Hu Moments Based Handwritten Digits Recognition Algorithm

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Abstract: - Digits recognition in digital images is an active research area where license plate recognition is one among most widely used applications. Handwritten digits recognition represents the other branch of this research field. In this paper we propose an algorithm for handwritten digits recognition based on Hu moments. Since handwritten digits can have very different shapes any template based recognition is very difficult. Hu moments are invariant to many transformations like rotation and scaling and proposed algorithm achieves acceptable recognition ratios even in the initial form, without any preprocessing which can significantly increase recognition success. Algorithm was adjusted and tested on images from well known MNIST standard test database.

Key-words: - Handwritten digit recognition, Pattern recognition, Invariant moments, Hu moments, Image processing

1 Introduction

Pattern recognition is the science of making inferences based on data. Handwritten digit recognition is very popular topic of research for many years. It is usually based on patterns – sets of images of handwritten digit. In this paper we used subset of well-known MNIST handwritten digits database.

Generally speaking, images can include various deformations (e.g., quantization noise, illumination differences, or any number of other 'natural" and instrumental sources of variability (e.g., mixed pixels).

Because of that, the first step of a number recognizer can involves pre-processing which include the size and aspect ratio of normalized image, the interpolation technique of pixel values, etc.

The second step is feature extraction. The selection of appropriate feature extraction method is probably the single most important factor in achieving high recognition performance. In this paper a feature extraction method based on moment invariants was applied to handwritten digits. Invariant features have the strength of keeping the same value despite geometric transformations (rotation, scaling, translation etc.). We experimentally tested a new feature extraction method with increasing the number of Moment Invariants by examining different areas of the image. The hypothesis is that increasing the dimensionality of the feature set without increasing the complexity of the extraction, process achieves better results. The feature extraction method uses moments up to the 7th order, it can increase the number of features per set without the usual noise problems related to higher order moments.

The third step is the classification process which needs features that contain enough information about the class, and that is where a limited number of Moment Invariants have problems. We used support vector machines (SVM) classifiers for each digit.

The rest of paper is organized as follows. In Section 2 we present related work and Section 3 is an overview of Feature Extraction methods used and it also introduces terms later used. Next, in Section 4 we describe our proposed algorithm and in Section 5 we discuss achieved results. Section 6 concludes the paper.

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2 Related work

Recognizing digits problem is widespread research area. A number of evaluation works have been done in a field of patern recognition which includes a diferent type of feature extraction and classification. Large number of feature types and extraction techniques are combining in researches like

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structural and statistical feature sets combining SVM classifier [1], [2], [14] and NFCE (normalization-cooperated feature extraction) [8]. In order to explore more discriminative features for increasing the reliability and the recognition rate Zhang, Bui and Suen [17] extracted seven sets of features. This methods are: gradient-based wavelet features, MAT-base directional features, complex wavelet features, binary gradient directional, median filter gradient, image thinning distance and geometrical features. They also used ensemble classifiers to suppress the error rate. Based on that strategy they achieved excellent reliability of 99.96%

Pattern recognition was often achieved using linear and quadratic discriminants [1], the k-nearest neighbor classifier [2] or template matching [3] and Neural Networks [4]. These methods are basically statistic. The problem of using these recognition methods is having to construct a classification rule without having any idea of the distribution of the measurements in different groups. Support Vector Machine (SVM) has gained prominence in the field of pattern classification. They are forcefully competing with other techniques such as template matching and Neural Networks for pattern recognition. Some interesting attempts are made in the field of handwritten digit recognition using neural networks in [7], [13], [19]. An artificial neural Network as the backend is used for performing classification and recognition tasks. In the off-line recognition system, the neural networks have emerged as the fast and reliable tools for classification towards achieving high recognition accuracy.

In [9] is described genetic programing technique which does not need an explicite feature selection metod as feature selection and classifier creation are intricately and implicitly related. Genetic programming (GP) is a method for using natural selection and genetics as a basis for automatically creating computer programs. It differs from genetic algorithms (GA) who is applied on into local regions to sample the optimal set of local regions from where an optimal feature set can be extracted with the best discriminating features [10].

Some papers are based on feature vector [11], [21] and combine with normalization function based on moment [8], while Nemour and Chibani [6] used Tangent vectors.

There are segmentation based recognition of handwritten touching pairs of digits using structural features [20] as well as ones involving contour information, using a Fourier descriptives of digit contours [5].

It is also necessary to mention that in the works of such patterns using different types of databases USPS [6], and MNIST database–widely used in recent years for testing new feature extraction methods [17].

Various techniques and algorithms were proposed and different results were achieved. Since the results are not fully acceptable for real life usage, the field which is dealing with this problem is still very active and in progress.

3 Feature Extraction

The computation of the Moment Invariants is based on SATs (called Summed-area Tables). The original Hu moments set had 7 moments. This set of moments is invariant to translation, scale change, mirroring and rotation. Because of that, it is very useful as extraction method for shape contour. A contour is a list of pixels that represent a curve on an image. Edge detection filters can be used to find the edge pixels that separate different segments in an image but they don't give any information about those edges as entities. What we need is to be able to assemble those edge pixels into contours in order to extract various contour features and gain some knowledge about them.

Many of algorithms for approximation used nowadays are improvements of this algorithm.

The most common task associated with contours is matching them in some way with one another. One of the ways to compare two contours is to compute their characteristic called contour moments computed by integrating over all of the pixels of the contour.

Moment (p,q) of a digital image $f(x,y)$ of size MxN is defined as

$$m_{p,q} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) x^p y^q$$

where p is the order of x and q is the order of y.

A central moment is basically the same as the moments just described except that the values of x and y used in the formulas are displaced by the mean values

$$\mu_{p,q} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)(x - x_{avg})^p (y - y_{avg})^q$$

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where $x_{avg} = \frac{m_{10}}{m_{00}}$ and $y_{avg} = \frac{m_{01}}{m_{00}}$.

The normalized moments are the same as the central moments except that they are all divided by an appropriate power of m_{00}

$$\eta_{p,q} = \frac{\mu_{p,q}}{m_{00}^{\frac{p+q}{2}+1}}$$

Hu invariant moments are linear combinations of the central moments and here is how are defined seven Hu moments:

$$h_1 = \eta_{20} + \eta_{02}$$

$$h_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$h_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$h_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$h_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})((\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2) + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) (3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2)$$

$$h_6 = (\eta_{20} - \eta_{02})((\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$h_7 = (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})(3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03}) (3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2)$$

Hu moments are very important since they are scale and rotation invariant contour descriptors.

4 Our Digit Recognition Algorithm

Our algorithm is constructed around a modular architecture of feature extraction and digit classification unit. It implements conducts digit analysis, or more precisely, digit's contour feature and it's Hu invariant moments as digit descriptors. After that, it classifies shown posture using developed model and additional stabilization is performed. Algorithm has several phases, which can be seen on Figure 2.

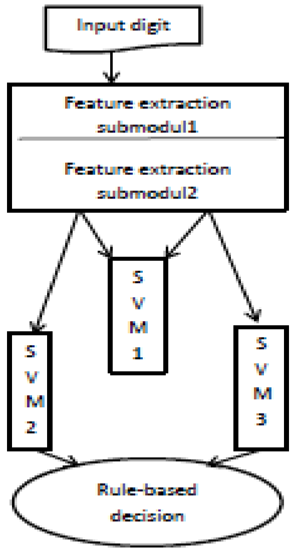

Figure 1. Algorithm phases diagram

Image of the digit is an input for the feature extraction module, which transfers the extracted feature toward SVM classifier (Fig. 1.)

On Figure 2. we can see digits from MNIST database

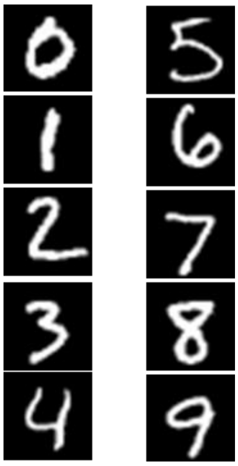

Figure 2. digit from MNIST database

Used databases: There are numbers of image databases of handwritten digit, used for testing the classification techniques in research. Some of well-known is CENPARMI, CEAR, MNIST [22] and MADBase [3]. In this paper, we used MNIST (modified NIST) database as the training and test data sets. From the digit images with resolution 128x128 pixels, we obtained 24-bit picture in the BMP format with special pint.net program.

On Figure 3. we can see variants of same digits from MNIST database.

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Figure 3. Digits from MNIST database

Feature extraction: We are characterizing shape of the digit by finding it's contour. Contour can have too many points and that can be bad for generalization of contour. We are calculating Hu invariant moments for every digit contour. The source of the program is written in DEV-CPP standard program, reading variant of each digit, and calculating all Hu-moments. In feature extraction submodule1, we calculated average, dispersion, minimum and maximum of invariant moments for each digit.

Digit classification: handwritten digit can be written on various ways and in different angles. Hu moments are invariant to scale and rotation and represent a good choice as contour descriptors in our case. Hu invariant moments are calculated (Eq. 1) and the next step is comparing sum of distance Hu moment from average of Hu moment for each digit in our prepared representation model. After some testing, chosen metric is

$$D_x = \sum_{i=1}^{7} \left| m_i^X - m_{iavr}^X \right| \qquad (2)$$

where m_i^X are

$$m_i^X = sign(h_i^X)\log\left|h_i^X\right|$$

and h_i^X are the Hu moments of X digit respectively.

We have 20x10 digit saved in our recognition model of different digit. The model is formed averaging 20 different images of the same digit per posture. Number of points on this posture model contours after approximation can be seen in Table 1. Also, in Table 2. we can see average of calculated Hu moments for each 10 digit. Besides the fact that the moments from different digit are different, we can see the order of each Hu moment and better understand why we used formula (2) and logarithmic function in matching contours.

Tested	**HU invariant moments**						
digit	h1	h2	h3	h4	h5	h6	h7
0	0.502173	2.319420	3.795490	4.358360	8.825610	5.844000	8.619880
1	0.307689	0.679129	2.896330	3.514170	6.893180	4.162950	7.421990
2	0.429369	1.732090	2.198660	3.452340	6.610130	4.534640	6.450770
3	0.496831	1.526030	2.506500	3.438310	6.739360	4.550700	6.748520
4	0.498229	2.390750	2.051800	3.645620	6.784220	5.389630	6.920420
5	0.425920	1.590810	2.401100	3.300850	6.454590	4.332310	6.376560
6	0.508847	1.977560	2.291970	2.770320	5.465290	3.946160	5.585990
7	0.396014	1.602900	1.486630	2.424370	4.835650	3.593480	4.529920
8	0.586528	1.773370	3.578000	4.532250	8.934810	5.784630	8.870740
9	0.530706	1.708130	2.118460	2.980550	5.662520	3.942380	6.169670

Table 2. Hu moments of tested digit (average)

The program performance for character recognition largely depends on the feature extraction approach and classification/learning scheme. Many experiments have shown high performance and high level of correct recognition [18], bat some of them are not so efficient [9].

The software that has been developed for our work and provides implementation of the described algorithm has high performance and good results of digit recognition.

5 Experimental Results

Proposed algorithm was tested under limited number of digit sets. The metric that was used was absolute value of the difference between Hu moments for the tested digit and averages obtained from the testing set normalized by standard deviation.

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Table 3 presents results of the classification based only on this simple metrics.

	0	1	2	3	4	5	6	7	8	9
0	85		5		5				5	
1	5	80		5		10				
2			60	5		10		20	5	
3				45		20		25	10	
4			20		60	10			10	
5	5			20		45		20	10	
6		5					60	25		10
7			5					85		10
8	5		10			5			80	
9				10	5		15	10		60

Since no pre-processing is included, like thinning method in order to excluded influence of transformation errors (due to rounding problems) and noise, when using an extended moment invariants sets results are satisfied.

The original Hu's moments set had 7 moments but it was proved that two of the moments were dependent on the other. Also, we empirically determined that all moments are equally not affect the accuracy of results, so that further analysis will be based on only certain moments, not all. For further statistical features submodule2 we will use Hu moment of 2rd, 3rd and 4rd order in combination with distances.

The handwritten digits are classified into three groups. The criteria are singularity of recognition. In the first group are 0, 1, 7, 8, in the second are 2, 4, 6 and 9, and in the third is 3 and 5. The testing starts with 1st group in described order, which means that testing start with conditions for digit 1. If classifier is satisfied, that means that tested digit is 1. If it is not satisfied, we continue with next listed digit in group.

If the digit we tested is not in group1, we continue with group2 in the same way. At the end, if the digit is not in group1 and 2, that means that digit is 5, although it should meet the criteria in classifier.

Overall achieved recognition rate is around 63%. Table 3. among other information tells us that the best classification are having digits from group1 Also, the worst result has pick digits from group 3.

The best testing results for 1st group is with Hu moment 3rd order. For this group it is sufficient only this moment. For results for 2nd group it is necessary to test all 3 Hu moments. Testing order is also very important for the result, because unique criteria is for this digit.

6 Conclusion

The results showed that the method based on Hu moment could potentially be used as a first stage for digits recognition. The method is fast and very easy to implement, although the accuracy is not comparable to other methods described in the literature. Further work is needed to improve the accuracy, especially regarding the criteria to choose between classifiers, but also to increase the number of samples digits tested.

Further work could include pre-processing implementation using thinning method in order to exclude influence of transformation errors (due to rounding problems) and noise when using an extended moment invariants sets would be useful.

In order to get better results, we intend to develop a new improved classification combined method using the rotation invariant and non-rotation invariant features.

References

[1] Dejan Gorgevik, Dusan Cakmakov, Vladimir Radevski: H*andwritten digit recognition by combining support vector machines using rule-based reasoning*, Proceedings of the 23th International Conference on Information Technology Interfaces, Skopje, vol.1, pp. 139 - 144, June 2001

[2] Dejan Gorgevik, Dusan Cakmakov - *Combining SVM Classifiers for Handwritten Digit Recognition,*16th International Conference on Pattern Recognition, Skopje, vol.3 , pp. 102 – 105, 2002

[3] Sherif Abdleazeem, Ezzat El-Sherif, *Arabic handwritten digit recognition, , International Journal of Document Analysis and Recognition* International Journal of Document Analysis and Recognition (IJDAR),Vol 11, No. 3, pp. 127-141, 2008

[4] Mandana Hamidi, Ali Borji, *Invariance analysis of modified C2 features: case study hand written digit recognition*, Machine Vision and Application, Vol.21, No.6, pp. 969-979, 2010

[5] Dahai Cheng, Hong Yan, *recognition of handwritten digits based on contour information*, Pattern Recognition,Vol.31, No.3, pp. 235-255, March 1998.

[6] Hassiba Nemmour, Youcef Chibani, *Incorporating Tangent Vectors in SVM Kernels for Handwritten Digit Recognition*, Signals, Circuits and Systems (SCS), 3rd International conference on, 2009

[7] P. Yu. Izotov*a*, N. L. Kazanskiy*a*, D. L. Golovashkin*a* and S. V. Sukhanov,

CUDA_Enabled Implementation of a Neural Network Algorithm for Handwritten Digit Recognition, Optical Memory and Neutral Networks, Vol.20, No.2, pp. 98-106, 2011

[8] Cheng-Lin Liu, Kazuki Nakashima, Hiroshi Sako, Hiromichi Fujisawa, *Handwritten digit recognition: investigation of normalization and feature extraction techniques,* Pattern Recognition, Vol.37, No.2, pp. 265-279, February 2004

[9] A.D. Parkins, A.K. Nandi, *Genetic programming techniques for handwritten digit recognition*, Signal Processing, Vol.84, No.12, pp. 2345-2365, December 2004

[10] Nibaran Das, Ram Sarkar, Subhadip Basu, Mahantapas Kundu, Mita Nasipuri, Dipak Kumar Basu, *A genetic algorithm based region sampling for selection of local features in handwritten digit recognition application,* Applied Soft Computing, Vol.12, No.5, pp. 1592-1606, May 2012

[11] O. Mayora-Ibarra, F. Curatelli, *Handwritten digit recognition by means of a holographic associative memory,* Experts System with Applications, Vol.15, No.3-4, pp. 399-403, October-November 1998

[12] Jacek Mandziuk, Lokendra Shastri, *Incremental class learning approach and its application to handwritten digit recognition,* Information Sciences, Vol.141, No.3-4, pp. 193-217, April 2002

[13] Takuma Yamaguchi, Minoru Maruyama, Hidetoshi Miyao, Yasuaki Nakano, *Digit recognition in a natural scene with skew and slant normalization,* International Journal of Document Analysis and Recognition (IJDAR), Vol.7, No.2-3, pp. 168-177, July 2005

[14] Luiz S. Oliveira and Robert Sabourin, *Support Vector Machines for Handwritten Numerical String Recognition,* Ninth International Workshop on Frontiers in Handwriting Recognition, IWFHR 2004, PP 39-44, 26-29 October 2004

[15] Kunihiko Fukushima, *Neocognitron for handwritten digit recognition*, Neurocomputing, Vol.51, pp. 161-180, April 2003

[16] Ernst Kussul, Tatiana Baidyk, *Improved method of handwritten digit recognition tested on MNIST database*, Image and vision Computing, Vol.22, No.12, pp. 971-981, 2004

[17] Miao Kang, Dominic Palmer-Brown, *A modal learning adaptive function neural network applied to handwritten digit recognition,* Information Sciences, Vol.178, No.20, pp. 3802-3812, October 2008

[18] Ping Zhang, Tien D. Bui, Ching Y. Suen, *A novel cascade ensemble classifier system with a high recognition performance on handwritten digits,* Pattern Recognition, Vol.40, No.12, pp. 3415-3429. December 2007

[19] Jukka Heikkonen, Mika Mntynen, *A computer vision approach to digit recognition on pulp bales,* Pattern Recognition Letters, Vol.17, No.4, pp. 413-419, April 1996

[20] Bailing Zhang, Minyue Fu, Hong Yan, *A nonlinear neural network model of mixture of local principal component analysis: application to handwritten digits recognition*, Pattern Recognition, Vol.34, No.2, pp. 203-214, February 2001

[21] Hasan Soltanzadeh, Mohammad Rahmati, *Recognition of Persian handwritten digits using image profiles of multiple orientations,* Pattern Recognition Letters, Vol.25, No.14, pp. 1569-1576, October 2004

[22] Cheng-Lin Liu, Kazuki Nakashima, Hiroshi Sako, Hiromichi Fujisawa, *Handwritten digit recognition: benchmarking of state-of-the-art techniques*, Pattern Recognition, Vol.36, No.10, pp. 2271-2285, October 2003

[23] Loo-Nin Teow, Kia-Fock Loe, *Robust vision-based features and classification schemes for off-line handwritten digit recognition,* Pattern Recognition, Vol.35, No.11, pp. 2355-2364, November 2002

[24] Monji Kherallah, Lobna Haddad, Adel M. Alimi, Amar Mitiche, *On-line handwritten digit recognition* based *on trajectory and velocity modeling*, Pattern Recognition Letters, Vol.29, No.5, pp. 580-594, April 2008