A Dynamic Transform Noise Resistant Uniform Local Binary Pattern (DTNR-ULBP) for Age Classification

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Abstract
Local binary pattern (LBP) captures the local information of a texture effectively and thus plays a dominant role in many image processing applications. A LBP with (8, 1) or (8, 2) derives $2^8=256$ different patterns, to reduce this dimensionality uniform local binary patterns (ULBP) are derived and it has been proved that they capture fundamental properties of texture. The major disadvantage of LBP is they are prone to noise and this noise may convert a ULBP into Non-ULBP (NULBP) and this degrades the overall performance. To overcome noise problem in NULBP windows the present paper proposes Dynamic transform noise resistant ULBP (DTNR-ULBP). The DTNR-ULBP identifies floating NULBP windows. A NULBP window falls into floating window, if the absolute difference of one or more neighboring pixels with central pixel falls within the range of threshold. A floating window is considered as a noisy window. The DTNR-ULBP complements one or more floating bits to transforms the floating window into ULBP. The proposed model is dynamic because it transforms one or more floating bits depending on the need instead of all floating bits thus reduces the variation of LBP code. The proposed DTNR-ULBP recovers from the distorted image patterns. The proposed DTNR-ULBP overcomes the noise effect and improves overall age classification rate, and it is tested on FG-NET aging database.

Keywords: Dimensionality; floating window; distorted image patterns; threshold; least significant bit, Compliment bit(s).

Introduction
We can easily classify a person’s age group from a facial image of the person and this categorization is often quite precise. This ability is a difficult task for the computer vision community. In order to begin researching the issues involved in this process, this research addresses the limited task of age classification of a mugshot facial image into a baby, young adult, and senior adult. Any progress in the research community’s understanding of the remarkable ability that human’s have with regard to facial image analysis will go a long way toward the broader goals of face-recognition and facial-expression recognition. In the long run, the automatic precise age identification will assist robots in numerous ways. However, in the shorter term too, an improvement of our understanding of how humans may classify age from visual images can be used in the domain of indexing into a face database by the person’s age, in the area of newspaper-story understanding, and in the application areas such as gathering population age-statistics (for example, getting the ages of patrons at entertainment and amusement parks or in television network viewer-rating studies.). The Previous computational work on face-images has been carried out in two distinct paradigms. In the first case researchers extracted initially features such as the eyes, nose, etc., then they relate these features geometrically, and finally they use the geometric relationships to aid in analysis and recognition [25, 26]. The second paradigm treated the complete face image as an input vector and performed analysis and recognition [3, 4, 7, 27, 28]. Age classification is performed in the literature based on identifying various features i.e. local, global, regional and geometrical aspects of facial image. Out of these local features are very popular because they capture significant information in a precise manner. Local binary pattern (LBP) recently [1] and it captures local information of the face precisely. The Uniform LBP [2] is derived on LBP to reduce the dimensionality and majority of the neighborhood windows are ULBP. The ULBP windows contain the most fundamental information of facial textures. Various researchers used LBP variants for age classification [3, 4, 5, 6, 7]. The only and major problem of LBP is they are prone to noise thus a ULBP may be transformed in to a non-ULBP (NULBP). To addresses this, the present paper derived DTNR-ULBP for effective age classification.

The rest of the paper is organized as follows: Section 2 elaborates local binary pattern and its variants. Section 3 presents the algorithm of the proposed model. Section 4 provides results and its discussions and section 5 concludes the paper.

Local binary pattern (LBP)
The Local Binary Pattern (LBP) was introduced by Ojala et al. [1] in 1996. The LBP operator transforms an image into integer codes called as LBP codes describing local patterns. Initially the neighborhood is converted into binary patterns by considering the signs of the pixel differences between a pixel and its neighboring pixel. The binary values are multiplied by the corresponding weights and the summation of these corresponding weights results the LBP code for the corresponding central pixel. This process is repeated on the entire image in an overlapped manner. This mechanism transforms the image into LBP codes. The transformation process is given in equation 1 and 2

$$b_i = S(P_c - P_l)S(x) \geq 0 \text{ then } S(x) = 1 \text{ Otherwise } S(x) = 0 \quad (1)$$
Based on equation 2 the LBP code for above Fig.1 is 231.

The basic advantages of LBP are
1) The exact intensities are discarded, and only the relative intensities with respect to the center are preserved. Thus, LBP is less sensitive to illumination variations.
2) By extracting the histogram of micro-patterns in a patch, the exact location information is discarded, and only the patch-wise location information is preserved. Thus, LBP is robust to alignment error.
3) LBP features can be extracted efficiently, with less complexity which enables real-time image analysis.
4) LBP’s are invariant to monotonic gray level transformation means they are resistant to lighting or brightening effects.

The basic disadvantages of LBP are
1) LBP is sensitive to noise. A small noise may convert a homogeneous neighborhood into non homogeneous. This limits its performance.
2) The reliability of LBP decreases significantly under large illumination variations. Complex local interactions may happen whenever there is a lighting effect. This results the violation of basic LBP assumption that gray-level changes monotonically.
3) The other disadvantage of the basic LBP is it is sensitivity to random and quantization noise in uniform and near-uniform image regions such as the forehead and cheeks.

**Uniform and non-uniform LBP**

In literature ULBP are derived based on the transitions from 0 to 1 or 1 to 0 in a circular manner on the binary bits of the binary patterns generated by the LBP. The advantage of ULBP is they are treated as fundamental properties of texture and they hold more than 85% of texture properties. The LBP codes are defined as uniform patterns ‘u’ , if they have at most two circularly bitwise transitions from 0 to 1 or vice versa, and non-uniform patterns if otherwise [2]. A local binary pattern is u2-uniform or simply called uniform if U <=2. For example “11000000” is a uniform pattern as U=2 and the pattern “10101010” is non-uniform as U=8. Uniform patterns mainly represent flat region, corner, edge end, edge and spot [2]. In uniform LBP mapping, one separate histogram bin is used for each uniform pattern and all non-uniform patterns are accumulated in a single bin treating them as miscellaneous. LBPw2,2 indicates a coding scheme in which u2-uniformLBP codes of P neighbors with a radius of R. Most LBP's in natural images, textures and human faces are uniform patterns [2, 10]. For example LBPw8,1 accounts more than 90% in texture images [2] and LBPw8,2 accounts 90.6% in facial images [8]. In LBPw8,1 and LBPw8,2 the number of patterns are reduced from 2²⁰ to p(p-1)+3. Thus considering only ULBP’s will retain almost the fundamental or significant properties of the texture and also reduces overall dimensionality. That’s why ULBP’s are statistically more significant and there is need to estimate more reliably and accurately the occurrence probabilities of ULBPs. In contrast NUULBP’s are statistically significant and they occupy only small portion. In the literature the non-uniform patterns are grouped into one label to suppress noise and by this number of patterns are reduced considerably. The main issue is a little noise may transform a ULBP into NULBP and this degrades the performance because it suppresses the fundamental property of the image. This is one of the main reasons to consider NUULBP’s by many researchers in various applications. If a NULBP is transformed into ULBP by a fraction of noise it is not going to affect the overall performance.

Some researchers extracted information from non-uniform patterns for classification and other purposes [9, 11-14]. Liao et al. measured most frequently occurred patterns (Dominant LBP) in a texture image for various applications [9]. Researchers also derived information from non-uniform patterns based on pattern uniformity measure and the number of ones in the LBP codes [11, 12]. Some others explored information from LBP (both ULBP and NULBP) based on random subspace approach [14] and principal component analysis (PCA) [13] and stable transition [29]. These approaches explored some useful information from NUULBP. These methods tend to be sensitive to noise. In literature local ternary pattern (LTP) was proposed [15] to tackle the image noise in uniform regions. In LTP the pixel difference is encoded as a 3-valued code. LTP and its variants partially solve the noise-sensitive problem to some extent [15, 16, 17, 18, 19]. However the dimensionality of LTP histogram is very large for example LTPw8,1 and LTPw8,2 exhibits a histogram of 3³ =6561 bins. Further the LTP is split into positive and negative LTP. That is LTP is treated as two separate channels of LBP. The uniform LTP is obtained if and only if both the channels are uniform and this leads to high complexity. Further LTP is not much resistant to the noise, if the noise changes one of the neighboring pixel grey level values beyond threshold into threshold level.
Proposed dynamic transform noise resistant- ULBP (DTNR-ULBP) method

In this paper, we propose a DTNR-ULBP to address this issue. The sign of pixel differences is used to compute LBP and its variants are vulnerable to noise when they are small. Initially the DTNR-ULBP identifies floating windows among NULBP windows. No ULBP window forms a floating window. The neighboring pixels of the NULBP window are treated as floating bits in the present paper if they satisfy the following equation 2.

\[ |P_n - P_c| \leq t \]  

(3)

Where \( P_n \) and \( P_c \) are the gray level value of neighboring and central pixel and \( t \) is the threshold. If at least one pixel of the NULBP window satisfies the above condition, then the window is called the floating window. The floating bits are subject to noise because of their small variation of values with respect to central pixel.

A NULBP window can be transformed in to ULBP, if it forms a floating window. The fundamental information of the facial image texture will be lost especially when a ULBP is transformed into NULBP by noise. And no information is lost when a NULBP is transformed in to ULBP because any how we are treating all NULBP’s into one label called miscellaneous. Further uniform patterns are more likely to occur compared with non-uniform patterns in natural images [3], [15].

The proposed approach applies the threshold only to NULBP windows and determines the floating state bits and try to transom it into ULBP if possible. That is the reason the proposed approach is called as DTNR-ULBP. A non-uniform pattern is generated only if no uniform pattern can be formed. A noise may change a uniform pattern into an unstable non-uniform pattern, the proposed DTNR-ULBP corrects many distorted non-uniform patterns back to uniform patterns based on the dynamic transformation.

\[
\begin{align*}
89 & \quad 74 & \quad 179 & \quad \vdots \\
187 & \quad 75 & \quad 72 & \quad \vdots \\
26 & \quad 75 & \quad 70 & \quad \vdots 
\end{align*}
\]

Figure 2(a): The 3x3 neighborhood of the image.

In the above Fig. 2(a), the 3x3 window with 8 neighbors i.e \( P=8 \) and \( R=1 \) forms a NULBP. Out of these 8 neighboring pixels, \( n_2 \), \( n_3 \), \( n_4 \) and \( n_6 \) form the floating bits for a threshold 3 and this results a floating window. The floating bits are shown in Fig. 2(b) with red color. A neighboring bit forms a floating bit if the corresponding pixel satisfies the equation 2. A floating window may be transformed in to uniform window (ULBP) by complementing one or more floating bits from least significant bit (LSB). The above floating window will be transformed into ULBP by complementing all floating bits \( (n_2, n_4 \) and \( n_6 \) ) i.e. 10100101 .

\[
\begin{align*}
98 & \quad 22 & \quad 22 & \quad \vdots \\
10 & \quad 24 & \quad 23 & \quad \vdots \\
26 & \quad 10 & \quad 5 & \quad \vdots 
\end{align*}
\]

Figure 3(a): The 3x3 neighborhood of the image.

There are four floating bits \( (n_2, n_3, n_4 \) and \( n_7 \) ) in the above 3x3 floating window. The floating window of Fig.3 is converted into ULBP either by complementing all four floating bits or any one of the bit. In such case the least significant floating bits will be complemented first. Thus the code variation is minimized. In this case n-th floating bit will be complemented to transform the NULBP into ULBP (10000000). This is the novelty of the proposed method and the method is dynamic while transforming NULBP into ULBP and It minimizes the LBP code variation.

The proposed algorithm of DTNR-ULBP

1. Consider 3x3 window of an image and choose the threshold ‘t’.
2. If the window forms a NULBP
   
   Test for floating window case
   
   Complement one or more floating bits from least significant bit (LSB) and test for ULBP
   
   If ULBP is formed then convert
   
   Otherwise retain the NULBP window

3. Repeat step 2 on entire image in an overlapped manner.

Results and Discussion

The present paper tested the efficacy of the proposed DTNR-ULBP on FG-NET facial image for age classification. The DTNR-ULBP model classified the human age into four groups i.e. child(1-15), young (15-30), middle age (30-60) and senior persons(>60). The present paper classified age groups without adding any noise and also by adding impulsive noise on FG-NET facial database images. To
classify human age into four groups the DTNR-ULBP used Naïve Bayes, Liblinear (SVM), Multilayer perceptron (neural network using back propagation), Ibk (Knn based) and J48 (Decision based) classifiers.

The Naïve Bayes classifier [21] works on a simple, but comparatively intuitive concept. Also, in some cases it is also seen that Naïve Bayes outperforms many other comparatively complex algorithms. It makes use of the variables contained in the data sample, by observing them individually, independent of each other. Support Vector Machines [20] are supervised learning methods used for classification, as well as regression. The advantage of Support Vector Machines is that they can make use of certain kernels in order to transform the problem.

A multilayer perceptron (MLP) [22] is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a direct graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network [21, 22]. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable [23, 24].

A decision tree is a predictive machine-learning model that decides the target value (dependent variable) of a new sample based on various attribute values of the available data. The internal nodes of a decision tree denote the different attributes; the branches between the nodes tell us the possible values that these attributes can have in the observed samples, while the terminal nodes tell us the final value (classification) of the dependent variable.

Ibk algorithm implements the k-nearest neighbor algorithm. Nearest neighbor” learning is also known as "Instance based" learning. K-Nearest Neighbors, or KNN, is a family of simple: Classification and regression algorithms based on Similarity (Distance) calculation between instances. Nearest Neighbor implements rote learning. It's based on a local average calculation. It's a smoother algorithm. Some experts have written that k-nearest neighbours do the best about one third of the time. It's simple for the classification purpose.

The Table 1 and 2 shows age classification on FG-NET facial images based on ULBP and proposed DTNR-ULBP using the above five classifiers without noise and with introducing impulsive noise. The threshold considered for this is 3. The results clearly indicate a high classification rate for DTNR-ULBP when compared to the ULBP. To compare the performance rates of the five classifiers a graph is plotted for the proposed DTNR-ULBP based on the average age classification rate, and it is displayed in the Fig.4. The Liblinear ad Multilayer perceptron classifiers are showing a high classification rate when compared to other classifiers. The ULBP has shown a significant variation in age classification between noisy and non-noisy facial images. This is because a small noise transforms a ULBP window into NULBP and thus it degrades the overall performance. The proposed DTNR-ULBP overcomes this by identifying the floating windows based the threshold. The proposed method is dynamic because it only complements one or more floating bits from LSB to transform the NULBP window into ULBP instead of all floating bits. Thus the LBP code variation is minimal in the proposed DTNR-ULBP.

<table>
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<th>Method</th>
<th>ULBP</th>
<th>DTNR-ULBP</th>
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</thead>
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LBP may be transformed into ULBP. M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen, “Face recognition using prominent LBP model,” International journal of applied engineering research (IJGSP), vol.6, No.1, pp.9-17, Nov-2013, ISSN: 2074-9082.


**Figure 4**: Comparison graph with and without noise.

Conclusion
The present paper proposed DTNR-ULBP to overcome the noise related problems in estimating ULBP. A NULBP is treated as noisy pattern and that’s why they are not usually considered for classification and other related applications. However many researchers in the literature made use of NULBP and showed the improved performance. The main reason for this is, due to noise there is a greater chance of transformation of a ULBP into NULBP window. The present paper mainly addresses this problem. In the same way a NULBP may be transformed into ULBP due to noise. We strongly believe that, this transformation does not affect the performance. The novelty of the DTNR-ULBP is, it complements the floating bits from LSB and verifies after each conversion whether the window is transformed into ULBP. Thus DTNR-ULBP minimizes the LBP code variation. The results indicate the improved performance of the DTNR-ULBP over ULBP.

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