UNIWERSYTET TECHNOLOGICZNO-PRZYRODNICZY
IM. JANA I JĘDRZEJA ŚNIADECKICH W BYDGOSZCZY
ZESZYTY NAUKOWE NR 260
TELEKOMUNKACJA I ELEKTRONIKA 15 (2011), 5-17

INVARIANT GABOR-ZERNIKE DESCRIPTOR FOR POSTAL APPLICATIONS

Tomasz Andrysiak, Mirosław Miciak, Rafał Boniecki

Institute of Telecommunications,
Faculty of Telecommunications and Electrical Engineering
University of Technology and Life Sciences (UTP)
ul. Kaliskiego 7, 85-789 Bydgoszcz, Poland
[andrys, miciak, raboni]@utp.edu.pl

Summary: In this paper a new solution of handwritten digits recognition system for postal applications is presented. Moreover, in this paper, a new method of handwritten characters recognition is introduced. The proposed algorithm is applied to classification of post mails on the basis of zip code information. In connection with this work the research was conducted with numeric characters used in real post code of mail pieces. Moreover, the article contains basic image processing for instance filtration binarization and normalization of the character. The main objective of this article is to use the Gabor filtration and Zernike moments to obtain a set of invariant features, on basis of which postal code will be recognized. The reported experiments' results prove the effectiveness of the proposed method. Furthermore, sources of errors as well as possible improvement of classification results will be discussed.

Keywords: Character recognition, Gabor filters, Zernike moments.

1. 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 (Fig. 1) 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 % effectiveness for all mails [9], 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.

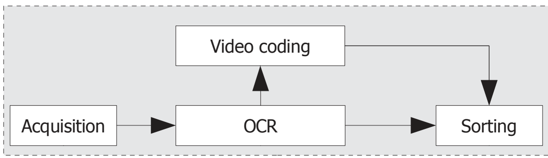


Fig. 1. The automatic sorting system – mail flow

The main problem is that operators of the video coding unit have lower throughput than an OCR and induce higher costs [9]. 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% of the whole mainstream, it is important to improve the possibility of segment recognizing of handwriting. This paper presents the proposal of a system for recognition of handwritten characters, for reading post code from mail pieces.

2. SYSTEM OVERVIEW

The process of character recognition process can be divided into stages: image grayscale normalization, filtration and binarization, normalization, Gabor and Zernike moments calculating, Principal Component Analysis, feature vector building, and character recognition stage. The first step of the image processing is image grayscale normalization. The colorful image most often represented by three coefficients: Red, Green and Blue (RGB) from the acquisition unit must be converted to the gray scale image. The next step of processing of the image of mail piece is digital filtration and binarization. The final stage of preprocessing is coordinate normalization. The proposed method of character recognition was shown on Fig. 2. Additionally, our solution proposed the use of the preliminary classification stage. The aim of the preliminary classification stage 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 subgroups. The analysis of the elements belonging to different groups does not allow to indicate the clear membership rules classes of character, but rather may show their geometrical features. Additionally, pre-classification module can be used to determine rejection of non-digit character too. Based on the feature vector (G,E,Z) recognition, the classification attempts to identify the character based on the calculation of Euclidean distance between the features of the character and of the character models [2].

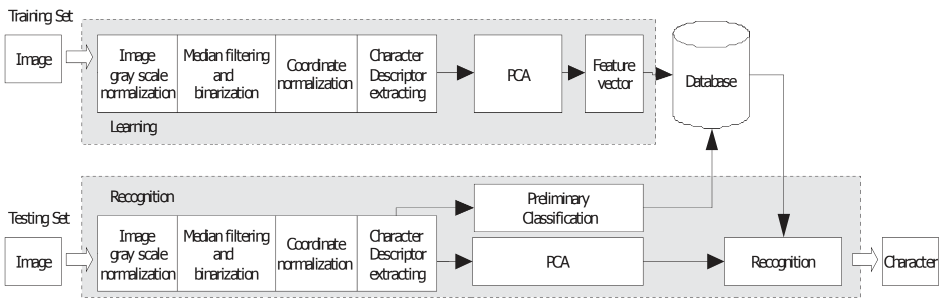


Fig. 2. The proposed method of character recognition

2.1. Image grayscale normalization

Before filtering the image, we normalize all its regions to a certain mean and variance. Normalization is performed to remove the effects of sensor noise and gray level deformation. Moreover, the extraction of salient points, performed later in our method, depends on the illumination variance in the image. Therefore, in order to achieve illumination and contrast invariance, we normalize the image [37].

Let $I(x, y)$ denote the gray value at the pixel (x, y), E and V be the estimated mean and illumination variance in the image I, respectively, and $I_n(x, y)$ stand for the normalized gray level value at the pixel (x, y).

For all the pixels in the image I, the normalization process is defined as follows [4,5]:

$$I_n(x,y) = \begin{cases} E_0 + \sqrt{\frac{V_0(I(x,y)-E)^2}{V}} & if\ I(x,y) > T_n, \\ E_0 - \sqrt{\frac{V_0(I(x,y)-E)^2}{V}} & otherwise, \end{cases} \tag{1}$$

here E_0 and V_0 are the desired mean and variance values, respectively, E and V are the computed mean and variance in the given image, described by

$$E = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x,y), \tag{2}$$

$$V = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I(x,y) - E)^2, \tag{3}$$

respectively. In our case, $E_0 = 100, V_0 = 100$ and $T_n = 128$. In result of the operation of luminance levels normalization we obtain image I_n.

2.2. Median filtering and binarization

In the next step, we perform median filtering and binarization. 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 convolution operation. The new value of point of image is counted on the basis of neighboring points value. Every value is classified and it has influence on new value of point of the image after filtration. 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. This is particularly important when applied to images that contain addresses data with salt and pepper noise coming from e.g. not uniform writing surfaces. The applied filter is median filter, with mask 3x3. After filtration the binarization stage is applied. Due to the use of images that contain mostly text, we decided to use the histogram-based thresholding method. These types of methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. The histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the class in the image. However, the binary image is given by

$$I_b(x,y) = \begin{cases} 1 & if\ I_n(x,y) > T_b, \\ 0 & otherwise, \end{cases} \tag{4}$$

where T_b is a threshold value, such as the intensity of the first minimum that occurs after the maximum value of the intensity histogram. Additionally, this technique can be applied in recursive form, as the method to clusters in the image in order to divide them into smaller clusters. As result the binary stream of digit is received, which is sent to the next stage of processing.

Fig. 3. Images of the digits: from the preprocessing stage, after filtration and after binarization

2.3. Coordinate normalization

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. we change the $[x, y]$ coordinate system into an invariant system of $[x', y']$ coordinates such as

$$[x', y', 1] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -P & -Q & 1 \end{bmatrix} \times \begin{bmatrix} 1/\sigma_x & 0 & 0 \\ 0 & 1/\sigma_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{5}$$

where

$$P = \frac{m_{10}}{m_{00}}, \qquad Q = \frac{m_{01}}{m_{00}}, \tag{6}$$

$$\sigma_x = \sqrt{\frac{m_{20}}{m_{00}} - P}, \quad \sigma_y = \sqrt{\frac{m_{02}}{m_{00}} - Q}, \tag{7}$$

for moments of order $k + l$ defined as

$$m_{k,l} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^k y^l I_b(x, y). \tag{8}$$

In reality, we haven't got these parameters starting right now, so we use new coordinate system where the center is equal 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 a good candidate point of the center of image as a product of normalization stage.

3. FEATURE EXTRACTION FOR CHARACTER RECOGNICTION

Each character in the image is characterized by a given localized spatial frequency or a narrow range of dominant localized spatial frequencies that differ significantly from dominant frequencies of other character. Gabor filters encode the character images into multiple narrow frequency and orientation channels [8,13].

3.1. Gabor filters

The general functional of the two-dimensional Gabor filter family can be represented as a Gaussian function modulated by a complex sinusoidal signal. Specifically, a two dimensional Gabor filter $G(x, y)$ can be formulated as [11]:

$$G\left(x,y;\lambda,\theta_k\right)=g\left(x,y;\sigma\right)\exp\left(\frac{2\pi x_{\theta_k}}{\lambda}i\right) \tag{9}$$

and $g\left(x,y;\sigma\right)$ is a Gaussian function with form:

$$g\left(x,y;\sigma\right)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{x_\theta^2+y_\theta^2}{2\sigma^2}\right), \tag{10}$$

where

$$x_{\theta_k}=x\cos\theta_k+ysix\theta_k\,, \tag{11}$$

$$y_{\theta_k}=-x\sin\theta_k+y\cos\theta_k$$

and σ is the standard deviation of the Gaussian envelope along the *x* and *y* dimensions, and λ and θ_k are the wavelength and orientation, respectively.

A rotation of the $x - y$ plane by an angle θ_k will result in a Gabor filter at orientation θ_k .

The θ_k is defined by

$$\theta_k=\frac{\pi}{n}\left(k-1\right),\qquad k=1,2,\ldots,n\qquad n\in N\,, \tag{12}$$

where *n* denotes the number of orientations.

A particular Gabor elementary function can be used as the mother wavelet to generate a whole family of Gabor wavelets. Examples of a particular set of 2D Gabor wavelets are presented in Fig. 4.

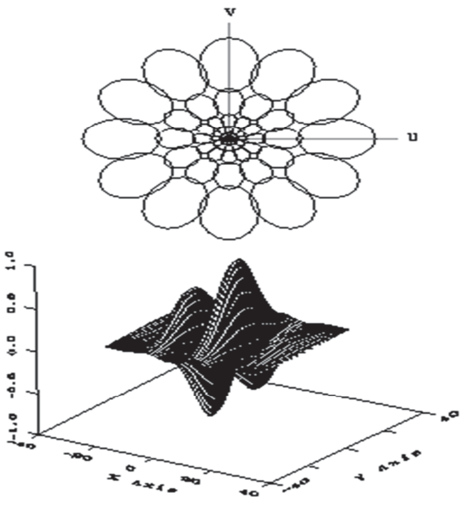


Fig. 4. Gabor Wavelets

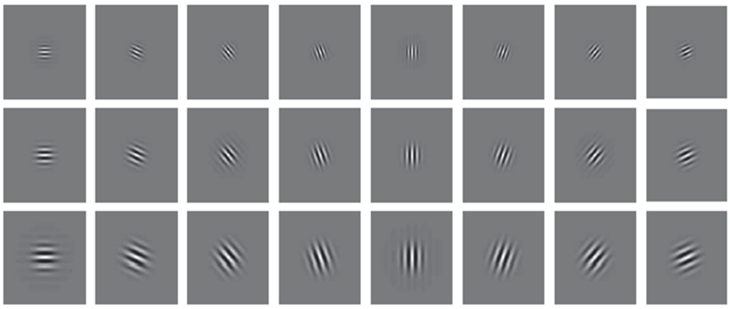


Fig. 5. The kernels of Gabor wavelets at three scales and eight orientations

The odd and even components of the above signal are as follows:

$$G_o\left(x, y; \lambda, \theta_k\right) = g\left(x, y\right)\cos\left(\frac{2\pi x_{\theta_k}}{\lambda}\right), \tag{13}$$

$$G_e\left(x, y; \lambda, \theta_k\right) = g\left(x, y\right)\sin\left(\frac{2\pi x_{\theta_k}}{\lambda}\right), \tag{14}$$

where G_e and G_o are the even-symmetric and odd-symmetric Gabor filters.

3.2. Gabor energy features extraction

The simplest idea to obtain other features than just filter responses is to apply a threshold to the Gabor filter results. The motivation for such an approach is the analogy to the function of simple cells which can be modeled by a linear weighted spatial summation, characterized by Gabor weighting functions and followed by a half-wave rectification [22].

The threshold Gabor features are computed as follows:

$$G_{T_o}\left(x, y; \sigma, \lambda, \theta_k\right) = \chi\left(G_o\left(x, y; \sigma, \lambda, \theta_k\right)\right), \tag{15}$$

$$G_{T_e}\left(x, y; \sigma, \lambda, \theta_k\right) = \chi\left(G_e\left(x, y; \sigma, \lambda, \theta_k\right)\right), \tag{16}$$

where

$$\chi\left(z\right) = \begin{cases} 0 & for \quad z < 0, \\ z & for \quad z \geq 0, \end{cases} \tag{17}$$

$G_o\left(x, y; \sigma, \lambda, \theta_k\right)$ and $G_e\left(x, y; \sigma, \lambda, \theta_k\right)$ are the odd and even components of Gabor filter responses, respectively.

The Gabor Energy feature is a combination of symmetric and asymmetric Gabor filter results. Gabor Energy is related to the model of a specific type of selective neuron orientation in the primary visual cortex called the complex cell [28]. Gabor Energy is given by

$$E(x,y;\sigma,\lambda,\theta_k)=\sqrt{G_{T_o}^2(x,y;\sigma,\lambda,\theta_k)+G_{T_e}^2(x,y;\sigma,\lambda,\theta_k)}\,, \tag{18}$$

where $G_{T_o}(x,y;\sigma,\lambda,\theta_k)$ and $G_{T_e}(x,y;\sigma,\lambda,\theta_k)$ are the threshold responses of the linear symmetric and asymmetric Gabor filters, respectively.

The Gabor Energy feature is also closely related to the local power spectrum. Local power spectrum features are obtained using the same filter bank as in the computations of Gabor Energy features:

$$P(x,y;\sigma,\lambda,\theta_k)=E^2(x,y;\sigma,\lambda,\theta_k)\,. \tag{19}$$

3.3. Zernike moments of power spectrum

Zernike moments (ZM) are the projection of the power spectrum $P(x,y,\rho,\theta)$ on the orthogonal basis V_{pq}. The Zernike moments of order p with repetition q are defined as follows [32,36]:

$$ZM_{pq}=\frac{p+1}{\pi}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}P(x,y,\sigma,\lambda,\theta_k)V_{pq}^*(x,y)\,. \tag{20}$$

The Zernike polynomials:

$$V_{pq}(x,y)=R_{pq}(\rho)\exp(jq\theta) \tag{21}$$

are a complete set of complex valued functions orthogonal on the unit disk *D*: $x^2+y^2\le 1$, where $p\ge 0$, and $p-|q|$ is even positive integer.

The polar coordinates (ρ,θ) in the image domain are related to the Cartesian coordinates (x,y) by:

$$\rho=\sqrt{x^2+y^2}\quad,\quad \theta=\arctan(y/x)\,. \tag{22}$$

The Zernike polynomials $V_{pq}(x,y)$ are orthogonal basis set and satisfy the following condition:

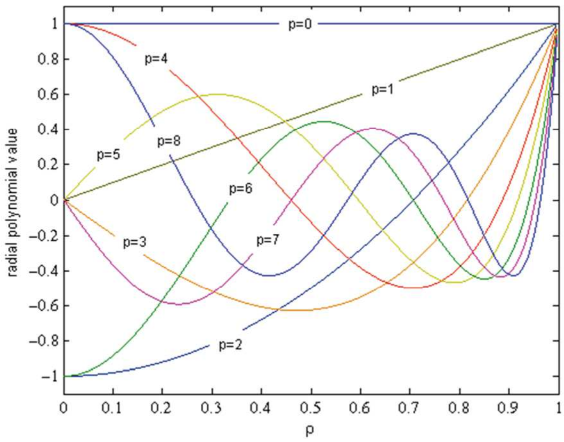
$$\iint_D V_{pq}^*(x,y)V_{p'q'}(x,y)dxdy=\frac{\pi}{n+1}\delta_{pp'}\delta_{qq'}\,. \tag{23}$$

The radial polynomial $R_{pq}(\rho)$ is given by:

$$R_{pq}(\rho)=\sum_{l=0}^{(p-|q|)/2}F_{p|q|l}\,\rho^{p-2l}\,, \tag{24}$$

where

$$F_{p|q|l}=\frac{(-1)^l(p-l)!}{l!\left(\frac{p+|q|}{2}-l\right)!\left(\frac{p-|q|}{2}-l\right)!}\,. \tag{25}$$



p=0
p=4
p=1
p=8
p=5
p=6
p=3
p=7
p=2
radial polynomial value
ρ

$$d^{(Q)(D)}(G,E,Z)=\sum_i\left[\frac{\left|G_i^{(Q)}-G_i^{(D)}\right|}{\sigma_G}+\frac{\left|E_i^{(Q)}-E_i^{(D)}\right|}{\sigma_E}+\frac{\left|Z_i^{(Q)}-Z_i^{(D)}\right|}{\sigma_Z}\right], \tag{31}$$

where i is the number of the extracted features and σ_G, σ_E, σ_Z are standard deviations of vector features *G*, *E* and *Z* over the entire database, respectively.

5. EXPERIMENTAL RESULTS

In this section we present the results of classification with proposed method. Especially for evaluation experiments, we extracted some digit data from various paper documents from different sources e.g. mail pieces post code, bank checks, etc. The character samples were scanned with 600 dpi in color and stored in special data collections [12] in form 24 bit RGB and 8 bit grayscale images. It is important that in the case of images with heterogeneous background to perform directional filtering for 0, 45 and 90 degrees. Character image is normalized according to specification of the second paragraph. Based on geometric and central moments, center of gravity and main axis angle can be achieved. For experimental purposes, the character image sizes are ranged from 32x32, 64x64, 128x128 to 256x256 pixels. Similar scenario was carried out for grayscale levels, where 2,4,8,16,32 and 64 levels were tested. In total, the datasets contain the digit patterns of above 150 writers. In this way were collected about 1400 different patterns for training and testing sets.

In our solution, we use odd and even component pairs of Gabor filters with the quadrature phase relationship. Each pair of the Gabor filters is tuned to a specific band of spatial frequency and orientation. There are some important points to note in selecting the channel parameters σ, λ and θ_k. Four values of orientation are used: 0, π/8, π/4, 3π/8, π/2, 5π/8, 3π/4, 7π/8. In our experiments for each orientation we select three spatial frequencies. This gives a total of 24 Gabor channels (8 orientations combined with 3 frequencies) [13,19].

The Principal Component Analysis module in proposal system generate a set of data, which can be used as features in building feature vector stage shown on Fig. 2. For instance when we use input features from Gabor features and Zernike moments calculation stage (GEZ) calculation stage, as a result we obtained 18 values vector, using Cattell's criterion [17]. Thus the use of PCA method [14,17,29] made it possible to reduce the dimensionality of classification vectors. For proposed method, after reducing the dimensions of the vector space of 120 features (GEZ) up to 20 in the prepared application to more than 3 times shorter test sets classification. It turned out that the reduction of classification vectors affected the effectiveness of the classification method used (31), where the characteristics were obtained for the 120 efficiency level of 96.2%, while after reduction to 16 features were obtained 97.9 % of correctly classified characters from our database. The best results were obtained for the GEZ character feature vector using $d^{(Q)(D)}(G,E,Z)$ similarity measurement. The results obtained for testing 5 sets defined in ratio 3:7 of all samples (testing set/learning set).

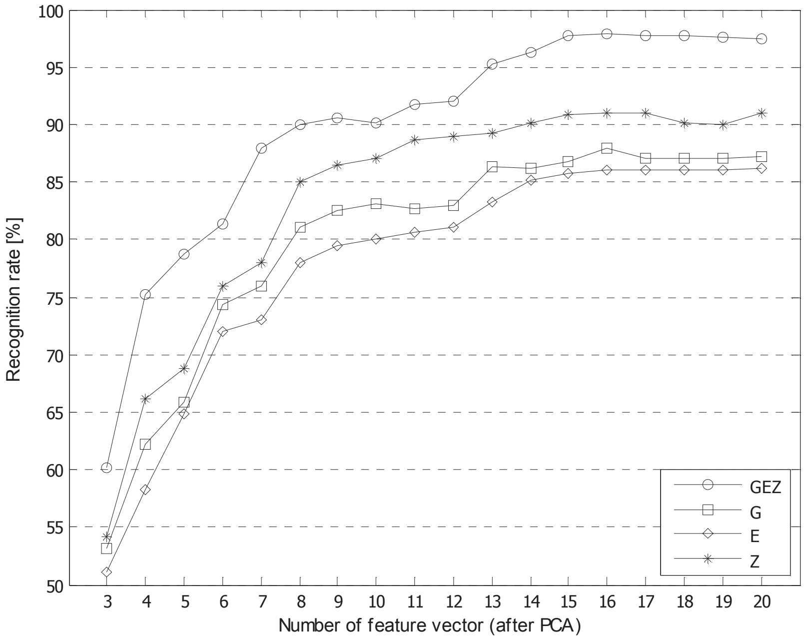


Fig. 7. Recognition rate for our database characters using features: G, E, Z, and GEZ

6. SUMMARY

The article presents an approach to optical character recognition, specifically used in the recognition of zip code digits. Although, the area is well known and explored, with successful examples of both scientific and commercial implementation, however efficiency of mail sorting systems is imperfect. The author hopes that this solution may be supportive for the previous works [24,25,26] and other approaches such as [2,6,15,21]. The most common optical character recognition methods are based on modified quadratic discriminant function, hidden Markov models, normalized Fourier descriptors, MLP-SVM.

In the article, we presented the idea and implementation of use of the Gabor filtration and Zernike moments in the process of character recognition in postal applications. In order to optimalize those procedures, in the first stage we prepared the pre-processing character image using gray scale and coordinate normalization, and median filtering.

In the article, approach to the optical character recognition was presented and tested. In our method, we performed the estimation of character features using Gabor filter responses equation (26), energy Gabor features (27) and Zernike moments of power spectrum (28). The second approach was based on the joined features GEZ (31). After experiments we concluded that Zernike features (Z) and energy Gabor features (E) were the most appropriate for character descriptor, respectively. Better results were achieved by GEZ features.

The main advantages of the method are: finding geometric relations of the character by our method, invariance to background noise, low computational complexity, working with grayscale images. Disadvantages: low value of the rejections, unclear data reduction from PCA, need to use preprocessing. Further work will include Rough Sets theory upgraded to all alphanumerical signs.

BIBLIOGRAPHY

[1] Arif T., Shaaban Z., Krekor L., Baba S., 2005. Object Classification via Geometrical, Zernike and Legendre Moments, Journal of Theoretical and Applied Information Technology, vol. 7, no. 1, pp. 31-37.

[2] Aissaoui A., 1999. Normalised Fourier Coefficients for Cursive Arabic Script recognition, Universite Mohamed, Morocco.

[3] Andrysiak T., Choraś M., 2003. Hierarchical object recognition using Gabor wavelets. Proc. Comput. Recogn. Syst., KOSYR, Miłków, Poland, pp. 271-278.

[4] Andrysiak T., Choraś M., 2005. Image Retrieval Based on Hierarchical Gabor Filters, International Journal Applied Mathematics and Computer Science (AMCS), vol. 15, no. 4, pp. 101-110.

[5] Andrysiak T., 2001. Recognition of handwritten characteres using Gabor features, II Krajowa Konferencja Naukowo-Szkoleniowa KOSYR.

[6] Bellili A., Giloux M., 2003. An MLP-SVM combination architecture for handwritten digit recognition, International Journal on Document Analysis and Recognition, Springer-Verlag.

[7] Choraś R., Andrysiak T., 1995. Gabor transforms in image processing, Proceedings of Signal Processing, Chapter Circuits and Systems, Poland Section IEEE, pp. 31-34.

[8] Choraś R., Andrysiak T., Śrótek M., 2001. Zastosowanie funkcji Gabora w przetwarzaniu, analizie i rozpoznawaniu obrazów, II Krajowa Konferencja Naukowo-Szkoleniowa KOSYR.

[9] 2000Forella G.,. Word perfect, Postal Technology. UKIP Media & Events Ltd. UK.

[10] Fluseer J., Zitova B., T. Suk, 2009. Moments and Moment Invariants in Pattern Recognition, Wiley Knowledge For Generations.

[11] Gabor D., 1946. Theory of communication, Journal Institute of Electrical Engineers, vol. 93, no. 26, pp. 429-457.

[12] Horstmann C.S., Cornell G., 2002. Core Java 2-Advanced Features, Sun micreosystems Press A Prentice Hall Title.

[13] Jain A., Ratha N., Lakshmanan S., 1997. Object detection using Gabor filters. Pattern Recognition, Vol. 30, No 2, pp. 295-309.

[14] Jolliffe I.T., 2002: Principal Component Analysis, Springer Series in Statistics, 2nd ed., Springer.

[15] Kaufmann G., Bunke H., 2000. Automated Reading of Cheque Amounts, Pattern Analysis & Applications, Springer-Verlag.

[16] Khotanzad A., 1990. Invariant Image Recognition by Zernike Moments, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 5, pp. 920--930.

[17] Kim K., 2003. Face Recognition using Principle Component Analysis, DCS, University of Maryland.
[18] Ledesma R.D., 2007. Determining the Number of Factors to Retain in EFA: an easy-to-use computer program for carrying out Parallel Analysis, PAR&E, vol. 12.
[19] Lee T.S., 1996. Image representation using 2D Gabor Wavelets, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 10, pp. 959-971.
[20] Liao S.X., Pawlak M., 1996. On image analysis by moments, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, pp. 254–266.
[21] Liu C., Sako H., 2002. Performance evaluation of pattern classifiers for handwritten character recognition, International Journal on Document Analysis and Recognition, Springer-Verlag.
[22] Marcelja S., 1980. Mathematical description of the responses of simple cortical cells, Journal of the Optical Society of America, vol. 2(7), pp. 1297-1300.
[23] Mehrotra R., Namuduri K.R., Ranganathan N., 1992. Gabor filter – based edge detection, Pattern Recognition, vol. 25, no. 12, pp. 1479-1494.
[24] Miciak M., 2004. The Algorithms of Handwritten Characters Recognition For Postal Application, Signal Processing 2004 Workshop Proceedings, pp. 75-79.
[25] Miciak M., Maszewski M., 2007. Character Recognition Based on Fourier Transfrom and CDWT in Postal Applications, Advances in Soft Computing 45, Computer Recognition Systems 2, pp. 462-469, Springer.
[26] Miciak M., R. Boniecki, A. Marchewka, 2010. The Complex System to Postal Code Recognition. IPoCC 2010, Position of Postal Services in Modern Communication Society, pp. 216-221, Pardubice.
[27] Mukundan R., 2004. Some Computational Aspects of Discrete Orthogonal Moments, IEEE Transactions on Image Processing, vol. 13, no. 8, pp. 1055-1059.
[28] Porat M., Zeevi Y.Y, 1988. The generalized Gabor scheme of image representation in biological and machine vision, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 10, No 4, pp. 452-468.
[29] Shlens J., 2005. A Tutorial on Principal Component Analysis, available at: www.cs.princeton.edu/picasso/mats/PCA-Tutorial-Intuition_jp.pdf
[30] Smith L.I. A Tutorial on Principal Components Analyzing – Discusion and singular value decomposition, available at: www.cs.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf
[31] Su Y.M., Wang J.F., 2003. A novel stroke extraction method for Chinese characters using Gabor filters, Pattern Recognition, vol. 36, no. 3, pp. 635-647.
[32] Sun-Kyoo H., Whoi-Yul K., 2006. A novel approach to the fast computation of Zernike moments, Pattern Recognition vol. 39, pp. 2065-2076.
[33] Teague M.R., 1998. Image Analysis Via the General Theory of Moments, Opt. Soc. Amer., vol. 70, pp. 920-930.
[34] Teague M.R., 1980. Image analysis via the general theory of moments, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 70, no. 8, pp. 920-930.
[35] Teh Ch., Chin R.T., 1998. On Image Analysis by the Methods of Moments, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 10, no. 4, pp. 496-512.

[36] Wallin A., 1995. Complete sets of complex Zernike moment invariants and the role of pseudo invariants, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 17, pp. 1106-1110.

[37] Il Kang H., Lim S., Il Kim K., Ik Son Y., 2005. A Normalization Based Image Affine Estimation Technique for Computer Vision, Proceedings of the 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 1553-1556.

INWARIANTNY DESKRYPTOR GABORA-ZERNIKA DLA ZASTOSOWAŃ POCZTOWYCH

Streszczenie

W artykule przedstawiono nowe rozwiązanie zadania rozpoznawania znaków pisanych ręcznie dla zastosowań pocztowych. Zaproponowano algorytm klasyfikacji przesyłek pocztowych działający na podstawie informacji zawartej w zapisie kodu pocztowego. Ponadto w artykule opisano podstawowe operacje przetwarzania wstępnego tj. filtracje, binaryzacje oraz normalizacje obrazu znaku. Głównym nacisk położono na wykorzystanie filtracji Gabora i momentów Zernike do uzyskania zbioru cech na podstawie których rozpoznawano kod pocztowy. Otrzymane wyniki eksperymentów pozwoliły wykazać skuteczność proponowanej metody. Dodatkowo w pracy przedstawiono źródła potencjalnych błędów w procesie rozpoznawania, jak również zaproponowano możliwości poprawy wyników klasyfikacji.

Słowa kluczowe: rozpoznawanie znaków, filtracja Gabora, momenty Zernika