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Computing the Principal Local Binary Patterns for face recognition using data mining tools

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ABSTRACT

Local Binary Patterns are considered as one of the texture descriptors with better results; they employ a statistical feature extraction by means of the binarization of the neighborhood of every image pixel with a local threshold determined by the central pixel. The idea of using Local Binary Patterns for face description is motivated by the fact that faces can be seen as a composition of micro-patterns which are properly described by this operator and, consequently, it has become a very popular technique in recent years. In this work, we show a method to calculate the most important or *Principal* Local Binary Patterns for recognizing faces. To do this, the attribute evaluator algorithm of the data mining tool Weka is used. Furthermore, since we assume that each face region has a different influence on the recognition process, we have designed a 9-region mask and obtained a set of optimized weights for this mask by means of the data mining tool RapidMiner. Our proposal was tested with the FERET database and obtained a recognition rate varying between 90% and 94% when using only 9 uniform Principal Local Binary Patterns, for a database of 843 individuals; thus, we have reduced both the dimension of the feature vectors needed for completing the recognition tasks and the processing time required to compare all the faces in the database.

1. Introduction

Nowadays, the use of cryptographic techniques has become an essential requirement for a huge amount of applications. In most cases, the weakness of security systems still remains on the verification of the identity of the remote user. In relation to this, in the last 15 years there has been an intensive research to develop new security systems, much of them involving the so-called biometric features (Bowyer, Hollingsworth, & Flynn, 2008; Hao, Anderson, & Daugman, 2006; Zhao, Chellappa, Phillips, & Rosenfeld, 2003). A great number of theoretical and experimental innovations have made automated biometric authentication not only technically feasible, but also extremely popular. Automated biometric systems are being widely used in many applications such as surveillance, digital libraries, forensic work, law enforcement, human computer intelligent interaction, and banking, among others. For applications requiring high levels of security, biometrics can be integrated with other authentication tools, such as smart cards and passwords.

In general, a biometric system is a pattern recognition system that makes a personal identification by determining the authenticity of a specific physiological or behavioral characteristic possessed by the user. One of the most popular biometric techniques to identify users is face recognition. Thus, an automated face recognition system is commonly based on extracting a set of features from the user's face, either geometric characteristics or some information of textures and shapes of the different elements in a human face (Li & Jain, 2005). Among others, the main advantages of using facial recognition systems include their reliability, providing non-collaborative user recognition and incorporating some additional information, such as facial expressions. As a consequence, it is an emerging research area and, in the next few years, it is supposed to be extensively used for automatic human recognition systems in many different areas, such as access control, human–machine interfaces, robotics, etc.

Face recognition systems are often classified depending on the method used to obtain the face features. On the one hand, holistic methods use the whole face region as the raw input; they include well-known techniques, such as Principal Components Analysis (PCA) (Turk & Pentland, 1991) or Linear Discriminant Analysis (LDA) (Etemad & Chellappa, 1997), among others. On the other hand, local or feature-based methods extract facial features, such as eyes, nose and mouth; their locations and local statistics are the input to the recognition stage. Some of most used algorithms for local feature analysis are Elastic Bunch Graph Matching (EBGM) (Wiskott, Fellous, Kuiger, & von der Malsburg, 1997) and, more recently, Local Binary Patterns (LBP) (Ahonen, Hadid, & Pietikäinen, 2004; Ojala, Pietikäinen, & Harwood, 1996).

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Local Binary Patterns (LBP) were introduced as a robust descriptor of microstructures in images (Ojala et al., 1996). The main advantages of this operator are its tolerance to illumination changes, its computational simplicity and its invariance against changes in gray levels. Ahonen et al. (2004) published a novel approach: in their study they present the LBP operator as a powerful texture descriptor applicable to face recognition. This method involves dividing the face image into regions and applying the LBP operator in all of them. Once the operator has been applied, the histogram of each region is computed. Since each face region contributes in a different way for the recognition process, a specific weight is assigned to each histogram. Afterwards, the similarity distance between two faces is obtained by comparing the histograms of each region, and the recognition process is then completed.

Although the original algorithm had a high recognition rate (around 94%), this method presents two main drawbacks: it needs a large feature vector and the assignment of the specific weights to each part of the face was not much precise. As a consequence, our work firstly aims at reducing the dimensions of the feature vectors required to perform the face recognition process using the LBP operator. To do this, we propose the use of what we call the Principal Local Binary Patterns, which include the most relevant information required to recognize a face; they will be calculated by means of data mining tools. On the other hand, we have also designed a 9-region mask, belonging to the most important face areas related to face recognition, such as the eyes, the nose or the mouth; then, a proposal for calculating the weights assigned to each face region – using data mining tools, as well – will be also introduced. The experiments show that our method gives accurate results and that using data mining tools allows to reduce the feature vector necessary to compare the faces in the database without affecting the final recognition rate.

The paper is organized as follows: firstly, Section 2 presents the LBP operator and some recent extensions to the original algorithm. Then, the method designed for computing the Principal Local Binary Patterns and for assigning the weights to each face region is described in Section 3. After that, Section 4 shows the results of the experiments implemented on the FERET database and compares them to previous works. Finally, some concluding remarks and future works are shown in Section 5.

2. Local Binary Patterns

The basic LBP operator was introduced by Ojala et al. (1996). This operator labels the pixels of an image and thresholds each neighborhood of 3×3 pixels by using the central pixel value; thus, the gray value of each pixel g_p in the neighborhood is compared to the gray value g_c of the central pixel. If g_p is greater than g_c, then it is assigned '1', and '0' if not. The LBP label for the central pixel of each region in the image is obtained as:

$$\mathrm{LBP}_P(x,y) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, \quad \text{where } s(x) = \begin{cases} 1, & x \geqslant 0 \\ 0, & x < 0 \end{cases}. \tag{1}$$

Subsequently, this operator was extended to capture operator neighborhoods of different dimensions (Ojala, Pietikäinen, & Mäenpää, 2002). For this, a circular neighborhood – which is obtained using bilinear interpolation – around the central pixel is used, where the position (x,y) of g_p is determined by $(-R\sin(2\pi p/R), R\cos(2\pi p/R))$. R is the ratio between pixel p and the central pixel c. This way, a neighborhood (P,R) of P points of radius R with respect to the central pixel is obtained. This extension is commonly referred as $\mathrm{LBP}_{P,R}$. An example is shown in Fig. 1.

Another extension introduced by Ojala et al. was the so-called uniform LBP. These patterns can be used to find the pixels that belong to flat areas, contours, corners, etc. A pattern is uniform if the bit transitions contained in its binary value are not greater than 2. For example, the string '01000000' is uniform, as it only has one transition. On the contrary, the string '01010101' is not uniform, since it contains more than 2 bit transitions.

Ahonen et al. (2004) proposed a novel face recognition system based on a LBP representation of the face. The individual sample image is divided into R small non-overlapping blocks (or regions) of the same size. The histograms of the LBP codes, H^r, with $r = \{1,2,\ldots,R\}$ are calculated over each block and then concatenated into a single histogram representing the face image. A block histogram can be defined as:

$$H^r(i) = \sum_{x,y \in block_r} I(f(x,y) = i), \quad i = 1,\ldots,N, \tag{2}$$

where N is the number of bins (number of different labels produced by the LBP operator), $f(x,y)$ is the LBP label at pixel (x,y) and I is the indicator function.

Ahonen's study proposes to assign a larger weight to the eyes and to the mouth than to the forehead and to the cheek, respectively. This is because not all the face regions contribute in the same way to the process of identifying a person. For classification, χ^2 dissimilarity measure is used, defined as:

$$\chi^2(S,M) = \sum_{r,i} \frac{(S^r(i) - M^r(i))^2}{S^r(i) + M^r(i)}, \tag{3}$$

where S and M correspond to the sample and the model histograms.

Once compared all the histograms and obtained the distances between images, a nearest-neighbor classifier is utilized for determining the class belonging to each person in the database. The system was tested by using the FERET database (Phillips, Wechsler, Huang, & Rauss, 1998; Phillips, Moon, Rizvi, & Rauss, 2000) and achieved a success rate ranging between 94% and 97% in the identification process.

As mentioned before, there are two main drawbacks for this algorithm: first, it needs a high dimensional feature vector to get a proper identification, and, moreover, the selection of weights for each face region is somehow arbitrary. In order to overcome these problems and improve the recognition rate, some proposals have been presented in recent years. Thus, Zhang, Huang, Li, Wang, and Wu (2004) proposed to use an AdaBoost machine learning system to select the most important regions or blocks of the face, thereby achieving a smaller feature vector.

Huang, Li, and Wang (2005) improved Zhang's method by incorporating Jensen-Shannon divergence into AdaBoost algorithm. This results in increasing the recognition rate and reducing the feature vector, as well. Moreover, an extension to the original operator, called Multi-Scale LBP Block (MB-LBP), was presented by Liao, Zhu, Lei, Zhang, and Li (2007). In this study, the subregions of the face are taken as individual pixels, encoding not only microstructures but also macrostructures of image patterns, hence providing a more complete image representation than the basic LBP operator.

The success of LBPs has inspired many other variations. Among others, we can cite the works of Meng, Gao, Wang, Lin, and Zhang (2010), where LBPs are combined with a threshold for resolving traditional LBPs weakness of extracting global features; Kellokumpu, Zhao, and Pietikinen (2011) considered the use of LBPs in the recognition of actions; Nanni, Lumini, and Brahnam (2010) presented some LBP-based descriptors and proposed texture descriptors for the representation of biomedical images; Liao, Law, and Chung (2009) also proposed the dominant local binary patterns (DLBP), which make use of the most frequently occurred patterns of LBP to improve the recognition accuracy, combined with Gabor-based features to give additional global textural information to the DLBP features; Wang, Yau, and Wang (2009) considered