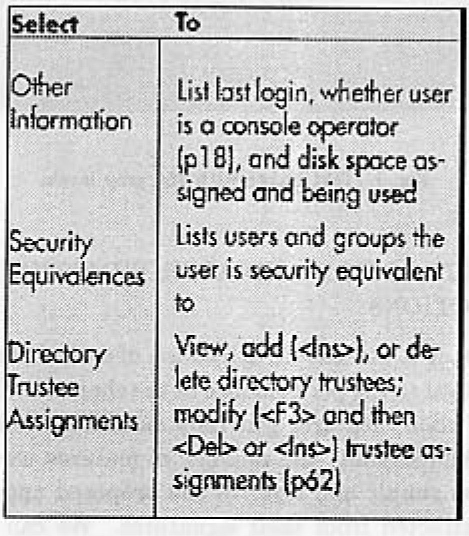


Fig. 2. The histogram and the application of the new threshold selection method.



Select	To
Other Information	List last login, whether user is a console operator (p18), and disk space assigned and being used
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Fig. 3. Image of Fig. 1 after global thresholding.

technique we can produce one-dimensional, functional representations for the whole character and for the four segments.

To extract features from the one-dimensional signatures, it is desirable to approximate these signatures by a powerful approximation technique. This approximation technique must always be applicable and must have significant characteristics such

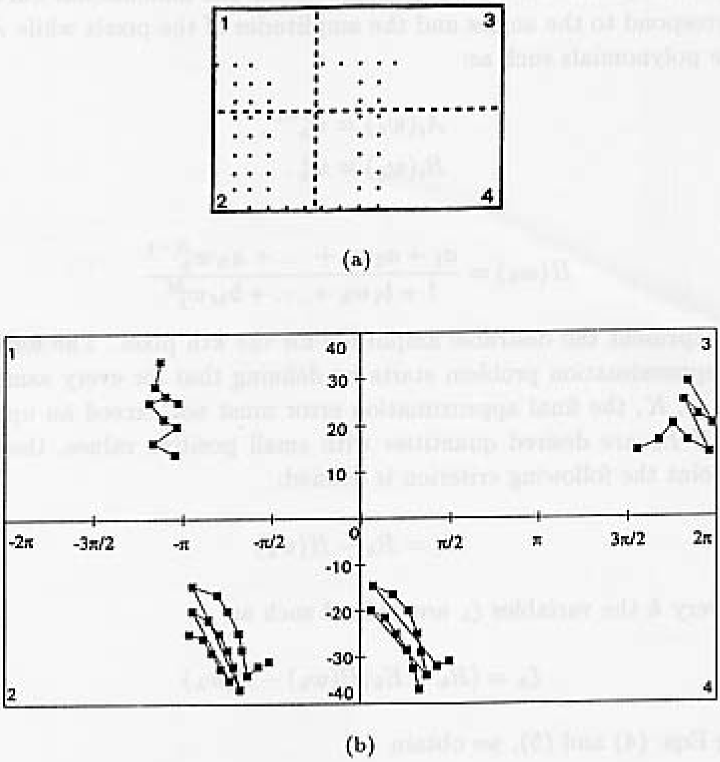

Fig. 4. (a) The scaled character. (b) The four segments.

as convergence to the global solution, low computational cost and most importantly, powerful approximation abilities. On the other hand, it is well known that rational functions with a small number of coefficients can sufficiently approximate curves. For these reasons, we choose to apply a new approximation technique which is based on the optimum approximation of real, rational functions via linear programming. According to this method, the linear approximation problem is formulated based on the minimax criterion, and the optimum solution is derived by using the revised Simplex algorithm.[19]

Generally, by the rational approximation method K sampling points can be approximated by a rational function of the following form:

$$H(w_k) = \frac{A(w_k)}{B(w_k)} = \frac{\sum_{i=1}^{N} a_i A_i(w_k)}{1 + \sum_{i=1}^{M} b_i B_i(w_k)} \tag{1}$$

where

w_k, $k = 1, \ldots, K$ are independent variables
a_i and b_i are unknown coefficients
N and M are suitable integer variables
$A_i(w_k)$ and $B_i(w_k)$ are polynomials of w_k with unit coefficients, and $B(w_k) > 0$ for every k.

According to the above definitions, and for each one-dimensional curve, w_k and $H(w_k)$ correspond to the angles and the amplitudes of the pixels while $A_i(w_k)$ and $B_i(w_k)$ are polynomials such as:

$$A_i(w_k) = w_k^{i-1} , \quad B_i(w_k) = w_k^i . \tag{2}$$

Therefore

$$H(w_k) = \frac{a_1 + a_2 w_k + \ldots + a_N w_k^{N-1}}{1 + b_1 w_k + \ldots + b_M w_k^M} \tag{3}$$

Let R_k represent the desirable amplitude for the kth pixel. The formulation of the linear approximation problem starts by defining that for every sampling point k, $k = 1, \ldots, K$, the final approximation error must not exceed an upper bound. Therefore, if E_k are desired quantities with small positive values, then for every sampling point the following criterion is defined:

$$E_k = R_k - H(w_k) \tag{4}$$

Also, for every k the variables ξ_k are defined such as

$$\xi_k = (R_k - E_k)B(w_k) - A(w_k) \tag{5}$$

Combining Eqs. (4) and (5), we obtain

$$R_k - E_k = H(w_k) + \frac{\xi_k}{B(w_k)} \tag{6}$$

From the above equation it is clear that for a good approximation the quantities:

$$d_k = \frac{|\xi_k|}{B(w_k)} \tag{7}$$

must not exceed an upper bound. Now, if

$$d = \underset{k=1,\ldots,K}{\text{maximum}} |d_k| \tag{8}$$

and

$$\xi = \underset{k=1,\ldots,K}{\text{maximum}} |(R_k - E_k)B(w_k) - A(w_k)| \tag{9}$$

then the minimax approximation problem takes the following form:

maximize d

subject to

$$|(R_k - E_k)B(w_k) - A(w_k)| \le \xi' \quad B(w_k) \ge d\xi' \quad k = 1, \ldots, K \tag{10}$$

The above optimization problem is not linear, but it may be converted to a linear one through the following transformations:

$$\begin{aligned} \xi &= \frac{1}{\xi'}, \\ a'_i &= \frac{a_i}{\xi'}, \quad \text{for } i = 1, \ldots, N \\ b'_i &= \frac{b_i}{\xi'}, \quad \text{for } i = 1, \ldots, M \end{aligned} \tag{11}$$

Now, the approximation problem (10) takes the following linear form

maximize d

subject to

$$\begin{aligned} (R_k - E_k)\xi + (R_k - E_k)\sum_{i=1}^{M} b'_i B_i(w_k) - \sum_{i=1}^{N} a'_i A_i(w_k) &\le 1 \\ -(R_k - E_k)\xi - (R_k - E_k)\sum_{i=1}^{M} b'_i B_i(w_k) + \sum_{i=1}^{N} a'_i A_i(w_k) &\le 1 \\ -\xi - \sum_{i=1}^{M} b'_i B_i(w_k) + d &\le 0 \\ \text{for } k = 1, \ldots, K \text{ and } \xi d &\ge 0 \end{aligned} \tag{12}$$

As can be observed from above, the variable d represents the minimax approximation error that is obtained from the solution of the linear problem (12). In the proposed OCR method the value of this variable for each one-dimensional signature is specified as a feature of the character. Thus, for each character six recognition coefficients are derived, where d_1, d_2, d_3 and d_4, correspond to the minimax approximation errors of the four segments, d_5 is obtained from

$$d_5 = d_1^2 + d_2^2 + d_3^2 + d_4^2 \tag{13}$$

and d_6 is the minimax approximation error derived from the signature of the whole character. The auxiliary feature d_5 is not independent, but obviously its value depends on the shape of the entire character. Often, in the classification procedure, while some of the first four features are not similar, d_5 is taken as a similar one because it is permitted by its classification threshold values.

As an example, the application of the linear programming rational approximation technique for the character υ is shown in Figs. 5 and 6. Figure 5 shows the approximated curves for the four segments of the character and Fig. 6 depicts the signature approximation for the whole character. For these approximations both the values of N and M are equal to 3 and as can be observed from the results these values are suitable for the satisfactory approximation of the signatures. Specifically, for the particular character υ the following values were determined for the feature

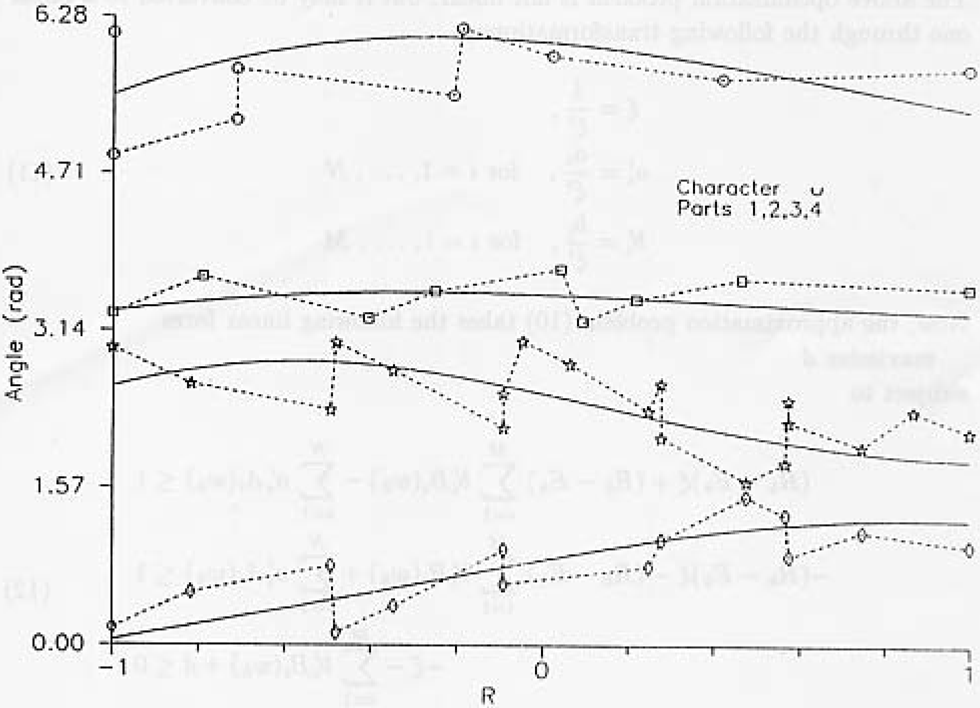

Fig. 5. Rational approximation for the four segments.

coefficients:

$$d = \begin{vmatrix} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \\ d_6 \end{vmatrix} = \begin{vmatrix} 0.25534 \\ 0.48123 \\ 0.61466 \\ 0.34253 \\ 0.79193 \\ 3.02024 \end{vmatrix} \tag{14}$$

It is noted that the above values of the feature vector correspond to 9, 19, 9 and 14 pixels in each one of the four character segments, respectively. In comparison with the values of the first four feature coefficients the large value of d_6 occurs because the pixel angles range from 0 to 2π.

In order of comparison, let us consider a similar recognition procedure by using the least squared method. Here the approximation problem for each quadrant and for the whole character has the form:

$$\text{minimize } J = \sum_{k=1}^{K} [R_k - F(w_k)]^2 \tag{15}$$

where K is the total number of sampling points, and

$$F(w_k) = a_1 + a_2 w_k + \ldots + a_N w_k^{N-1} \tag{16}$$

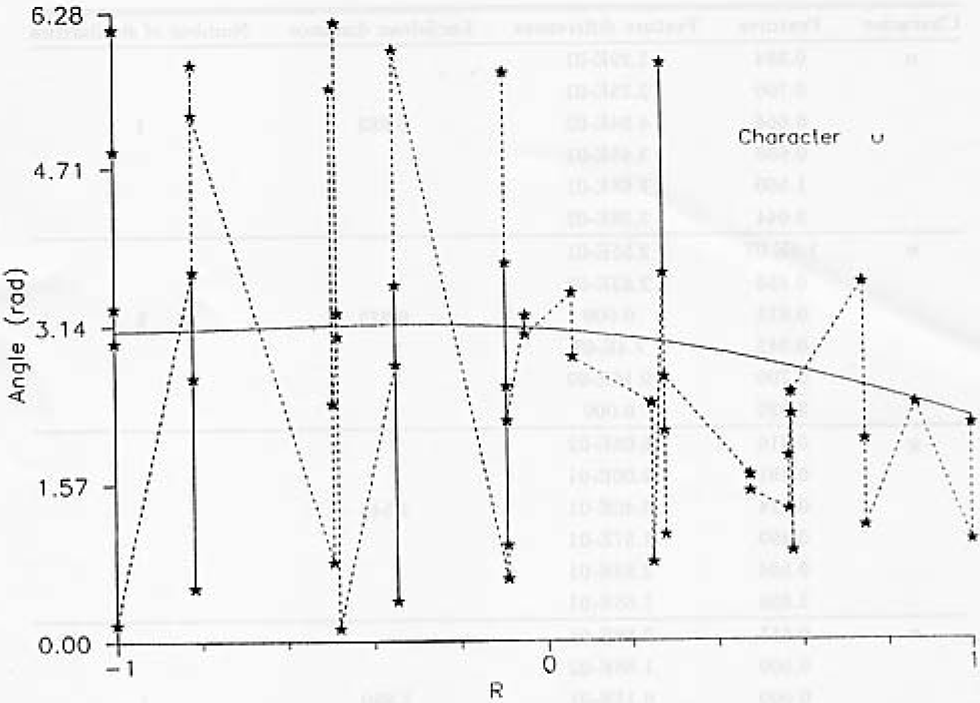

Fig. 6. Rational approximation for the whole character.

Table 2 shows the results of the application of the above procedure to the same with the Table 1 characters.

Table 1. Classification results for the character υ.

Character	Features	Feature differences	Euclidean distance	Number of similarities
α	0.153	1.02E-01		
	0.706	2.24E-01		
	0.173	4.41E-01	0.481	1
	0.706	3.64E-01		
	1.051	2.59E-01		
	3.062	4.21E-02		
ν	0.132	1.22E-01		
	0.664	1.83E-01		
	0.356	2.58E-01	0.470	1
	0.615	2.72E-01		
	0.963	1.71E-01		
	2.971	4.94E-02		

Table 1. (*Cont'd*)

Character	Features	Feature differences	Euclidean distance	Number of similarities
o	0.384	1.29E-01		
	0.706	2.25E-01		
	0.664	4.94E-02	0.883	1
	0.688	3.45E-01		
	1.560	7.68E-01		
	3.044	2.38E-02		
υ	1.0E-07	2.55E-01		
	0.453	2.83E-02		
	0.615	0.000	0.273	5
	0.342	7.4E-07		
	0.700	9.16E-02		
	3.020	0.000		
χ	0.316	6.08E-02		
	0.281	2.00E-01		
	0.274	3.40E-01	1.543	1
	0.499	1.57E-01		
	0.504	2.88E-01		
	2.856	1.65E-01		
τ	0.615	3.59E-01		
	0.500	1.88E-02		
	0.000	6.15E-01	1.880	1
	0.000	3.43E-01		
	0.628	1.64E-01		
	1.323	1.70E-00		
σ	0.266	1.10E-02		
	0.706	2.25E-01		
	0.327	2.88E-01	0.643	2
	0.706	3.64E-01		
	1.175	3.83E-01		
	3.044	1.30E-02		
Δ	0.552	2.96E-01		
	0.438	4.36E-02		
	0.651	3.64E-02	0.481	2
	0.472	1.30E-01		
	1.143	3.51E-01		
	3.007	1.30E-02		

In comparison with the polynomial approximation and the least squared method, the choice of rational functions and the LRA technique, is related with significant advantages. Specifically, rational approximation technique is less sensitive to noise because it minimizes the maximum absolute differences and not the sum of the squared differences. Also, clearly a rational polynomial can more efficiently fit difficult data because it has a numerator and a denominator. Therefore, for equivalently

Table 2. Results derived by the least-squared method.

Character	Features	Feature differences	Euclidean distance	Number of similarities
α	0.074	0.261		
	1.948	0.075		
	0.234	1.135	10.580	2
	2.160	1.467		
	8.525	2.547		
	140.225	10.097		
ν	0.110	0.226		
	2.091	0.217		
	0.520	0.850	26.927	3
	1.356	0.663		
	6.492	0.514		
	103.230	26.899		
o	0.292	0.044		
	3.152	1.279		
	1.028	0.342	58.357	2
	2.795	2.101		
	18.888	12.909		
	73. 271	56.857		
υ	0.078	0.258		
	0.922	1.851		
	1.370	5E-08	7.687	3
	0.675	0.018		
	3.187	2.791		
	123.214	6.914		
χ	0.555	0.219		
	0.523	1.3501		
	0.527	0:842	12.462	2
	1.006	0.313		
	1.872	4.107		
	141.780	11.651		
τ	0.186	0.149		
	0.332	1.541		
	0.0	1.370	125.975	1
	0.0	0.693		
	0.145	5.834		
	4.307	125.821		
σ	0.582	0.247		
	1.714	0.160		
	0.615	0.755	16.3686	2
	2.341	1.648		
	9.134	3.155		
	146.085	15.956		

Table 2. (*Cont'd*)

Character	Features	Feature differences	Euclidean distance	Number of similarities
Δ	0.703	0.368		
	1.251	0.622		
	2.846	1.477	53.378	1
	1.771	1.077		
	13.299	7.320		
	182.966	52.837		

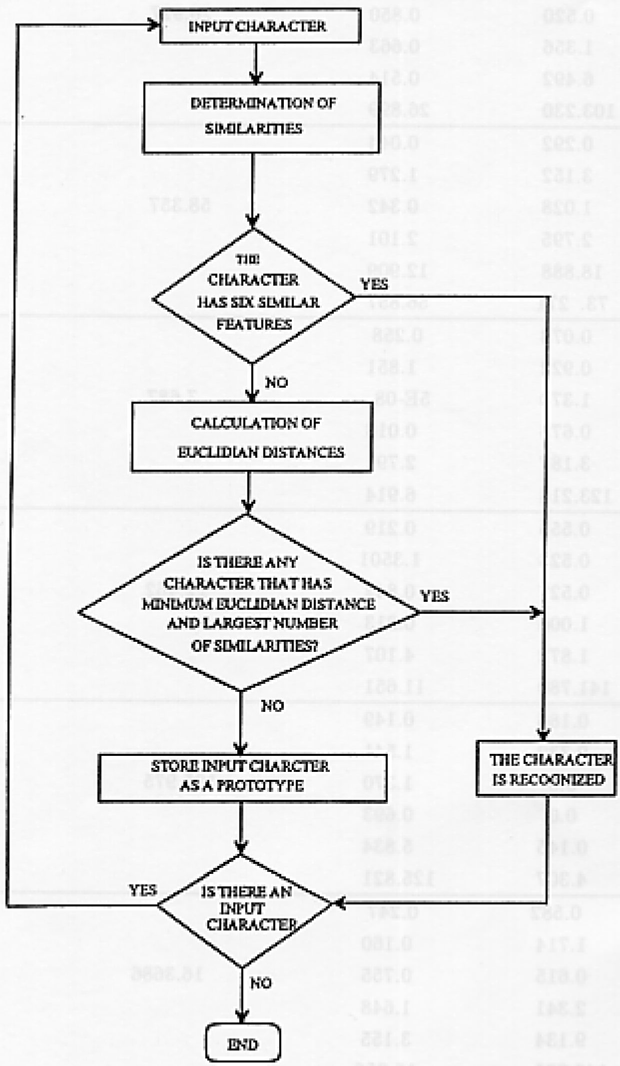

Fig. 7. Flow chart of the classification technique.

fitting results, rational functions need fewer coefficients than polynomials. Additionally, because in the least-squared method calculated terms are of high power, the coefficients derived from the least-squared method are unstable in magnitude if the order of the polynomial exits an upper bound.

4. CLASSIFICATION TECHNIQUE

According to the feature extraction procedure, a feature vector $d = (d_1, d_2, d_3, d_4, d_5, d_6)^T$ is derived from the input character. The classification technique classifies the feature vector d into known feature vectors of the prototype characters. In the proposed approach a suitable classification technique is applied which first determines the absolute distances between the input and the prototype features according to the following equation:

$$|d_i - p_i| = D_i, \quad i = 1, \ldots, 6 \tag{17}$$

where d_i and p_i are the values of the input and prototype features. If D_i is less or equal to a suitable threshold value then d_i and p_i are defined as similar. If this is true for only one character and for the corresponding six features then the character is recognized. Otherwise, the Euclidean distance is calculated according to the relation:

$$J = \sqrt{\sum_{i=1}^{6} (d_i - p_i)^2} \tag{18}$$

The character is recognized if it has the smallest Euclidean distance and if the Euclidean distance is less or equal to a suitable threshold value. If a character is not recognized then it is saved as a prototype. The flow chart of the classification technique is shown in Fig. 7.

Obviously, the classification of the characters by using the criterion of the minimum Euclidean distance, operates by taking into account their predetermined similarities. Specifically, in this classification process, the characters that have the largest number of similar features are examined first and therefore the computational cost of the classification procedure is drastically reduced. As an example of the classification technique, Table 1 gives the values of the features for the character υ and for a set of Greek characters. Taking the threshold values D_i, $i = 1, \ldots, 6$ equal to 0.1, 0.05, 0.01, 0.01, 0.1 and 0.05, respectively, the input character υ is recognized as identical to the prototype υ, because they have five similar features in the d_2, d_3, d_4, d_5 and d_6 coefficients and additionally their Euclidean distance has the smallest value. It is noted that as we can observe from the Table 2, while we define triple threshold values, the least-squared method results in fewer similarities too.

According to the above, the proposed OCR method consists of the following main steps:

<u>*Step 1*</u>: Scanning of the text.

<u>*Step 2*</u>: Optimal threshold operation.

Step 3: Filtering.
Step 4: Rotation of the document.
Step 5: Segmentation.
Step 6: Normalization and scaling of the characters to a 64 × 64 rectangular.
Step 7: Signatures extraction.
Step 8: Features extraction by using the linear rational approximation algorithm.
Step 9: Classification.

5. EXPERIMENTAL RESULTS AND PERFORMANCE OF THE OCR METHOD

In practice, the development of an OCR system is related with the requirements of its users. Therefore, a low-cost OCR software is easy to implement and to satisfy specific recognition restrictions. This means that we must specify the conditions under which the performance of the OCR is measured. Until now, there is not an OCR product that really reads all the Latin typewritten characters. "The best products do a good job on clean documents, but they all degrade in performance as the document quality (or scanner quality) degrades".[20]

It is well known that to have an impressive performance, in commercial OCR products, millions of character's feature vectors are used as training sets. Additionally, the training set that is used comes from a variety of fonts, it varies in image quality, and it is suitable for the variability of the documents that the OCR system is expected to handle. Difficulties that are associated with insufficient features can be overcome by using a large number of prototypes in combination with a suitable classifier and a syntactic pattern recognition technique. Except for the above difficulties, for a good performance, an OCR system must give sufficient solutions to a variety of many other problems that are associated with the preprocessing phase, such as the scanning quality and the segmentation. Most of the segmentation problems are related with touching and overlapping characters, and with the presence of images in the document. Also, the performance is degraded if we have multifonts and multishape characters to recognize.

The performance of an OCR system depends very much on the shape of the characters. Therefore, it is unrealizable to operate an OCR system with all the character types. Also, it is obvious that to build a faultless OCR system we must use a combination of methods that has already been used and those that will be proposed in the future. In other words, for desirable character recognition results, various OCR approaches and complementary algorithms must be able to integrate with each other. On the other hand, future OCR systems will use more sophisticated techniques, such as morphological and fuzzy logic approaches. The new OCR method does not avoid all the above difficulties. The main scope of this paper is to propose a new powerful set of features for OCR that are based on the approximation of the characters' signatures by using a suitable linear programming optimization technique. The new feature extraction technique is general and it can be used in other pattern recognition applications.

The proposed OCR method is implemented for IBM 80386 and IBM 80486 computers. The documents are scanned in 300–500 dpi resolutions by using a HP scanner. It is noticed that, because of the better segmentation of the documents, the performance of the OCR system is increased for high scanning resolution. The training character set consists of approximately 5,000 characters of Times type fonts, while the test set is about 30,000 characters. The scanned documents are from a laser printer and the size of the characters is limited to $8 \sim 20$ points.

Because of the division of the characters to the four quadrants, it is difficult to classify a "noisy" character in a different class and it is easier to reject it. However, there are significant morphological similarities between Greek and Latin characters, as for example the pairs of (o,o), (O,O), (T,T), (A,A), etc. characters. Additionally, there are some other characters that are confused because of their matching shapes. For example, the characters that our method confuses are $(8, \theta)$, (o, σ), (ι, i), (u, v, ν, υ), etc. Therefore, a syntactic pattern recognition technique can prove to be very effective in distinguishing these extremely similar characters. In our OCR system, the characters that have been classified in another character class are about 0.8%, while 1.3% of characters have been rejected. The above performance varies according to the quality of the documents, that is the performance increases for clean documents and decreases as the document quality worsens. For example, if the document is not clean, then the segmentation process results in several joined characters and it confuses the whole recognition procedure and increases the processing time. Under normal conditions, with a 486 machine, the processing time of the recognition procedure (Steps 5–9) is about $35 \sim 42$ cps.

6. CONCLUSIONS

This paper presents a new efficient technique for optical character recognition. The proposed approach is based on a set of only six features. After preprocessing, each character is first divided into four segments and for the feature extraction process. Next, one-dimensional representations are obtained for the entire character and for the four segments that correspond to the signatures of the characters. Subsequently, a suitable linear rational approximation technique is applied and the signatures are approximated by rational functions. The approximation error for each signature is specified as a feature of the character. The approximation procedure used has significant advantages in low computation time, and in the ensured convergence of the linear problem to the global optimal solution.

The final step of the proposed OCR method is the classification procedure which is simple and fast due to the small number of classification features. First, the features' similarities are determined between the prototypes and the input character, and second, if necessary, the minimum Euclidean distance classifier is applied.

The OCR approach is independent of the character type and has been successfully applied to a variety of typewritten fonts. In the experiment described a mixed typewritten text of Latin and Greek characters were used and the recognition rate reached was satisfactory. It is certain that the combination of the proposed method with other sophisticated techniques will greatly increase the recognition rate.

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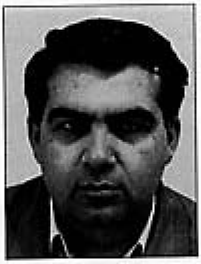
Received 20 May 1992; second revision 20 April 1993.



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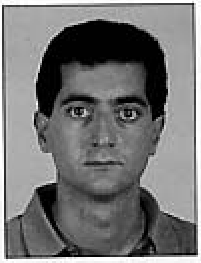

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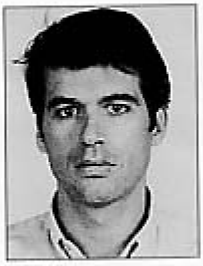

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