# Isolated Handwritten Digit Recognition Using LPQ and LBP Features

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# Isolated Handwritten Digit Recognition Using LPQ and LBP Features

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## ABSTRACT*

Several approaches for handwritten digits recognition are proposed an appearance approach based on feature extraction. In this paper we process handwritten digit image without any normalization method using Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) extracted from the complete image as well as from different regions of the image by applying a uniform grid sampling to the image. LBP and LPQ is a very efficient feature descriptor for handwritten which is arise from variations in size, shape and slant. Moreover, the SVM has been employed as classifier which has better responses. The experimental study is conducted on CVL dataset and achieved high recognition rates which is comparable with the state of the art.

## CCS CONCEPTS

• **Applied computing** → **Document management and text processing**• **Computing methodologies** → Artificial intelligence; *Redundancy*; Computer vision.

## KEYWORDS

Handwritten digits recognition, Local Binary Pattern, Local Phase Quantization, CVL dataset.

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## 1 INTRODUCTION

Handwritten digits recognition has been the leading research problem of the document recognition and analysis community for over three decades. This paper concentrates on isolated digits recognition as classical pattern recognition problem that offers a wide applications field. The main challenges in recognizing handwritten digit come from variations in shape, size, inclination and, most importantly, differences in the individuals writing style.

Over the years, various handwritten isolated digit recognition systems reporting high recognition rates have been proposed. The recent system on this problem targets to enhance the performance by enhancing two most significant component of any pattern recognition system, the feature extraction or/and classification methods [1],[2],[3],[4],[5]. Combination of different feature extraction methods and combination of different classifiers to enhance the recognition rates on CVL dataset have been investigated in this regard. The CVL Single Digit dataset is introduced a new challenging dataset for benchmarking, which has been collected generally among students. This dataset has been used in the HDRC competition for recognition of handwritten digits organized in conjunction with ICDAR 2013 [6]. The main objective of this competition is to evaluate and compare recent systems in handwritten digits recognition.

Among significant contributions from the view point of classification, authors in leCun et al. 1995 [1] , Dundar et al. 2016 [2], Lauer et al. 2007 [3] and Yamashita and Wakahara ,2016 [4] present different classification algorithms on the recognition task like convolutional neural network [1], [2], Support Vector Machine [3],[5],[7],[8],[9], Neural Networks [1],[3], Hidden Markov Models (HMM) [4] and K Nearest Neighbors (KNN) have been explored[2], [3], [4], [10].

As for systems that focus on feature extraction methods, we may find methods that are based on combination of statistical and structural features [11] and using a genetic algorithm for finding the most effective features combination from a large pool of features [12]. An interesting work is reported by Gattal et al. 2014 [7] investigates the different combination of statistical and

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structural features for handwritten digits recognition. These features include the contour, skeleton, global, moments, profile and projection features are extracted from the whole or different regions from digits. In another similar study, Gattal et al. 2016)[9] proves how the combination of oriented Basic Image Features (oBIFs) and the background concavity features can be effectively enhanced the performance of isolated handwritten digits recognition without any size normalization. Recently, Gattal et al. 2017) [10] proposed to use the texture-based encoding based on oriented Basic Image Features (oBIF) Column histogram scheme for achieving high recognition rates on MNIST dataset without deskewing.

The objective of our study is to use the texture-based encoding based on Local Binary Pattern (LBP) [13] [14] and Local Phase Quantization (LPQ) [15] which has previously been used for face recognition, writer identification and gender classification to achieve high recognition rates on non-normalized isolated handwritten digits. The paper is organized as follows. In section 2, we review the used features based on Local Binary Pattern (LBP) and Local Phase Quantization (LPQ). The section 3 details the experiment conducted along with a comparative analysis and discussion on the realized results. Finally, we conclude the paper with a discussion on future perspectives on the subject.

## 2 PROPOSED APPROACH

In our study on isolated handwritten digit recognition, we have chosen to employ a combination of Local Binary Pattern (LBP) and Local Phase Quantization (LPQ). The both features allow capturing the textural information in digits for a discriminator y representation. Each of these features is discussed in the following sub-sections followed by their computational details for our specific problem.

### A. Local Binary Patterns (LBP)

Local binary patterns (LBP) [13] has been applied to a number of classification problems. Generally, the LBP descriptor is applied on binarized handwritten digit image, in its simplest form, is created in the following step:

- For each pixel, we compute the LBP value for the current pixel using the selected neighborhood around it;
- A value 0 is assigned to all neighbors having intensity value less than the value of current pixel. however, all neighbors having value equal to or greater than the current pixel value are assigned a 1;
- The LBP value is converted the binary number sequence of 0s and 1s of into its equivalent decimal.
- The algorithm is repeated for all pixel;

Equation 1 summarizes the computation of LBP codes while Figure 1 depicts the same idea visually.

$$LBP_{P,R} = \sum_{P=0}^{P-1} 2^P s(i_P - i_c) \text{ where } \begin{Bmatrix} s(x) = 1, x \geq 0 \\ s(x) = 0, x < 0 \end{Bmatrix} \quad (1)$$

Where $P$ represents neighbor number pixels, $i_P$ is the gray level of neighboring pixel while $i_c$ denotes the gray level of the central pixel.

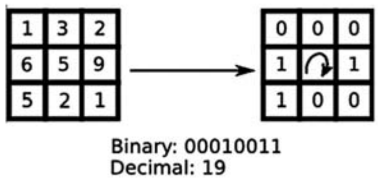


**Figure 1: LBP Computation Steps [14]**

### B. Local Phase Quantization (LPQ)

LPQ (Local Phase Quantization) algorithm proposed by Ojansivu and Heikkila [15], is based on the blur invariance property of the Fourier phase spectrum. The local frequency features can be extracted using selective frequency filters. More specifically LPQ extracts local information using Short-Time Fourier Transform (STFT) computed over a rectangular neighborhood *Nx* of size *M* by *M* at each pixel position x of the image $f$(x):

$$F(\mathrm{u,x}) = \sum_{y \in Nx} f(x-y) e^{-j2\pi u^T y} = w_u^T f_x, \quad (2)$$

Where *Nx* is the neighborhood $f(x - y)$ is the function value in the neighborhood, $w_u$ is the basis vector of the 2-D discrete Fourier transform (DFT) at frequency $u$, and $f_x$ is a vector containing all image samples from *Nx*.

Only four complex coefficients are considered in LPQ, each corresponding to the 2-D frequencies: $u_1 = [a,0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$, and $u_4 = [a,-a]^T$, where $a$ is the first frequency and where the phase of DFT is shown to be invariant to centrally symmetric blur [15]. A more detailed description in [15] can be found. The diagram of the computing LPQ as can be seen in Figure 2.

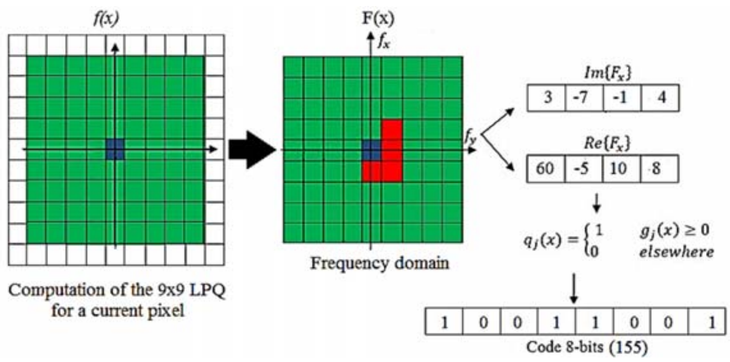


**Figure 2. The diagram of the computing LPQ**

### *C. Combination strategy*

The combination strategy represents a texture- based descriptor which is a compound between the Local Binary Pattern (LBP) and Local Phase Quantization (LPQ). This combination image is adding matrix of LBP image and LPQ image by adding corresponding elements. The sizes of LBP image and LPQ image must be the same. Then the two images implicitly expand to match each other (see figure.3).

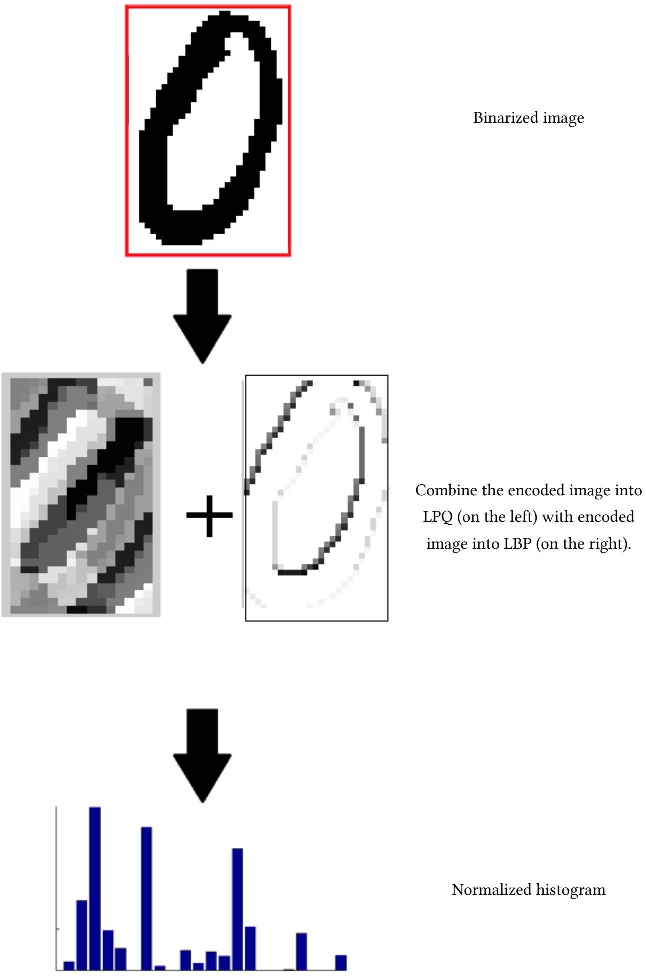


**Figure 3: combination strategy**

The descriptor is produced by computing a combination image histogram over the whole image as well as from different regions of the image. The features vector is normalized by the maximum value of the histogram.

It was concluded that LBP and LPQ based features are mutually complementary, because LBP captures the local appearance detail; while LPQ extract shape information in the frequency domain. A simple combination strategy allows to increase the performance of the isolated handwritten digit recognition system.

Uniform grid sampling [16] is applied to the digit image for producing rectangular regions for sampling where each region is of the same size and has the same shape. The combination strategy features are extracted from different regions separately. Figure 4 shows an example of a digit split into a 2x2 grid.

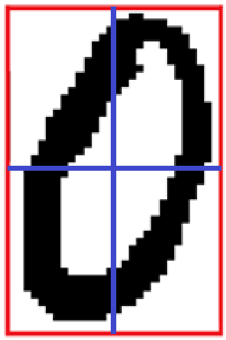

**Figure 4: Splitting a digit using a uniform grid (2x2).**

## 3 EXPERIMENTAL RESULTS

The experiments were carried out on the CVL Single Digit database [6]. The database contains 7,000 digits for training, a validation set of same size and an evaluation set comprising of 21,780 digits. All digit images are binarized using the method Sauvola binarization [17] method prior to feature extraction. The features are extracted directly from the binary digit images without any size normalization.

The classification is based on multi-class Support Vector Machine (SVM) using the one-against-all implementation [18]. Two important parameters required for training the SVM include the regularization parameter (C) and the Radial Basis Function (RBF) kernel parameter (σ).

We carried out an experiments series to evaluate the effectiveness of the proposed approach used the texture-based encoding based on Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) features for digit recognition. The LPQ are generated using different parameter values of the local window size $w(w \in \{3 \times 3,5 \times 5,7 \times 7,9 \times 9,11 \times 11,13 \times 13,15 \times 15,17 \times 17,19 \times 19,21 \times 21\})$ from the whole image. Likewise, the classic LBP feature is also extracted from the whole image. However, the Combination Strategy (CS) is evaluated using the best configuration of the LBQ from the whole Image.

The system performance is quantified using the standard recall measure computed in a similar manner as in the ICDAR 2013-digit recognition competition [15]. The experiments performances are summarized in Table I.

**Table 1: Recognition results on different features**

| Feature | | Dimension | Recall (%) |
|---|---|---|---|
| LPQ | $w = 3 \times 3$ | 256 | 68.57 |
| | $w = 5 \times 5$ | 256 | 78.57 |
| | $w = 7 \times 7$ | 256 | 82.82 |
| | $w = 9 \times 9$ | 256 | 85.94 |
| | $w = 11 \times 11$ | 256 | 87.20 |
| | $w = 13 \times 13$ | 256 | **87.90** |
| | $w = 15 \times 15$ | 256 | 87.72 |
| | $w = 17 \times 17$ | 256 | 86.75 |
| | $w = 21 \times 21$ | 256 | 85.41 |
| | $w = 23 \times 23$ | 256 | 79.37 |
| LBP | | 256 | **59.66** |
| CS | $w = 11 \times 11$ | 256 | 91.15 |
| | $w = 13 \times 13$ | 256 | **92.20** |
| | $w = 15 \times 15$ | 256 | 92.15 |
| | $w = 17 \times 17$ | 256 | 91.60 |

It can be seen from Table 1 that the recall measure of the different local windows sizes $w$ of the LPQ varies significantly. The LPQ features extracted from the whole image are generated using $w = 17 \times 17$ outperform all other parameters reporting a recall measure 87.90%. In addition to the LPQ, we obtain a modest result using the classic LBP feature, and it was valued at 59.66%. To obtain the best results, we consider the Combination Strategy (CS) gives the best results using $w = 13 \times 13$ realizes a recall measure rate of 92.20%.

In order to improve the system performance, we also evaluated the Combination Strategy scheme using $w = 13 \times 13$ for the Whole Image (WI) as well as from different image regions by applying a Uniform Grid Sampling (UGS) to the image. Table 2 summarizes the recognition results on the Combination Strategy by applying the UGS method. A highest recognition rate of 95.34% is achieved when the Combination Strategy scheme extracted from whole image as well as from 1x2 grid making a feature vector of dimension 768.

**Table 2: Recognition results on the Combination Strategy using UGS.**

| Combination Strategy | | Dimension | Recall (%) |
|---|---|---|---|
| Using WI | Using UGS | | |
| No | 1x2 grid | 512 | 94.27 |
| | 2x1 grid | 512 | 88.46 |
| | 2x2 grid | 1024 | 91.82 |
| | 1x3 grid | 1024 | 92.08 |
| | 3x2 grid | 1536 | 89.90 |
| Yes | 1x2 grid | 768 | **95.34** |
| | 2x1 grid | 768 | 93.63 |
| | 2x2 grid | 1280 | 94.41 |
| | 1x3 grid | 1280 | 94.61 |
| | 3x2 grid | 1792 | 92.98 |

We also computed the recall for each of the digit classes distinctly to find the challenging classes from the view point of recognition. Class-wise recognition rates of these experiments are presented in Table3. In general, the recall values are more or less consistent across different digit classes. Relatively low recall is achieved on some digits (3, 7 and 9). In addition, it must be noted that some pairs like ('3', '5'), ('9', '8') and ('7', '4') offer a relatively more challenging recognition problem due to low inter-class variation.

**Table 3: Recognition rates on individual classes**

| Computed Classes | Reference Classes: 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 96.74 | 0.51 | 0.60 | 0.05 | | 0.18 | 0.96 | | 0.78 | 0.18 |
| **1** | | 99.22 | 0.41 | | 0.09 | 0.05 | 0.09 | 0.14 | | |
| **2** | 0.64 | 0.55 | 96.28 | 0.28 | 0.05 | 0.05 | 0.23 | 0.87 | 0.96 | 0.09 |
| **3** | 0.28 | 0.73 | 0.92 | 93.62 | 0.28 | 1.19 | 0.05 | 0.69 | 1.15 | 1.10 |
| **4** | 0.05 | 1.01 | 0.18 | 0.00 | 95.73 | 0.05 | 1.10 | 0.46 | 0.28 | 1.15 |
| **5** | 0.32 | 0.37 | | 0.87 | 1.10 | 96.46 | 0.32 | 0.14 | 0.09 | 0.32 |
| **6** | 0.41 | 0.41 | 0.09 | 0.00 | 0.18 | 0.23 | 98.21 | | 0.46 | |
| **7** | 0.09 | 0.51 | 1.19 | 0.23 | 1.84 | 0.18 | 0.05 | 94.03 | 0.78 | 1.10 |
| **8** | 0.41 | 0.83 | 0.55 | 0.14 | 0.28 | 0.92 | 0.83 | 0.83 | 94.08 | 1.15 |
| **9** | 0.51 | 1.70 | 0.14 | 0.96 | 2.07 | 2.16 | | 0.64 | 2.75 | 89.07 |
| **Recall (%)** | | | | | | | | | | **95.34** |

We also compare the performance of the proposed method with state-of-the-art digit recognition systems submitted to the Digit Recognition Competition (HDRC) held in conjunction with ICDAR 2013. A total of 7 teams submitted 9 different systems to the HDRC 2013. Only 2 of these systems do not require any size normalization (Jadavpur and Tébessa I). The evaluation protocol considered in our experiments is the same as that of the competition to allow a meaningful comparison as summarized in Table 4.

**Table 4: Comparison of proposed method with state-of-the-art methods**

| Rank | Method | Precision (%) | Normalized Digits |
|---|---|---|---|
| 1 | Gattal et al. 2014[7] | 96.62 | No |
| 2 | **Proposed Method** | **95.36** | **No** |
| 3 | Gattal et al. 2016 [9] | 95.21 | No |
| 4 | Jadavpur | 94.75 | No |
| 5 | Tébessa I | 77.53 | No |

It can be seen from Table4 that the proposed method realizes a precision of 95.36% which is comparable to performance of the top 2 participants of the competition. It should however be noted that the proposed system extracts the features directly from binarized images and does not require any size normalization. Our system realizes the highest recognition rate. These results validate the effectiveness of the LBP and LPQ with simple combination strategy for recognition of isolated digits.

## 4 CONCLUSION

The objective of this paper is to improve the overall recognition rates by enhancing the feature extraction step of in isolated digit recognition systems.

We investigated the proposed combination strategy based on Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) for this purpose. The features are extracted of different parameter settings from the complete image as well as from different regions of the image by applying a uniform grid sampling while the classification is carried out using SVM.

The initial results obtained by the proposed method are very encouraging. Our further study on this subject will include investigation of other features as well as A feature selection mechanism to identify the most appropriate subset of features for this problem would also be interesting to explore.

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