

Character Recognition Using Radon Transformation and Principal Component Analysis in Postal Applications

Mirosław Miciak

University Technology and Life Sciences in Bydgoszcz
Faculty of Telecommunications and Electrical Engineering
ul. Kaliskiego 7, 85-791 Bydgoszcz, Poland
Email: miciak@utp.edu.pl

Abstract—This paper describes the method of handwritten characters recognition and the experiments carried out with it. The characters used in our experiments are numeric characters used in post code of mail pieces. The article contains basic image processing of the character and calculation of characteristic features, on basis of which it will be recognized. The main objective of this article is to use Radon Transform and Principal Component Analysis methods to obtain a set of features which are invariant under translation, rotation, and scaling. Sources of errors as well as possible improvement of classification results will be discussed.

I. INTRODUCTION

THE today's systems of automatic sorting of the post mails use the OCR (Optical Character Recognition) mechanisms. In the present recognizing of addresses (particularly written by hand) the OCR is insufficient.

The typical system of sorting consists of the image acquisition unit, video coding unit and OCR unit. The image acquisition unit sends the mail piece image to the OCR for interpretation. If the OCR unit is able to provide the sort of information required (this technology has 50 percent effectiveness for all mails), it sends this data to the sorting system, otherwise the image of the mail pieces is sent to the video coding unit, where the operator writes down the information about mail pieces.

The main problem is that operators of the video coding unit have lower throughput than an OCR and induce higher costs [1]. Therefore the OCR module is improving, particularly in the field of recognition of the characters. Although, these satisfactory results were received for printed writing, the handwriting is still difficult to recognize. Taking into consideration the fact, that manually described mail pieces make 30 percent of the whole mainstream, it is important to improve the possibility of segment recognizing the hand writing. This paper presents the proposal of a system for recognition of handwritten characters, for reading post code from mail pieces.

The process of character recognition process can be divided into stages: filtration and binaryzation, normalization, Radon transform calculating, accumulator analysis, Principal Component Analysis, feature vector building, and character recognition stage.

The first step of the image processing is binarization. The colourful image represented by 3 coefficients Red, Green and Blue from the acquisition unit must be converted to the image with 256 levels of grey scale. The next step of processing of the image of mail piece is digital filtration. The filtration is used for improving the quality of the image, emphasizing details and making processing of the image easier. The filtration of digital images is obtained by

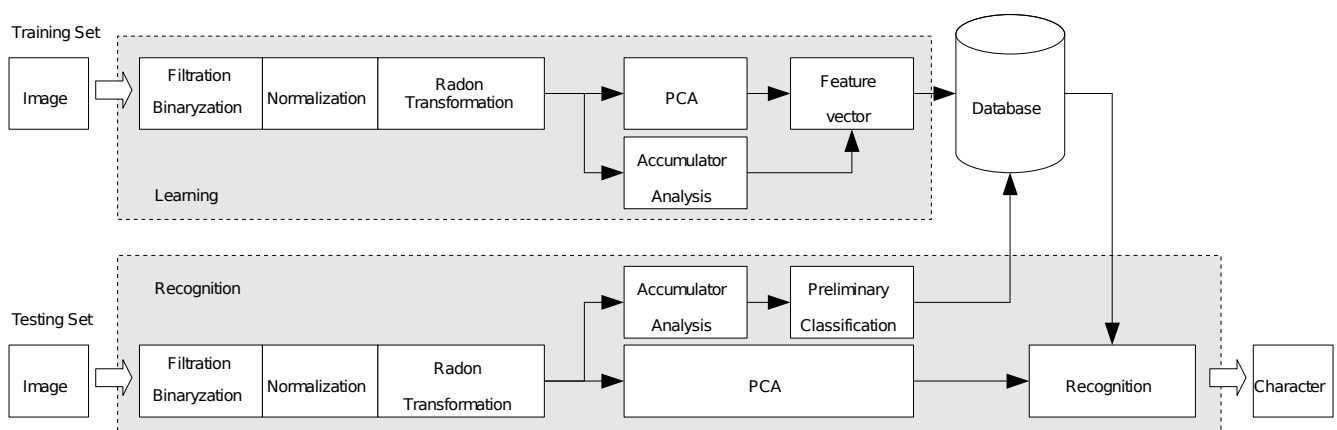


Fig 1. Character recognition system

convolution operation. The new value of point of image is counted on the basis of neighbouring points value. Every value is classified and it has influence on new value of point

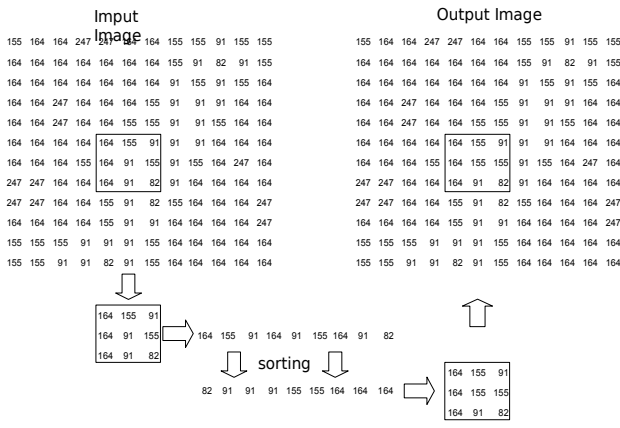


Fig 2. Median filtering

of the image after filtration [2].

In the pre-processing part non-linear filtration was applied. The statistical filter separates the signal from the noise, but it does not destroy useful information. The applied filter is median filter, with mask 3x3.

The image of character received from the acquisition stage have different distortion such as: translation, rotation and scaling. The character normalization is applied for standardization size of the character. Images there are translated, rotated and expanded or decreased. The typical solutions takes into consideration the normalization coefficients and calculate the new coordinates given by:

$$[x, y, 1] = [i, j, 1] \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -I & -J & 1 \end{bmatrix} \times \begin{bmatrix} m_i & 0 & 0 \\ 0 & m_j & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} \cos \beta & \sin \beta & 0 \\ -\sin \beta & \cos \beta & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

where: I, J is a center of gravity given by :

$$I = \frac{\sum_i \sum_j if(i, j)}{\sum_i \sum_j f(i, j)} \quad J = \frac{\sum_i \sum_j jf(i, j)}{\sum_i \sum_j f(i, j)} \quad (2)$$

In the reality we haven't got this parameters starting right now, so we use new coordinate system where center is equals to center of gravity of the character. The value of angle rotation is according to main axes of the image. The value of scale coefficient is calculated by mean value of variation of the character. So the center of gravity of the character is good candidate point of the center of image as a product of normalization stage.

II. RADON TRANSFORMATION

In recent years the Radon transform have received much attention. This transform is able to transform two dimensional images with lines into a domain of possible line parameters, where each line in the image will give a peak posi-

tioned at the corresponding line parameters. This have lead to many line detection applications within image processing, computer vision, and seismic [3][18]. The Radon Transformation is a fundamental tool which is used in various applications such as radar imaging, geophysical imaging, nondestructive testing and medical imaging [20].

The Radon transform computes projections of an image matrix along specified directions. A projection of a two-dimensional function $f(x,y)$ is a set of line integrals. The Radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. To represent an image, the radon function takes multiple, parallel-beam projections of the image from different angles by rotating the source around the centre of the image. The "Fig.3" shows a single projection at a specified rotation angle.

The Radon transform is the projection of the image intensity along a radial line oriented at a specific angle. The radial coordinates are the values along the x' -axis, which is oriented at θ degrees counter clockwise from the x -axis. The origin of both axes is the center pixel of the image .

For example, the line integral of $f(x,y)$ in the vertical direction is the projection of $f(x,y)$ onto the x -axis; the line integral in the horizontal direction is the projection of $f(x,y)$ onto the y -axis. The "Fig.4" shows horizontal and vertical

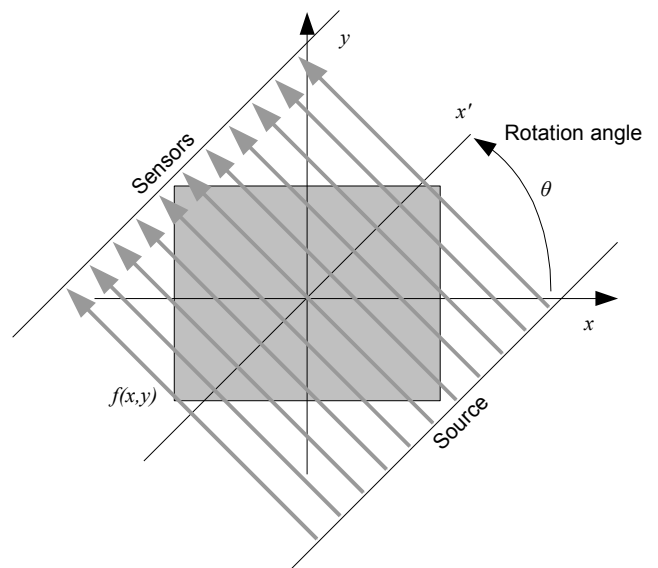


Fig 3. Single projection at a specified rotation angle

projections for a simple two-dimensional function.

Projections can be computed along any angle θ , by use general equation of the Radon transformation [23][24][25] :

$$R_{\theta}(x') = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - x') dy dx \quad (3)$$

where $\delta(\cdot)$ is the delta function with value not equal zero only for argument equal 0, and:

$$x' = x \cos \theta + y \sin \theta \quad (4)$$

x' is the perpendicular distance of the beam from the origin and θ is the angle of incidence of the beams. The "Fig. 5" illustrates the geometry of the Radon Transformation. The

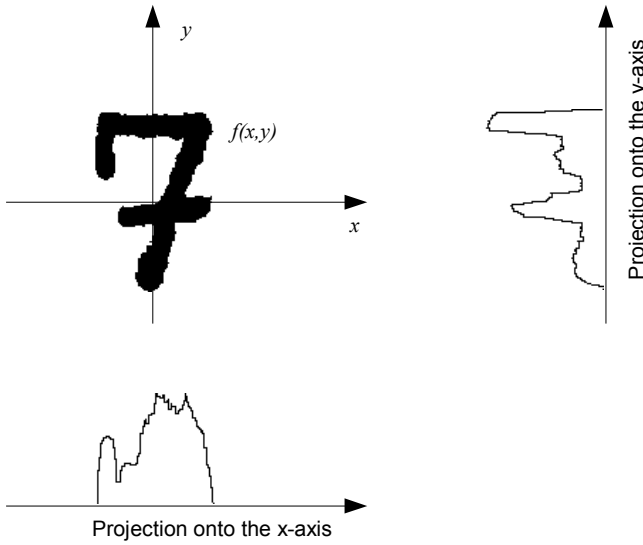


Fig 4. Horizontal and Vertical Projections of a Simple Function

very strong property of the Radon transform is the ability to extract lines (curves in general) from very noisy images. Radon transform has some interesting properties relating to the application of affine transformations. We can compute the Radon transform of any translated, rotated or scaled image, knowing the Radon transform of the original image and the parameters of the affine transformation applied to it.

This is a very interesting property for symbol representation because it permits to distinguish between transformed objects, but we can also know if two objects are related by an affine transformation by analyzing their Radon transforms [19]. It is also possible to generalize the Radon transform in order to detect parametrized curves with non-linear behavior [3][4][5].

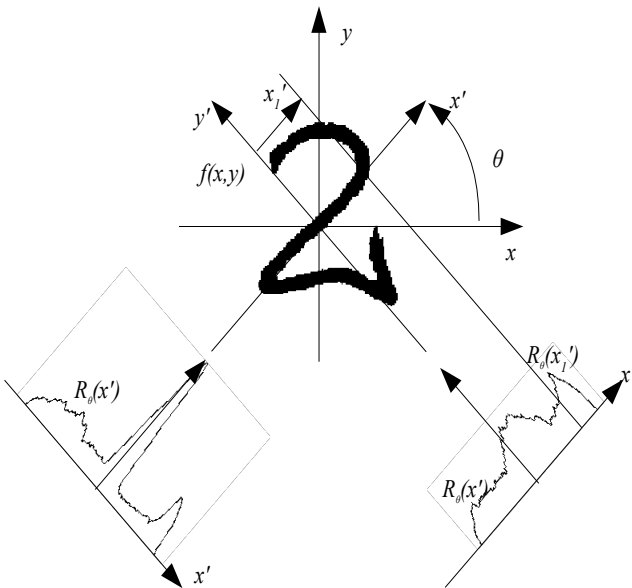


Fig 5. Geometry of the Radon Transform

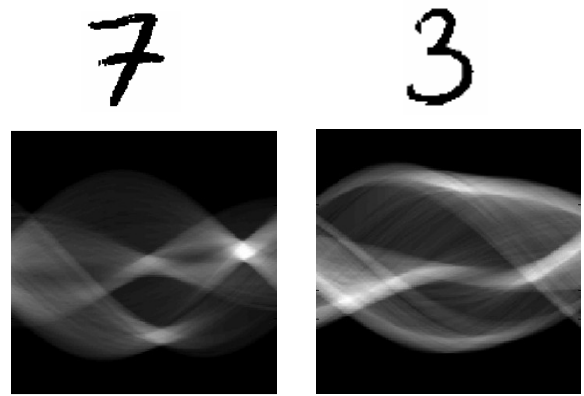


Fig 6 Sample of accumulator data of Radon Transformation

III. PRINCIPAL COMPONENTS ANALYSIS

PCA is mathematically defined [6][7][8] as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for a given data in least square terms. The main idea of using PCA for character recognition is to express the large 1-D vector of pixels constructed from 2-D character image into the compact principal components of the feature space [21].

PCA can be used for dimensionality reduction in a data set by retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data.

For all r digital images $f(x,y)$ from the normalization stage is creating column vector X_k by the concatenate operation, where $k=(1,...,r)$. For that prepared images we can calculate mean of brightness intensity M , difference vector R and covariance matrix Σ .

$$M_k = \frac{1}{r} \sum_{k=1}^r X_k \tag{5}$$

$$R_k = X_k - M_k \tag{6}$$

$$\Sigma = \frac{1}{r} \sum_{k=1}^r R_k R_k^t \tag{7}$$

where:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_r \end{bmatrix} \tag{8}$$

$$M = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_r \end{bmatrix} \tag{9}$$

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_r \end{bmatrix} \quad (10)$$

Principal components are calculating from the eigenvectors Φ_i and eigenvalues λ_i of the covariance matrix Σ . The eigenvectors Φ_i are normalized, sorted in order eigenvalue, highest to lowest and transposed, to obtain transformation matrix W , where K is the number of dimensions in the dimensionally reduced subspace calculated by:

$$\frac{\sum_{i=1}^K \lambda_i}{\sum_{i=1}^p \lambda_i} \geq p \quad (11)$$

where: p is assumed as threshold [21]. The matrix W is given by:

$$W = \begin{bmatrix} \Phi_1^1 & \dots & \Phi_1^K \\ \vdots & \dots & \vdots \\ \Phi_l^1 & \dots & \Phi_l^K \end{bmatrix} \quad (12)$$

After image projection into eigenvectors space we do not use all eigenvectors, but these with maximum eigenvalues, this gives the components in order of significance. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the input data. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions [21].

The projection of X into eigenvectors space is given by:

$$Y = W(X - M) \quad (13)$$

where:

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_r \end{bmatrix} \quad (14)$$

The final data set will have less dimensions than the original [8], after all we have r column-vector for each input image with K values :

$$Y_k = (y_1, y_2, \dots, y_K)^t \quad (15)$$

The PCA module in proposal system generate a set of data, which can be used as a features in building feature vector section. For instance when we use input matrix 8x8 from Radon transformation stage, as a result we obtained $K=8$ values vector, using Cattell's criterion [9].

IV. FEATURE VECTOR

Two sets of data received from the PCA module and accumulator analysis stage are used to create vector of features of character. The amount of data from Radon transformation depends from the image of character size and numbers of projections. For example, we use image with size 128x128

pixels and step θ equals one degree. With those parameters we can retrieve accumulator matrix with 180 width and 185 height cells. To produce feature vector we don't use all values from the accumulator. The reduction the accumulator data is possible by the resizing operation - when generally size of matrix is most commonly decreased. The most known scaling techniques are: method used with Pixel art scaling algorithms, Bicubic interpolation, Bilinear interpolation, Lanczos resampling, Spline interpolation, Seam carving [10][11] [12]. In our research we make tests with Linear, Bicubic and Bilinear methods. The results with other methods was very similar and do not have influence on the recognition rate of proposed system. As a result of resize operation in our system is a matrix 8x8 elements as in "Fig.7".

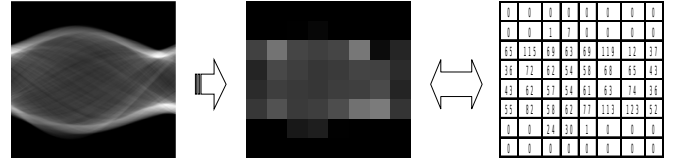


Fig 7. Scaling operation

The next step of vector features preparing is concatenate operation and Principal Component Analysis of resized matrix from Radon Transformation, see on "Fig.8".



Fig 8. Creating vector X by concatenate operation.

As a result of PCA is 8 element vector $L1-L8$ of main values from input data, which will be used to feature vector. The second set of data are: code of known character ZN as a Unicode [13] and number of local maximum LP from the Accumulator Analysis stage. The feature vector consists a 10 values "Fig.9".

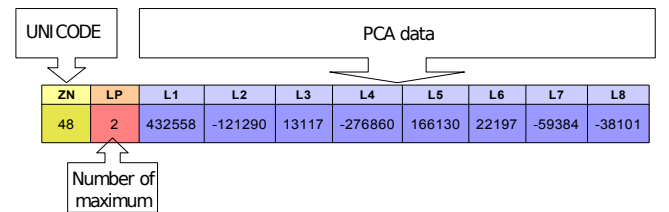


Fig 9. Creating feature vector in proposed system

V. PRELIMINARY CLASSIFICATION

The aim of the preliminary classification is to reduce the number of possible candidates for an unknown character, to a subset of the total character set. For this purpose, the selected domain is categorized into six groups with number of local maximum as in "Fig.10".

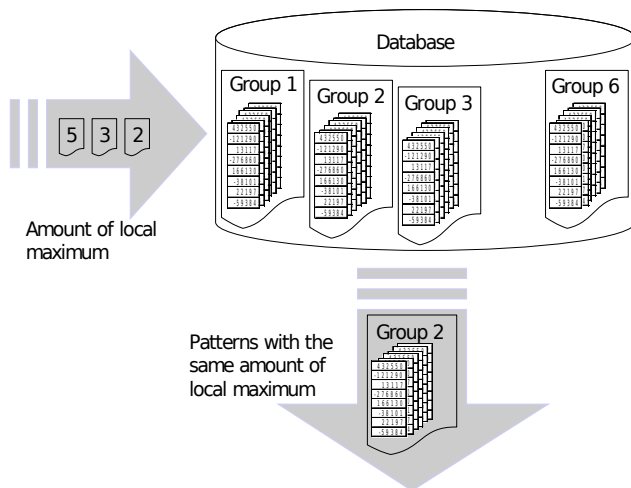


Fig 10. The organizations of feature vectors in database

The preliminary classification is based on the amount of local maximum calculating in the Accumulator Analysis stage “Fig.11”.

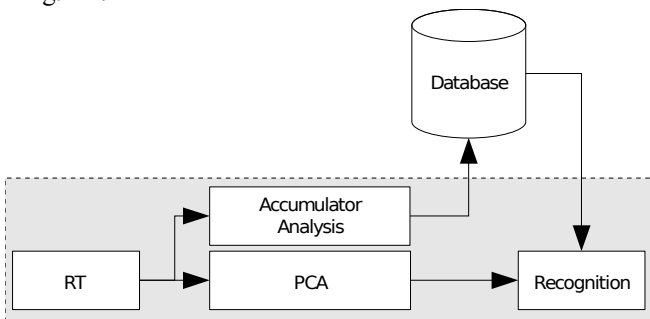


Fig 11. The Preliminary classification scheme

VI. RECOGNITION AND CLASSIFICATION

The classification in the recognition module compared features from the pattern to model features sets obtained during the learning process. Based on the feature vector Z recognition, the classification attempts to identify the character based on the calculation of Euclidean distance [22] between the features of the character and of the character models [14].

The distance function is given by:

$$D(C_i, C_r) = \sum_{j=1}^N [R(j) - A(j)]^2 \quad (16)$$

where:

C_i - is the predefined character,

C_r - is the character to be recognized,

R - is the feature vector of the character to be recognized,

A - is the feature vector of the predefined character,

N - is the number of features.

The minimum distance D between unknown character feature and predefined class of the characters is the criterion choice of the character [14].

VII. THE EXPERIMENT

For evaluation experiments, we extracted some digit data from various paper documents from different sources eg. mail pieces post code, bank cheque etc. In total, the training

datasets contain the digit patterns of above 130 writers. Collected 920 different digits patterns for training set and 300 digits for test set. Each pattern is represented as a feature vector of 10 elements.

Comparing results for handwritten character with other researches is a difficult task because are differences in experimental methodology, experimental settings and handwriting database. Liu and Sako [15] presented a handwritten character recognition system with modified quadratic discriminant function, they recorded recognition rate of above 98%. Kaufman and Bunke [16] employed Hidden Markov Models for digits recognition. They obtained a recognition rate of 87%. Aissaoui and Haouari [14] using Normalized Fourier Descriptors for character recognition, obtained a recognition rate above 96%. Bellili using the MLP-SVM recognize achieves a recognition rate 98% for real mail zip code digits recognition task [17]. In this experiment recognition rate 94% was obtained. The detailed results for individual testing sets was presented in Table I.

TABLE I.
RECOGNITION RATE FOR TESTING SETS

Testing Set	Recognition rate
Set 1	94.7 %
Set 2	94.2 %
Set 3	93.3 %

VIII. CONCLUSIONS

The selecting of the features for character recognition can be problematic. Moreover fact that the mail pieces have different sizes, shapes, layouts etc. this process is more complicated. The paper describes often used the character image processing such as image filtration, binaryzation, normalization and the Radon Transformation calculating.

The character recognition algorithms were proposed. In connection with this work the application included the algorithms is in progress. So far the application reached recognition speed 30 characters/sec without any optimization.

In the future work is planning to use another statistical methodology such as JDA/LDA. Moreover the will be upgraded to remaining all alphanumerical signs and special signs often placed on regular post mails.

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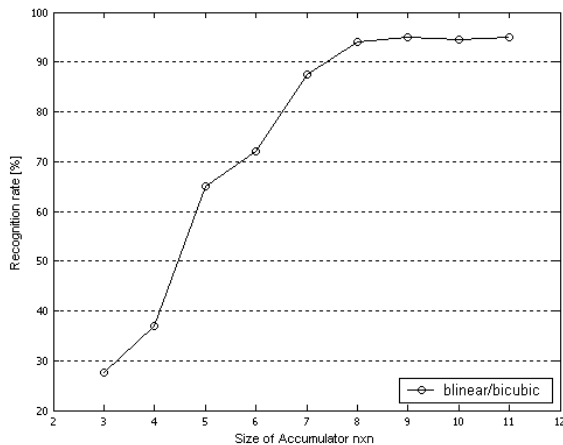


Fig 12. Influence of Accumulator size on recognition rate

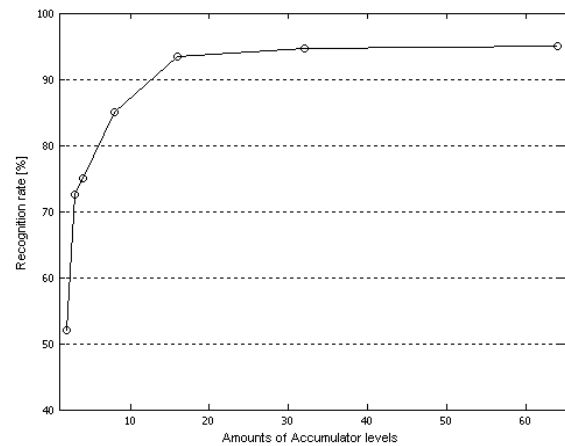


Fig 13. Influence of amount Accumulator levels on recognition rate

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