Modified Chain Code Histogram Feature for Handwritten Character Recognition

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Abstract. In this work, we have proposed modified chain code histogram (CCH) based feature extraction method for handwritten character recognition (HCR) applications. This modified approach explores the dynamic nature of directional information, available in character patterns, by introducing the Differential CCH which is termed as Delta (Δ) CCH. A comparable and higher recognition rate is reported which emphasizes that the dynamic nature of directional information captured by the ΔCCH is as important as that of CCH. All the experiments are conducted on MNIST handwritten numeral database. Finally, an improved recognition rate is observed at higher end by using combination of both the features which shows the effectiveness of dynamic directional feature in the classification of handwritten character patterns.

Keywords: Differential Chain Code Histogram, Handwritten Character Recognition, Misclassification Rate, Feature combination.

1 Introduction

Handwritten character recognition is an important application of human computer interface. The most significant part of any character recognition system is feature extraction which affects the recognition performance to an extent. The feature selection should be such that it holds all the variations of handwriting and hence makes it invariant with respect to shape variations caused by individuals. Chain code histogram (CCH) is one of the most successful feature extraction technique in character recognition task. The directional information captured by the CCH is the key method in identifying the exterior information of any shape or pattern. Hence, it has been widely used in Japanese, Devnagari, Oriya, Arabic handwritten character recognition applications with the higher recognition rate [1,2,3,4,5].

Dynamic information, i.e. the way feature vectors vary with respect to time, is also very much important in pattern classification as observed in automatic speech and speaker recognition tasks [6]. A very good performance is reported in all these tasks by using the dynamic information derived from the cepstral domain features like first and second derivative of mel-frequency cepstral coefficients [6,7,8]. Motivated by this approach, here we have proposed differential

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CCH feature extraction method by taking the successive derivatives of CCH feature which captures the dynamic nature of directional information available in character patterns.

In this work, we have developed a handwritten character recognition system by using the modified CCH feature. Differential CCH feature is computed by block processing approach and performance of the proposed feature is evaluated on MNIST handwritten numeral database [9]. The different information contained in CCH and differential CCH features are further exploited to make the character recognition system more robust and accurate by using score level fusion. Here we have used the well known vector quantization (VQ) based nonparametric modeling and nearest neighbor classification technique for pattern matching [10].

The organization of the remaining work is as follows: Section 2 describes the modified directional feature extraction technique. Section 3 describes the different stages of handwritten character recognition system based on modified CCH feature. Experimental results and discussion are presented in Section 4 and finally summary and future work are provided in Section 5.

2 Modified Chain Code Histogram (CCH) Feature Extraction

CCH is an extensively used technique in character recognition tasks. Considering the importance of dynamic directional information, a modified technique is used for finding the differential characteristics of CCH feature. Both the methods are explained in the following sections.

2.1 CCH Feature

The CCH method utilizes the contour shape of character pattern for feature extraction. In this method, the directional information of all contour points are captured. The complete steps involved in CCH feature computation are described below.

1. **Step 1:** Find out the contour representation of character pattern.
2. **Step 2:** Divide the complete image into a particular number of blocks by using a fixed block size.
3. **Step 3:** Compute the directional information of each contour pixel by considering the 8-directions as shown in Fig. 1 by using top-to-bottom or left-to-right traversing approach.

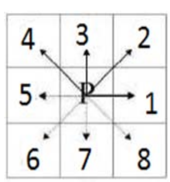

Fig. 1. Chain code directions (adopted from [3])

4. **Step 4:** The above step is repeated for each block by using block processing approach.
5. **Step 5:** Hence we get 8-directional CCH feature vector for the complete character image.
6. **Step 6:** Finally assuming direction 1 and 5, 2 and 6, 3 and 7 and 4 and 8, as same, we get 4-directional CCH feature vector.

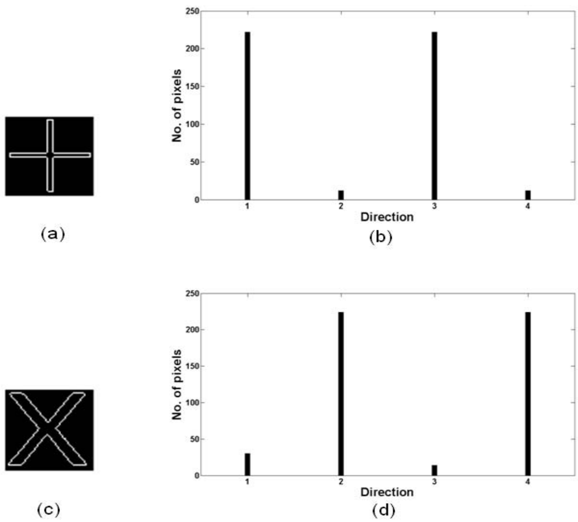

Fig. 2. (a) and (b) Contour and Chain code histogram representations for the symbol +, (c) and (d) Contour and Chain code histogram representations for the symbol ×

The CCH representations of the symbols + and × are shown in Fig. 2. As the major object part of the symbol image + is in the horizontal and vertical directions, so we find higher values at feature indices 1 and 3 i.e. more number of object pixels, in CCH representation of symbol + as shown in Fig. 2(b). On the other hand, we get more no. of object pixels at feature indices 2 and 4 in case of the symbol image × as the major object part is in slanted directions. As the object part is almost absent in horizontal and vertical directions so we get a few no. of object pixels at feature indices 1 and 3 for the same as shown in Fig. 2(d). This clearly illustrates the effectiveness of CCH in directional representation.

2.2 Differential CCH Feature

CCH feature provides the directional information of character patterns, but it does not convey any information about the variations available in the directional information with respect to spatial co-ordinates. This can give an additional level of information to discriminate any handwritten shape. To get this dynamic directional information, we have derived the differential CCH feature by taking the successive derivatives of the conventional CCH feature.

The differential CCH is computed from the 4-directional CCH feature vector by using the following polynomial approximations of the first and second derivatives [11].

$$\Delta\mathbf{c}(n) = \frac{\sum_{i=-r}^{r} i.\mathbf{c}(n+i)}{\sum_{i=-r}^{r} |i|} \tag{1}$$

$$\Delta\Delta\mathbf{c}(n) = \frac{\sum_{i=-r}^{r} i^2.\mathbf{c}(n+i)}{\sum_{i=-r}^{r} i^2} \tag{2}$$

where $\mathbf{c}(k)$ represents the 4-directional CCH feature vector of k^{th} block, i shows the position of preceding and succeeding blocks, and r shows the total no. of preceding or succeeding blocks to be used in Δ and $\Delta\Delta$ computation.

The CCH and ΔCCH feature representations of numeral images 0 and 8 are shown in Fig. 3. As the patterns of these numerals are almost confusing so we get a look like CCH feature representations in this case as shown in Fig. 3(b) and (e). Again we can clearly observe that variations of CCH feature lies only in positive range where as ΔCCH contains variations in both positive and negative range as shown in Fig. 3(c) and (f). This shows the bipolar characteristic of ΔCCH in comparison of unipolar CCH. This makes the differential CCH robust for classification of degraded characters. For instance, if a character image is degraded with noise or blurred, it may add some extra undesirable directional

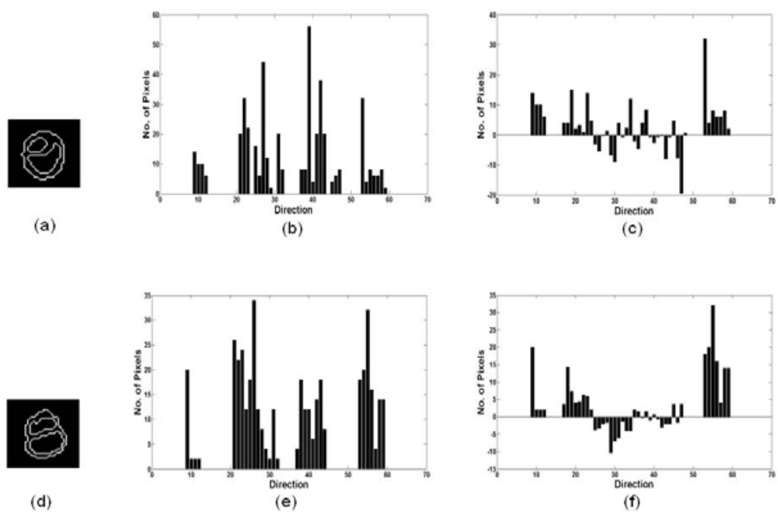

Fig. 3. CCH and ΔCCH feature representations for numerals 0 and 8; (a), (b), and (c) contour, CCH, and ΔCCH representations of numeral image 0, respectively; (d), (e), and (f) contour, CCH, and ΔCCH representations of numeral image 8, respectively.

information in case of CCH feature but this extra information is nullified in case of ΔCCH due to the differentiation operation.

3 Modified CCH Based Handwritten Character Recognition

The block diagram of modified CCH based handwritten character recognition system is shown in Fig. 4. The different stages used in this system are illustrated in the following sections.

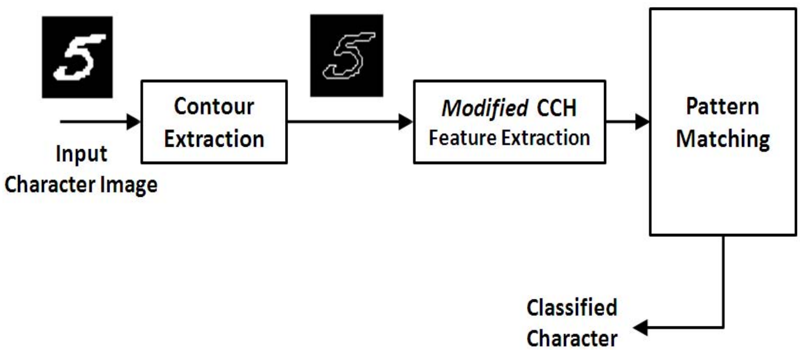

Fig. 4. Block diagram of the modified CCH based handwritten character recognition system

3.1 Contour Extraction

In this stage, the incoming gray scale images of characters are converted to binary images and resized to a default dimension. Here we take pixel value 1 as an object point and pixel value 0 as a background point. For contour extraction, consider a 3×3 window surrounded to every object point in the image. If any one of the four neighboring directions excluding corner directions has a background point then that object point is considered as a contour point. For instance, extracted contour of numeral image 5 is shown in Fig. 4.

3.2 Modified CCH Feature Extraction

In the feature extraction stage, modified CCH features are computed from the incoming contour image of the character. To capture the directional information of the contour, we have used the conventional CCH approach as described in Sec. 2.1. After getting the CCH features of the complete image, differential CCH features i.e. ΔCCH and $\Delta\Delta$CCH are computed by taking the first and second derivatives of the same as discussed in Sec. 2.2.

3.3 Pattern Matching

In the training phase, models are built for every individual class from their respective features. The extracted modified CCH features of each character class are fed to vector quantization (VQ) modeling stage. It builds a defined size of codebook for every character class by using binary split and k-mean clustering algorithm.

In testing stage, after finding the test feature set by using the same feature extraction technique, euclidean distances of this feature set is computed from all the code-vectors of the each character model. Then the test image is identified by using nearest neighbor classifier which works on minimum euclidean distance criterion.

4 Experiments and Outcomes

A robust character recognition system should be able to identify an unknown character image by classifying it to the correct character class. Generally performance of such a recognition system is measured in terms of recognition rate. Recognition rate is defined as the percentage of total number of samples of a class which are correctly classified. Again the percentage of total number of samples which are misclassified is termed as misclassification rate.

4.1 Experimental Details

For the present work, we have considered MNIST handwritten numeral database which includes $60,000$ training images and $10,000$ testing images. We have used 64×64 resized numeral images for our recognition task. For 4-dimensional CCH computation we have considered block size of 16×16 by taking the neighborhood object pixels in available directions as described in Sec. 2.1. Hence, we get total 16 no. of 4-dimensional feature set for CCH, 14 no. of 4-dimensional feature set for ΔCCH and 12 no. of 4-dimensional feature set for $\Delta\Delta$CCH in each image, respectively. In the VQ modeling stage, total 9 no. of 512-size codebooks are built for all numeral classes.

4.2 Experimental Results and Discussions

The performance of handwritten numeral recognition system for CCH, ΔCCH and $\Delta\Delta$CCH feature extraction techniques, in terms of recognition rate is given in Table 1. We can clearly see from the Tabel 1 that the performance of ΔCCH and $\Delta\Delta$CCH is almost comparable to that of CCH based recognition system. It is also observed from Table 1 that for some numerals like, 2, 6, and 9 the recognition rate is high in case of ΔCCH as compared to CCH, where as for remaining numerals we get better recognition accuracy in case of CCH feature. It shows that the dynamic information captured by the differential CCH is as significant as that of the directional information captured by CCH for the classification of handwritten numeral patterns.

Table 1. Individual recognition rate of handwritten numerals for CCH, ΔCCH and $\Delta\Delta$CCH features

Numeral Class	Recognition Rate (in %)		
	CCH feature	ΔCCH feature	$\Delta\Delta$CCH feature
0	98.50	98.20	98.00
1	98.94	98.76	98.76
2	92.80	93.60	93.70
3	94.09	93.31	90.79
4	95.20	94.70	94.30
5	96.52	95.71	95.02
6	98.32	98.72	97.73
7	93.74	93.08	93.08
8	93.75	92.27	88.98
9	90.49	90.80	90.70

Table 2. Misclassification rate of some misclassified numerals for CCH feature

Misclassified Class	Misclassification Rate (in %)									
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	–	0.00	0.30	0.10	0.10	0.00	0.20	0.10	0.40	0.30
2	0.60	1.00	–	1.70	1.10	0.20	0.30	0.60	0.80	0.90
5	0.00	0.00	0.12	1.51	0.00	–	0.58	0.12	0.70	0.46
6	0.49	0.49	0.00	0.00	0.49	0.10	–	0.00	0.00	0.10
8	1.17	0.32	0.64	0.53	0.85	0.53	0.64	0.32	–	1.27
9	0.31	0.31	0.20	0.31	3.37	0.00	0.10	4.70	0.20	–

Misclassification rate of some numerals with each numeral class is given in Table 2 and 3 for CCH and ΔCCH features, respectively. It is observed that the misclassification rate of numeral 0 with that of numeral class 3, 5, 6, and 9 is less in case of CCH than ΔCCH. But, for the numeral classes 2 and 8, the misclassification rate of the numeral 0 is less in case of ΔCCH. It shows that both the features carry some different information. This type of dissimilarity in misclassification rate of CCH with that of ΔCCH feature is also observed for other numeral classes like, 2, 5, 6, 8, and 9, as shown in Table 2 and 3. These observations strongly validates the point that the dynamic feature carries some different information in comparison to that of directional feature. Hence, the combination of CCH and ΔCCH features may give a better improved performance in pattern classification task.

The average recognition rate of complete handwritten numeral set for different feature extraction techniques is given in Table 4. The recognition rates of ΔCCH and $\Delta\Delta$CCH features are nearly equal to that of CCH feature over the huge MNIST handwritten numeral database. This shows the effectiveness of dynamic directional information in feature representation of handwritten characters. As discussed earlier, the different information representation of all these features is

Table 3. Misclassification rate of some misclassified numerals for ΔCCH feature

Misclassified Class	Misclassification Rate (in %)									
	0	1	2	3	4	5	6	7	8	9
0	–	0.00	0.10	0.50	0.10	0.10	0.40	0.10	0.10	0.40
2	0.50	0.90	–	1.60	0.60	0.40	0.50	0.60	0.80	0.50
5	0.35	0.23	0.12	1.39	0.00	–	0.35	0.23	1.04	0.58
6	0.30	0.30	0.00	0.00	0.39	0.00	–	0.10	0.20	0.00
8	1.06	0.53	0.21	1.27	0.74	1.48	1.53	0.53	–	1.38
9	0.41	0.20	0.00	0.61	3.68	0.00	0.10	3.78	0.41	–

Table 4. Average recognition rate of handwritten numerals for different features

Feature Extraction Technique	Recognition Rate (in %)
CCH	95.24
ΔCCH	94.92
$\Delta\Delta$CCH	94.11
CCH+ΔCCH+$\Delta\Delta$CCH	96.09

exploited by using the score level fusion of CCH, ΔCCH and $\Delta\Delta$CCH. We have used the max normalization technique to compensate the different range of scores followed by the simple sum rule of fusion. Finally, an improved recognition rate of 96.09% is reported in case of feature combination which gives an improvement of nearly 1% over the classical CCH approach. It is also significant from the fact that the reported improvement of 1% in recognition rate is nearly equals to 100 handwritten numeral examples over the 10,000 numeral samples of MNIST testing set.

5 Summary and Conclusions

We have presented modified chain code histogram feature extraction technique for handwritten character recognition task. A handwritten numeral recognition system is developed by using conventional CCH and differential CCH features and a comparable recognition rate is reported. All the experimental results show the effectiveness of dynamic directional information available in character images captured by differential CCH features. The different information available in CCH and differential CCH feature extraction techniques are exploited by score level fusion of CCH, ΔCCH, and $\Delta\Delta$CCH features. The improved performance justifies the importance of the proposed features extraction techniques over the large MNIST handwritten numeral database.

In future we may try to make the character recognition system more robust and accurate by exploring different classification techniques. Future work may include to find a better feature representation of character images by using different level of fusion.

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