An Application of Chain Code-Based Local Descriptor and Its Extension to Face Recognition

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Abstract –Local descriptors are widely used technique of feature extraction to obtain information about both local and global properties of an object. Here, we discuss an application of the Chain Code-Based Local Descriptor to face recognition by focusing on various datasets and considering different variants of this description method. We augment the generic form of the descriptor by adding a possibility of grouping pixels into blocks, i.e., effectively describing larger neighborhoods. The results of experiments show the efficiency of the approach. We demonstrate that the obtained results are comparable or even better than those delivered by other important algorithms in the class of methods based on the Bag-of-Visual-Words paradigm.

Keywords: face recognition; local descriptor; chain code; chain code-based local descriptor.

1. Introduction

Face recognition has been one of the most important problems of biometrics in the recent decades fully recognized by wide community of researchers. Its vast plethora of applications covers, among others, forensic sciences, driver's licenses and passport verification, missing identification, surveillance systems, social networks, etc. A relative easiness of usage (non-invasiveness), and low technological costs imply the immense development of various facial recognition approaches. However, many of them still suffer from some of typical problems occurring in image recognition such as lighting conditions, quality of old images, aging, pose of the subject, face occlusion, computing overhead, etc. There are many trends in face recognition. The most significant and comprehensively examined are the approaches originated from geometrical methods [1], principal component analysis (eigenfaces[2]), linear discriminant analysis (Fisherfaces[3]), EBGM (elastic bunch graph matching [4]), SVMs (support vector machines [5]), Gabor wavelets [6,7], information aggregation and fusion [8], neural networks [9], sparse representation [10], deep learning [11,12], Granular Computing and linguistic descriptors [13,14], and local descriptors [15,16]. For instance, the latter class of

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methods is, in general, invariant to lighting and pose changes. Other advantages of local descriptors are their relatively low computational cost and very intuitive processing scheme taking as an input the neighborhood of a given pixel and resulting in the value being the description of this surrounding. Next, histograms of such descriptions in the local areas are formed. Finally, the histograms are concatenated producing a description of the whole image.

The origin of the idea of local descriptors could be encountered in the area of texture analysis [17,18], and, in the sequel they could be found in applications to face recognition. A milestone was a publication authored by Ahonen et al. [15]. This paper describes a local descriptor, which converts the value of the grayscale level of the analyzed pixel to the value dependent on its neighborhood. The analysis of the neighborhood, see Fig. 1, determines which pixels from the surroundings have values greater or smaller than the examined, central pixel. Based on this finding, the pixels constituting the neighborhood are coded using zeros and ones. This new coding allows us to create the new value describing the tested pixel as digit value of the byte built from the eight bits (0 or 1 values).

Fig. 1 Visualization of the concept of the LBP

On the basis of LBP, a lot of variations of the approach were established. The most important that are worth mentioning include central symmetric LBP [16,19], improved local binary pattern (ILBP) [20], multi-scale block LBP [21,22], or Weber local descriptor (WLD) [23]. In addition, many papers describing linkages of local descriptors with different filters, like Gabor wavelets, have been published [6,24,25,26,27]. The extensive research on application of local descriptors in pattern recognition is still ongoing, as evidenced by numerous new studies in this field, e.g., [28,29,30,31,32,33,34,35,36,37,38,39,40,41,42]. Particularly, noteworthy is the recent trend of combining deep learning with local descriptors, see, for instance, [43,44,45]. Comprehensive survey study can be found in [7,46].

An interesting approach to local descriptors was described in [47]. In this method, called Full Ranking (FR), the use of the classical histogram is replaced by using a dictionary of available words, which is a direct incorporation of the Bag-of-Visual-Words (BoVW) paradigm [48]. As in the LBP case, the pixel neighborhoods are examined (Fig. 2). However, the pixels are

sorted and the indexes constitute a “word”. Finally, the word is replaced by the closest one appearing in the dictionary. The histograms of the words form the inputs to the classifiers.

Fig. 2 Neighborhoods considered in the Chan et al. [47] algorithm. After sorting by increasing values of the pixels, the indices form the word, the closest word from the available dictionary replaces the value of the analyzed pixel. Neighborhoods of the forms (a-c) are proposed in [47] while the neighborhood (d) has been drawn from the classic LBP algorithm. Hereafter, the forms of neighborhoods are denoted as *A*, *B*, *C*, and *D*, respectively.

Finally, in [49] proposed was a so-called Chain Code-Based Local Descriptor (CCBLD). This novel method applies the “words” built from the chain codes starting from the analyzed pixels. The code is created taking into account, for instance, the consecutive minima or maxima of the pixel values. It implies the replacement of the integer (usually 0 – 255) values by words created by only four letters. This type of description of the neighborhood of any pixel should help to obtain local description of an image. However, longer codes contain information on the more global structures than the neighborhood of an arbitrary shape, for instance 3x3. The details of the method are discussed in the next section.

The main objective of this study is to develop a novel extension of basic Chain Code-Based Local Descriptor (CCBLD), which is realized by an application of blocks of pixels instead of the single ones. The originality of the approach lays in the calculation of the chain-codes describing the neighborhoods of pixels taking into account the blocks of pixels. This simple procedure results in the significant increase of the accuracies for the most of the considered datasets. Moreover, this study shows the application of the BoVW paradigm to the more complicated structures such as apparently non-related blocks of pixels by building “words” describing the relations laying behind them. Furthermore, we present a comprehensive analysis of the dependency of the recognition rate on the dictionary length and the division of the image onto the subregions for which separate histograms are created and then concatenated into the holistic description of the image. Our aim is also to demonstrate the usefulness and applicability of CCBLD to various environments, lighting conditions, or age by testing its accuracy on numerous well-known face databases such as AT&T, FERET, Yale, CAS-PEAL, ColorFERET, Essex, and FG-NET.

Some preliminary experimental studies reported in [49] for the AT&T dataset and demonstrating some potential, are significantly expanded in this paper. Here, we discuss more comprehensive tests showing the accuracy of the CCBLD-based face recognition. Finally, we investigate some design aspects by studying an influence of preprocessing (e.g., cropping) on the recognition with CCBLD.

The paper is organized as follows. In Section 2, we discuss the main properties of Chain Code-Based Local Descriptor and present its extensions. The experimental results are described in Section 4. Conclusions and directions of future work are covered in Section 5.

2. Chain Code-Based Local Descriptor and its extension

Let us briefly recall the main idea behind the CCBLD. It is worth noting here that this local descriptor, in contrary to others, is created not on the basis of the size of the region itself (e.g., rectangle or circle) but the description of a selected pixel may (at least theoretically) come from a larger number of pixels (or blocks) depending upon the local properties of an image. In more detail, assume that we start from any arbitrary pixel $I(x,y)$ and that in one of the pixels $I_L(x-1,y)$, $I_U(x,y-1)$, $I_R(x+1,y)$, or $I_D(x,y+1)$ there is a higher gray-scale value than the $I(x,y)$ (and, it is the highest value in this cross-neighborhood). Then, the first letter of the description of the pixel $I(x,y)$ corresponds to one of the four considered pixels, namely “L”, “U”, “R”, or “D”. Next, the process continues starting from the pixel of this maximal value. Of course, the procedure has its limits since the gray-scale range of values and the number of pixels in any image are finite. Moreover, it is easy to see that the cycles are not possible. However, in case of two or more maxima, one can set some priorities as to the choice of the highest value. Finally, when the starting pixel exhibits the highest value, the description results in an empty chain. Similarly, any pixel of an image can be described by taking into account the consecutive minima using the same letters. The process is illustrated in Fig. 3.

Fig. 3 The process of finding the consecutive minima and maxima from the starting point (pixel of value 46)

Since the number of such string descriptions can be huge, a sound alternative is to introduce a dictionary of chosen possible words. The words not appearing in this dictionary can be matched to the nearest one present in the dictionary. The process of string comparison can be realized following a well-known Levenshtein distance (edit distance). Let us recall that in the determination of this distance we take into account the minimal number of insertions, replacements, and deletions which are needed to make words equal [50,51].

A final description of an image comes as a concatenation of histograms of dictionary words appearing in subregions of the image. It helps preserve both local (at the level of subregions) and global (as a result of concatenation) properties of an image. Formally, we write it down as

$$D = \left[w_{1,1}^+, \dots, w_{1,\frac{n}{2}}^+, w_{1,1}^-, \dots, w_{1,\frac{n}{2}}^-, \dots, w_{i,j}^+, \dots, w_{i,j}^-, \dots, w_{r,1}^+, \dots, w_{r,\frac{n}{2}}^+, w_{r,1}^-, \dots, w_{r,\frac{n}{2}}^- \right],$$

where $i=1, \dots, r$ is a number of image subregion, $j=1, \dots, n/2$ is a number of word in a dataset. The sign + denotes a word created by using the consecutive maxima rule while the sign – stands for the word built with the rule of minima. Similarly to what has been presented in [47], we create the dictionary by random picking up images and pixels in the database. As the classifier we propose is the nearest neighbor with the Hellinger similarity measure (also known as Bhattacharyya coefficient) comparison of the histograms (regarded as two vectors $\mathbf{x} = (x_1, \dots, x_n), \mathbf{y} = (y_1, \dots, y_n) \in \mathbb{R}^n$) is completed as follows [52]

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{1 - \frac{\sum_{i=1}^n \sqrt{x_i y_i}}{\sqrt{\sum_{i=1}^n x_i \sum_{i=1}^n y_i}}}.$$

As it will be shown in the experiments section, a simple modification to the above procedure can play a pivotal role in increasing the recognition rates. Instead of considering single pixels, we can take the blocks of pixels, which are then represented as the arithmetic means of the blocks of size $p \times p$, i.e.,

$$\bar{I}(x, y) = \frac{I(x - p, y - p) + \dots + I(x, y) + \dots + I(x + p, y + p)}{(2p + 1)^2},$$

for instance,

$$\bar{I}_L(x, y) = \frac{I(x - 3p - 1, y - p) + \dots + I(x - p - 1, y) + \dots + I(x - p - 1, y + p)}{(2p + 1)^2},$$

etc. An example of a process of word construction corresponding to a certain pixel is depicted in Fig. 4. The overall classification process is presented in Fig. 5.

Fig. 4 Example of finding the consecutive minima and maxima of averages of blocks, here the size of a block is $p=3$

Fig. 5 An overall processing scheme

3. Experimental studies

To demonstrate the efficiency of the proposed approach, we present experimental results obtained for seven commonly used face datasets. The results are compared with those obtained for the LBP method [15] and with Full Ranking descriptor presented in [47].

3.1. AT&T database

AT&T [53] is one of the most exploited facial datasets in scientific publications. It consists of 400 images of 40 people with 10 images per subject. The images are taken with relatively different mimic, emotion expression, pose, and light. They are 92 pixels in width and 112 pixels in height. For the purpose of our experiments we have divided the dataset choosing randomly 5 images of each person to the gallery and the rest 5 images to the testing set. The experiment was repeated 20 times. In each series of test we have created randomly a new dictionary of words. The experiments were done for various lengths of dictionary and divisions of the images in the subregions. However, no matter of the relation of the width to the height of the images, we have always selected the division in the form $n \times n$, i.e., the subregions have the same proportions as the original whole images. Table 1, Table 2, Table 3, and Table 4 contain the rank 1 recognition rates obtained with CCBLD local descriptor having the size of block surrounding the starting pixel of value $p=1$, $p=2$, $p=3$, and $p=4$, respectively, and for the dictionaries ranging from 10 to 300 words. Some additional results for these descriptors with longer dictionaries and split of the images are given in Table 5, where only the best results are detailed. We specified them by analyzing the progress of the recognition rates values for the dictionaries of lower length. In case of relatively simple dataset which is AT&T the dictionary of length 100 for basic CCBLD and 400 – 600 for block version of the descriptor is a well choice. The best division for this dataset is 3×3 or 4×4 subregions of the equal size. Fig. 6 visualizes the comparison for the first 10 ranks of 5 versions of CCBLD, LBP, and FR local descriptors. Hereafter the notion CCBLD($N \times p, M \times N, K$) refers to the descriptor with N -pixel wide neighborhood of central (starting) point, division of the image on M rows and N columns, and dictionary of length K . The plot shows the potential applicability of our CCBLD method pointing that it is a sound alternative for one of the best descriptors published ever.

The last series of tests with the AT&T data presented here concerns the verification of the methods on the images being preprocessed, namely, the faces are cropped (90 x 94 px), scaled, and the histogram are equalized. Our method produces over 98% recognition rate and for all the ranks outperforms the other descriptors. Fig. 7 stresses that when the images are preprocessed, a good level of recognition (over 98%) is achieved.

Table 1 Relation between rank 1 recognition rates and the dictionary length for the CCBLD with block size $p=1$

Division	Dictionary length													
	10	20	30	40	50	60	70	80	90	100	150	200	250	300
1x1	52.95	69.33	74.78	77.58	79.68	81.45	82.28	82.80	82.93	83.75	85.23	84.60	85.50	85.53
2x2	83.00	88.80	89.70	90.63	91.00	91.50	91.45	92.00	92.63	92.28	92.93	92.75	92.80	93.18
3x3	90.23	92.58	93.38	94.15	94.28	94.65	94.85	94.75	95.43	95.23	95.68	95.75	95.93	95.83
4x4	92.95	94.70	95.48	95.68	95.83	95.83	95.98	96.03	96.10	96.20	95.93	96.15	96.00	95.60
5x5	93.68	95.10	95.33	95.30	95.53	95.60	95.55	95.55	95.53	95.58	95.45	95.15	95.10	94.85
6x6	93.03	94.15	94.80	95.30	95.18	95.03	95.25	95.05	95.35	95.33	95.18	94.73	94.53	93.98
7x7	93.55	94.30	94.20	94.53	94.28	94.48	94.18	94.28	94.15	94.28	93.93	93.75	93.53	93.10
8x8	92.58	93.35	93.50	93.60	93.73	93.43	93.73	93.53	93.55	93.45	93.28	92.78	92.80	92.53
9x9	92.45	93.18	93.38	93.40	93.20	93.40	93.28	93.20	93.13	93.25	92.85	92.63	92.43	92.25
10x10	92.38	92.70	92.78	92.80	92.80	92.50	92.63	92.68	92.50	92.63	92.08	91.83	91.68	91.03

Table 2 Relation between rank 1 recognition rates and the dictionary length for the CCBLD with block size $p=3$

Division	Dictionary length													
	10	20	30	40	50	60	70	80	90	100	150	200	250	300
1x1	72.13	85.28	88.93	91.08	92.03	92.88	93.38	93.13	94.08	94.13	94.93	95.30	95.35	95.75
2x2	92.20	94.80	96.43	96.73	96.60	96.95	97.25	97.10	97.13	97.43	97.60	97.93	98.00	97.93
3x3	96.05	97.28	97.60	97.88	97.83	97.93	98.00	97.85	97.85	97.95	97.95	98.20	98.15	98.20
4x4	96.70	97.63	97.75	98.03	98.10	98.23	98.18	98.20	98.08	98.18	98.28	98.18	98.20	98.25
5x5	96.58	97.10	97.20	97.05	97.35	97.28	97.08	97.28	97.43	97.23	97.20	97.00	97.23	97.20
6x6	96.28	96.83	96.90	96.83	96.70	96.88	96.63	96.83	96.88	96.93	96.90	96.93	96.68	96.83
7x7	96.50	96.58	96.43	96.58	96.50	96.58	96.48	96.60	96.53	96.43	96.40	96.55	96.40	96.45
8x8	95.25	96.03	96.00	95.90	96.00	96.00	95.88	96.03	95.90	95.98	95.98	96.00	95.93	95.93
9x9	95.38	95.50	95.80	95.70	95.53	95.65	95.70	95.55	95.60	95.55	95.68	95.73	95.70	95.55
10x10	95.45	95.65	95.35	95.53	95.50	95.60	95.38	95.35	95.45	95.43	95.35	95.35	95.48	95.30

Table 3 Relation between rank 1 recognition rates and the dictionary length for the CCBLD with block size $p=5$

Division	Dictionary length													
	10	20	30	40	50	60	70	80	90	100	150	200	250	300
1x1	72.90	85.98	89.28	91.18	91.73	92.65	92.88	93.25	93.43	93.78	94.78	95.03	95.75	95.65
2x2	91.98	95.13	96.10	97.08	96.93	97.28	97.15	97.50	97.45	97.60	97.60	97.95	98.00	97.90
3x3	95.78	97.38	97.30	97.43	97.68	97.88	97.83	97.75	97.85	98.10	98.00	98.00	98.00	98.00
4x4	96.90	97.35	97.48	97.30	97.50	97.53	97.43	97.55	97.45	97.50	97.50	97.53	97.50	97.45
5x5	95.90	96.25	96.33	96.45	96.48	96.45	96.60	96.70	96.53	96.58	96.73	96.73	96.73	96.73
6x6	95.85	96.18	96.00	96.18	96.23	96.35	96.28	96.28	96.28	96.33	96.18	96.28	96.33	96.35
7x7	95.33	96.03	95.95	96.13	95.93	95.95	96.00	96.00	95.93	95.95	96.10	95.93	95.90	95.93
8x8	95.23	95.63	95.65	95.55	95.63	95.65	95.58	95.58	95.48	95.55	95.50	95.35	95.38	95.63
9x9	95.13	95.33	95.50	95.53	95.30	95.48	95.35	95.30	95.25	95.28	95.15	95.18	95.28	95.08
10x10	94.73	95.18	95.05	95.05	94.98	95.20	94.93	94.95	94.68	95.00	94.88	94.78	94.63	94.70

Table 4 Relation between rank 1 recognition rates and the dictionary length for the CCBLD with block size $p=7$

Division	Dictionary length													
	10	20	30	40	50	60	70	80	90	100	150	200	250	300
1x1	70.13	84.13	87.08	90.10	91.50	91.85	92.78	92.55	92.78	93.28	94.03	94.68	95.18	95.28
2x2	92.18	94.65	95.88	96.45	96.58	96.78	96.85	97.15	97.20	97.05	97.48	97.65	97.53	97.70
3x3	96.33	97.35	97.73	97.93	98.00	98.15	98.13	98.10	98.33	98.33	98.33	98.33	98.33	98.28
4x4	96.65	97.70	97.80	97.73	97.83	97.85	97.68	98.05	97.88	98.05	97.88	97.90	97.88	97.95
5x5	96.18	96.85	96.80	97.03	96.95	97.23	97.03	97.23	97.18	97.20	97.18	97.15	97.05	96.95
6x6	96.60	96.68	96.75	96.88	96.60	96.65	96.65	96.70	96.68	96.58	96.58	96.33	96.38	96.50
7x7	95.80	96.13	96.10	96.38	96.30	96.35	96.25	96.55	96.28	96.35	96.33	96.28	96.43	96.40
8x8	95.65	95.88	95.85	96.13	96.13	96.15	96.28	96.30	95.98	96.05	96.18	96.18	96.23	96.33
9x9	95.60	95.83	95.70	95.70	95.90	95.78	95.85	95.48	95.65	95.65	95.73	95.60	95.70	95.63
10x10	95.08	95.55	95.75	95.63	95.58	95.50	95.58	95.40	95.45	95.58	95.35	95.55	95.40	95.40

Table 5 Additional rank 1 recognition rates for selected division of images and sizes of descriptor's block for AT&T database

Block size (p)	Division	Dictionary length						
		400	500	600	700	800	900	1000
3	2x2	97.95	98.2	98.15	98.23	98.08	98	98.08
3	3x3	98.13	97.98	-	-	-	-	-
3	4x4	98.28	98.15	98.15	98.23	-	-	-
5	2x2	98	97.93	-	-	-	-	-
5	3x3	98.15	98.05	98.23	98.15	-	-	-
5	4x4	97.6	97.45	-	-	-	-	-

7	2x2	97.68	97.5	-	-	-	-	-
7	3x3	98.45	98.3	98.23	98.3	98.23	98.23	98.23
7	4x4	97.85	97.95	97.75	97.78	-	-	-
9	2x2	-	96.73	-	-	-	-	-
9	3x3	98.35	98.38	98.4	98.4	98.28	98.28	98.28
9	4x4	-	97.83	-	-	-	-	-
11	2x2	-	96.15	-	-	-	-	-
11	3x3	-	97.73	-	-	-	-	-
11	4x4	-	97.53	-	-	-	-	-

Fig. 6 Rank 1 - rank 10 recognition rates (%) obtained for chosen local descriptors for AT&T database

Fig. 7 Rank 1 - rank 10 recognition rates (%) obtained for chosen local descriptors for preprocessed images from AT&T dataset

3.2. FERET database

Now, we consider various subsets of the well-known Facial Recognition Technology (FERET) Database [54,55]. The first part of experiments was carried for merged grayscale image subsets called *ba*, *bk*, and *bj*, containing 600 photographs of 200 people (3 per subject). Similarly as in the AT&T case, we have run 20 series of experiments choosing randomly 2 images of each person for the training and 1 image for the testing set, respectively. The results show that the CCBLD in its simplest form, namely 1 pixel size neighborhood, outperforms the rest of the methods. Of course, the recognition rates are not high (73.75% for rank 1), but they show the potential hidden in this approach and suggest its ability to connection with other image processing/recognition methods to increase its efficiency (see Fig. 8). Similar experiments were conducted for the same set of images after a preprocessing step has been completed. First, the eyes were detected, next the images were rescaled, and the faces were cropped (size 100x140 px), finally the histograms of the images were equalized. The results are presented at Fig. 9. They show, again, that the applicability of our approach and the preprocessing step can slightly improve the efficiency of the method by yielding over 75% recognition rate.

The next series of experiments was run on the ColorFERET dataset. We have chosen 2,722 frontal photographs of 994 people (from 2 to 22 images per subject in various distances from the camera). The only preprocessing was grayscale conversion of all images. The results are depicted in Fig. 10. Finally, we have run similar tests for cropped and scaled (to the size 100x140 px) faces from the grayscale FERET pictures set called *fa*, *fb*, *ba*, *bk*, and *bj* (the operation was done for 3880 images). The results of comparison of CCBLD and other methods under consideration are presented in Fig. 11. All gathered results illustrate an evident potential of the proposed method.

Fig. 8 Rank 1 - rank 50 cumulated recognition rates (%) obtained for chosen local descriptors for preprocessed images from grayscale FERET subset

Fig. 9 Rank 1 - rank 50 recognition rates (%) obtained for chosen local descriptors for preprocessed images from grayscale FERET subset containing 600 images after preprocessing

Fig. 10 A comparison of rank 1 – rank 100 recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR for ColorFERET dataset

Fig. 11 A comparison of rank 1 – rank 100 recognition rates for the chosen methods in group of CCBLD, LBP, and FR for grayscale FERET dataset

3.3. Yale Face Database

Here we discuss the recognition problem using the 165 images of 15 people from the Yale Face Database [3]. The recognition rates obtained with chosen feature extractors are shown in Fig. 12. Here, we observe the dependency of the recognition rate on the division of the image onto the sub-blocks and, which is although very important, large dependency on the length of the dictionary.

Fig. 12 A comparison of rank 1 – rank 10 cumulated recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR for Yale Face Database

3.4. CAS-PEAL database

Here we report the results obtained for the CAS-PEAL database, see [56], precisely its subset containing 9,029 images of 1,040 people (from 3 to 49 per subject). The results are given in Fig. 13. For lower rank one can note that the chain-code based on blocks of pixels gives better results. However, one pixel-based chain code yields similar results for higher than 20 ranks.

Fig. 13 A comparison of recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR obtained with CAS-PEAL dataset

3.5 Essex Collection of Facial Images

The results deal with the subset faces94 from the Essex Collection of Facial Images[57] of 153 people (20 images per person) of size 180x200 px. They are depicted in Fig. 14. The plot shows that all the considered local descriptors bring good results here. However, also in this case the CCBLD outperforms both Full Ranking and LBP.

Fig. 14 A comparison of rank 1 – rank 10 recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR obtained with Essex Collection of Facial Images

3.6. Face and Gesture Aging Database (FG-NET)

The FG-NET database [58] consists of 1,002 images of subjects at the age between 0 and 69 with 6 to 18 images per person. The maximum time between photos being taken is 54 years. The results are presented in Fig. 15. In the second series of the experiments, the photographs were converted to the grayscale, cropped to the size 128x160 px, scaled, and the histograms were equalized. The recognition rates are illustrated in Fig. 16. Despite the fact that local descriptors themselves are not sufficient to bear the aging problem they can be potentially very useful in combination with other methods (see, for instance, [7]). The results show that CCBLD can be a good choice in comparison to other local descriptors, particularly when the images are preprocessed.

Fig. 15 A comparison of rank 1 – rank 50 recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR obtained with FG-NET dataset

Fig. 16 A comparison of rank 1 – rank 50 recognition rates (%) for the chosen methods in group of CCBLD, LBP, and FR obtained with FG-NET images after preprocessing

3.7. Computing time

In this section we demonstrate the average run times for chosen operations such as the time needed to creating dictionary, changing the text files covering the words describing the pixels of the corresponding images to the text files covering the words from the dictionary, creating histogram of words describing the image, and finally the time of comparison of two such histograms. The set of images chosen to this kind of experiments was the subset of 600 grayscale images from the FERET database (see section 3.2 for details). The values illustrating the dependencies of the speed of the algorithm upon the dictionary length, block size, and division of an image are included in Table 6, Table 7, and Table 8, respectively. As

it is seen from the tables the length of the dictionary has the most influence on the time of realization of the program.

Table 6 Computing time (in ms) of selected operations for the CCBLD version with block size 1x1, no division of an image, and dictionary length changing from 100 to 1000 words

Action	Dictionary length									
	100	200	300	400	500	600	700	800	900	1000
Creating dictionary	561	2636	5163	11529	19923	29001	40544	55474	74823	94489
Changing text image using dictionary	1950	3532	5229	6855	8540	10445	12548	14017	15819	17714
Creating histogram	193	196	197	198	198	204	200	199	201	200
Comparing two histograms	0.24	0.36	0.49	0.62	0.74	0.86	0.97	1.09	1.21	1.32

Table 7 Computing time(in ms) of selected operations for the CCBLD version; no division of an image, dictionary length set to 100, and block size changing from 1x1 to 15x15

Action	Block size							
	1x1	3x3	5x5	7x7	9x9	11x11	13x13	15x15
Creating dictionary	561	187	171	124	140	140	124	124
Changing text image using dictionary	1950	2033	2119	2075	2071	2008	1972	1982
Creating histogram	193	194	194	194	195	193	193	206
Comparing two histograms	0.24	0.24	0.24	0.25	0.24	0.24	0.24	0.24

Table 8 Computing time(in ms) of selected operations for the CCBLD version; no division of an image, dictionary length set to 100, block size set to 1x1, and the division of an image changing from 1x1 to 10x10

Action	Division of the image									
	1x1	2x2	3x3	4x4	5x5	6x6	7x7	8x8	9x9	10x10
Creating dictionary	561	452	670	561	702	468	655	483	530	670
Changing text image using dictionary	1950	1967	1901	1935	1958	1896	1912	1946	2003	1948
Creating histogram	193	193	195	196	198	200	203	204	208	211
Comparing two histogram	0.24	0.62	1.23	2.07	3.14	4.42	5.89	7.6	9.44	11.62

3.8. Noise/occlusion presence

In this subsection we study the case of noise or occlusion artificially added to the images. We have modified the images using Gaussian and salt and pepper noise to the images coming from AT&T and grayscale FERET datasets, respectively. The results are included in Table 9. Moreover, we have modified the images adding white rectangles of random size and placement which sizes were not more than 30x60 pixels in case of AT&T and 90x150 pixels in case of FERET. We have chosen the parameters giving the best results for original images. Furthermore, in one case we changed the way of calculating the value representing a block of pixels. Namely, instead of average we have chosen the median. This simple operation makes the algorithm more robust to the noise when compared to the other methods.

Table 9 Comparison of recognition rates (in percentage) for Gaussian noise, salt & pepper noise, and occlusion

Dataset	Noise	Gaussian noise					Salt and pepper noise					Occlusion
	Method	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%	
AT&T	CCBLD(1px,4x4,100)	83.88	61.50	36.43	19.75	13.95	81.25	61.55	37.08	18.30	9.08	36.35
	CCBLD(7px,3x3,400) – average of pixel block	97.43	95.40	93.58	90.90	87.48	97.45	95.60	95.83	93.70	89.38	63.30
	CCBLD(7px, 3x3,400) – median of pixel block	97.23	96.85	95.93	95.90	95.28	97.65	96.83	96.23	95.85	95.48	69.30

	LBP	83.68	61.20	33.58	16.08	6.88	83.53	62.83	39.50	21.58	11.40	32.23
	FR(D,5x5,300)	33.63	19.58	12.68	5.33	4.38	31.38	20.35	10.98	8.48	5.80	23.53
FERET	CCBLD(1px,7x7,400)	67.93	61.75	54.68	43.78	20.15	67.38	60.15	53.13	44.30	36.58	7.08
	LBP	63.95	61.18	53.60	49.68	33.45	62.30	56.85	55.18	53.70	44.83	7.53
	FR(D,4x4,500)	54.95	49.4	43.73	30.53	16.28	53.48	47.85	41.10	32.33	21.25	1.43

3.9. Similarity/dissimilarity measures performance

The last statistics presented here is the assessment of performance of 4 well-known similarity/dissimilarity measures used to compare the histograms of words, namely the Hellinger, chi-square, histogram intersection, and correlation measure, see Table 10. Taking into account these results we use the Hellinger measure to compare all the histograms in our proposal. However, histogram intersection would be a good alternative here. Some introductory results in this scope were obtained in [49] for the leave-one-out technique of classification.

Table 10 Comparison of recognition rates (in percentage) for Gaussian noise, salt & pepper noise, and occlusion for AT&T image dataset

Method	Hellinger	Histogram intersection	Chi-square	Correlation
CCBLD(1px,4x4,100)	96.20	95.88	93.30	93.80
LBP	97.00	96.83	97.00	93.20
FR(D,5x5,300)	94.23	94.93	94.90	93.53

4. Conclusions and future work

In the study, we have comprehensively examined the local descriptor called Chain Code-Based Local Descriptor. Moreover, we have extended its form to the description of the blocks of pixels surrounding the central block. We have discussed its application to various problems of face recognition by considering different publicly available datasets. The experimental results show that our approach is comparable or even outperforms other local descriptors-based methods such as LBP or Full Ranking. Future studies may contain, among others, the examination of the dependence of the gallery and testing set sizes on the recognition rate, the problem of high resolution images and the optimization of the algorithm using other than Levenshtein word similarity measures, histogram of words smoothing and inventing other methods of its construction, for instance, incorporation of the color information, an application to other fields of biometrics or image analysis such as texture analysis or noise detection, examination of various methods of finding the paths constituting chain codes, or, finally, the invariance problem. In addition, it is worth to study a combination of CCBLD with deep learning.

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