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Noise-Resistant Local Binary Pattern with an Embedded Error-Correction Mechanism

PODILA MOUNIKA 1*,S. BHARGAVI LATHA2 *

1. M.tech,Dept of CSE Gokaraju Rangaraju Institute of Engineering and Technology.

2.Asst.Prof,Head-Dept of CSE, Gokaraju Rangaraju Institute of Engineering and Technology.

Abstract— Local binary pattern (LBP) is sensitive to noise. Lo- cal ternary pattern (LTP) partially solves this problem. However, both LBP and LTP treat the corrupted image patterns as they are. In view of this, we propose a noise-resistant LBP (NRLBP) to preserve the image local structures in presence of noise. The small pixel difference is vulnerable to noise. Thus, we encode it as an uncertain state first, and then determine its value based on the other bits of the LBP code. It is widely accepted that most image local structures are represented by uniform codes and Noise patterns most likely fall into non-uniform codes. Therefore, we assign the value of uncertain bit so as to form possible uniform codes. In such a way, we develop an error-correction mechanism to recover the distorted image patterns. In addition, we find that some image patterns such as lines are not captured in uniform codes. Those line patterns may appear less frequently than uniform codes, but they represent a set of important local primitives for pattern recognition. Thus, we propose an extended noise-resistant LBP (ENRLBP) to capture line patterns. The proposed NRLBP and ENRLBP are more resistant to noise compared with LBP, LTP and many other variants. On various applications, the proposed NRLBP and ENRLBP demonstrate superior performance to LBP/LTP variants.

I. INTRODUCTION

LOCAL binary pattern (LBP) operator transforms an image into an array or image of integer labels describing micro-pattern, i.e. pattern formed by a pixel and its immediate neighbors . More specifically, LBP encodes the signs of the pixel differences between a pixel and its neighbouring pixels to a binary code. The histogram of such codes in an image block is commonly used for further analysis. It has been widely used in texture classification, dynamic texture recognition facial analysis, human detection and many other tasks. Its popularity arises from the following advantages. Firstly, 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. Secondly, 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.

Although LBP has gained much popularity because of its simplicity and robustness to illumination variations, its sensitivity to noise limits its performance . In, uniform LBP was proposed to reduce the noise in LBP histogram. The LBP codes are defined as uniform patterns if they have at most two circularly bitwise transitions from 0 to 1 or vice versa, and non-uniform patterns if otherwise. 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.Most LBPs in natural images are uniform patterns .

Thus, uniform patterns are statistically more significant, and their occurrence probabilities can be more reliably estimated. In contrast, non-uniform patterns are statistically insignificant, and hence noise-prone and unreliable. By grouping the non-uniform patterns into one label, the noise in non-uniform patterns is suppressed. The number of patterns is reduced significantly at the same time. In , information in non-uniform patterns is extracted and also used for classification. LBP patterns that consider the most frequently occurred patterns in a texture image . Zhou et al. and Fathi et al.proposed to extract information from non-uniform patterns based on pattern uniformity measure and the number of ones in the LBP codes. Principal Component Analysis] and random subspace approach were utilized to extract information from the whole LBP histogram including both uniform patterns and non-uniform patterns. These approaches extract some useful information from non-uniform codes. However, they tend to be sensitive to noise. "Soft histogram" is another approach to improve the robustness to noise, e.g. a fuzzy LBP (FLBP) using piecewise linear fuzzy membership function and another using Gaussian-like membership function. A comprehensive comparison between LBP and fuzzy LBP in classifying and segmenting textures is given in . Instead of hard-coding the pixel difference, a probability measure is utilized to represent its likelihood as 0 or 1. However, the probability is closely related to the magnitude of the pixel difference. Thus, it is still sensitive to noise. Local ternary pattern (LTP) was proposed in to tackle the image noise in uniform regions. Instead of binary code, the pixel difference is encoded as a 3-valued code according to a threshold t . Then, the ternary code is split into a positive LBP and a negative LBP in order to reduce the dimensionality. LTP was shown less sensitive to noise, especially in uniform regions. Subsequently, many LTP variants were proposed.the SLSM is target-oriented and supervised by the knowledge of the specific targets in tracking application. Boosting approach is used for online construction of the target appearance model due to its strong ability in distinguishing the target from its background. Then the learned target model is incorporated to model the level set contour probabilities by a Bayesian manner, leading the curve converge to the candidate region with maximum likelihood of being the tracked target. Finally, samples extracted from accurate target region are fed back to the boosting procedure for target appearance update. We use the positive decrease rate to adjust the target learning pace over time, which enables tracking to continue under partial and total occlusion. In this paper, we firstly describe the proposed mechanise of 2-phase SLSM for single target tracking, whose preliminary results were also presented in the early conference paper Then we novelly propose the generalized multi-phase SLSM for dealing with multi-target tracking cases. Fig.1(b-g) shows some tracking examples of our method in various challenging cases..

II. NOISE RESISTANT LBP

Local binary pattern encodes the pixel difference zp= ip−ic between the neighboring pixel ip and the central pixel Ic.Let denote the LBP code of P neighbors at the distance of R to the center pixel. A code is also called a pattern. Let LBP P,R denote such a coding scheme for Each bit is obtained as: bB p=1 if z p ≥ 0, 0 if z p < 0 (1) LBP is widely used in many applications because of its simplicity and robustness to illumination variations. How ever, LBP is sensitive to image noise. In, uniform LBP was proposed to capture fundamental image structures and reduce the noise in LBP histogram. The uniformity U is defined as the number of circularly bitwise transitions from 0 to 1 or vice versa. A local binary pattern is u2 uniform or simply called uniform if U ≤ 2. For example, “11110000” is a uniform pattern as U = 2 , whereas "01010111" is a non-uniform pattern as U = 6 . LBP u 2 P,R indicates a coding and histogram mapping scheme in which u2 uniform LBP codes of P neighbors at the distance of R to the center pixel are utilized. Uniform patterns occur much more frequently than non-uniform patterns in natural images.It has been shown that LBPu28,1accounts for almost 90% of all patterns for texture images and LBP u 2 8,2 accounts for 90.6% for facial images. The occurrence probabilities

of non-uniform patterns are so small that they cannot be reliably estimated. Inclusion of such noisy estimates in the histogram would harm the classification performance. In addition, non-uniform patterns may be caused by the image noise. Therefore, when constructing the histogram, all non uniform patterns are grouped into one bin. This not only reduces feature dimensionality, but more importantly, the noise due to unreliable estimates of non-uniform patterns is greatly suppressed. The number of patterns is reduced significantly from 2P to P(P−1) + 3 . For example, LBP 8 , 2 consists of 256 patterns whereas LBP u 28, 2 has only 59 patterns. Uniform LBP successfully reduces the noise in LBP his- togram, but it is still sensitive to image noise. As a small noise will cause the pixel difference encoded differently. Ideally such a smooth region should be encoded as "11111111". Due to the image noise, it is encoded as "01010111" instead. LTP partially solves this problem by encoding the small pixel difference into a third state .

Algorithm 1 Histogram construction of the proposed NRLBP

for Every pixel in a patch **do**
  1. Derive the *uncertain* code $C(\mathbf{X})$ as in Eqn. (5), (6).
  3. Search *uncertain* bits $\mathbf{X}$ in the space $\{0,1\}^n$ so that $C(\mathbf{X})$ forms uniform LBP codes as in Eqn. (7).
  4. Construct the histogram.
  if $m = 0$ **then**
    Accumulate the non-uniform bin with 1.
  else
    Accumulate the bin of each pattern in S_{NRLBP} with $1/m$.
  end if
end for

III. EXPERIMENTAL RESULTS

We conduct comprehensive experiments to validate the advantages of the proposed NRLBP and ENRLBP. Table I summarizes the approaches compared with, the classifiers used and the applications tested on. The proposed approaches are compared with uniform LBP and uniform LTP. E.g.

for face recognition, LBP u28,2 and LT P u28 , 2 are used. Let N RLBP P,R , EN RLBP P,R denote the coding schemes for NRLBP and ENRLBP using P neighbors at the distance of R to the center pixel, respectively. The number of features for each patch is 59 for LBP u28 , 2, 118 for LT Pu28, 2 , 59 for N RLBP 8= , 2 and 107 for EN RLBP 8 2. Dominant LBP (DLBP), novel extended LBP (NELBP) and noise tolerant LBP (NTLBP) are compared as they extract information from non-uniform bins, similarly as our approaches do. We choose the dominant patterns that account for 80% of the total pattern occurrences, same as in . Fuzzy LBP (FLBP) is also compared. We implement fuzzy LBP using piece-wise linear fuzzy membership function

A. Face Recognition on the AR Database

For face recognition, we adopt a challenging experimental setting. Only one image per subject is used as the gallery (or training) set and all others are used as the probe set. In many real applications, we are not able to obtain multiple images per subject and we may have only one image per subject. On the AR database, the proposed approaches are compared with LBP/LTP variants on images injected with noise in order to demonstrate their noise-resistant property. The A R database is of high resolution and high image quality, and considered as a face database with almost no image noise. 75 subjects are chosen from the AR database, each with 14 images. For each subject, it contains images from 2 section. Each section contains 7 images: one neutral image, 3 images with different facial expressions and 3 images in different illumination conditions. We repeat experiments 6 times. For each trial, we use Image 1, 5, 6, 8, 12, 13 of each subject as the gallery set, respectively. The other 13 images of each subject are used as the probe set. It is a challenging experimental setting as face images with facial expression variations need to be identified just based on a single face image.

B. Texture Recognition on Outex-13 dataset

Outex-13 dataset consists of 68 classes of textures, each with 20 images. To test the noise-resistant property of the proposed approaches on the applications other than face recognition, we inject Gaussian noise and uniform noise of different noise levels onto the images of Outex-13 dataset, e.g. Gaussian noise of σ = 0. 05 and uniform noise Preprocessing in is useful to reduce noise. Thus, the noisy images are preprocessed in the same way as in. Sample images and preprocessed images are shown in the first and second row, respectively. We randomly choose 10 images from each class for training and the rest for testing. The proposed approaches are compared with 6 LBP/LTP variants. We extract features using 8 neighbors at the radius of one. Linear SVM is used as the classifier, which is implemented using LIBSVM package . The cost parameter C is chosen as 1. The experiments are repeated 5 times, and only the average performance is reported. summarizes the performance comparison on the Outex-13 dataset injected with Gaussian noise and uniform noise. The proposed NRLBP and ENRLBP consistently achieve comparable or better performance compared with other approaches.

C. Face Recognition on the Extended Yale B Database

The extended Yale B database contains 38 subjects under 9 poses and 64 illumination conditions. We follow the same database partition as in . The images with most neutral light source("A+000E+00") are used as the gallery images and all other frontal images are used as the probe images (in total 2414 images of 38 subjects). This dataset contains large illumination variations. The sample images are shown in the first row. Some images are taken under extreme lighting conditions. Even after photometric normalization, as shown in the second row, a large amount of image noise exist in the images. The proposed approaches are compared with 6 LBP/LTP variants using nearest-neighbor classifier with Chi-square distance, histogram intersection and modified G-statistic.

D. Face Recognition on the O2FN Mobile Database

The O2FN mobile face database is our in-house face database. It is designed to evaluate the face recognition algorithms on mobile face images, which are of low resolution and low image quality, and significantly corrupted by the noise. It contains 2000 face images of size 144 ×176 pixels from 50subjects. The images are self-taken by the users. The users are told to take roughly 20 indoor images and 20 outdoor images with minimum facial expression variations and out- plane rotations. Thus, the O2FN database mainly contains in-plane rotations and illumination variations. some samples of geometrically normalized and photometrically normalized images. The images are captured by O2 XDA frontal camera with native phone settings and without post processing. The images are severely distorted by the noise, e.g.

Gaussian noise, Salt & Pepper noise and motion blur. To reduce the noise and illumination variations, the images are photometric normalized as in . Even after the photometric normalization.

IV.CONCLUSION

LBP is sensitive to noise. Even a small noise may change the LBP pattern significantly. LTP partially solves this problem by encoding the small pixel differences into the same state. However, both LBP and LTP treat the corrupted patterns as they are, and lack a mechanism to recover the underlining image local structures. As the small pixel difference is most vulnerable to noise, we encode it as uncertain bit first, and then determine its value based on the other bits of the LBP code to form a code of image local structure. Uniform patterns represent local image primitives, and appear more frequently than non uniform patterns in natural images. In contrast, non-uniform patterns are less reliable, thus are more error-prone. Therefore, we assign the values of uncertain bits so as to form all possible uniform LBP codes. In such a way, we correct noisy non-uniform patterns back to uniform code. For LBP and LTP, a large group of local primitives, i.e. line patterns, are completely ignored. Thus, we propose extended uniform patterns and form those patterns as our ENRLBP patterns when determine uncertain bits. The proposed approaches show stronger noise-resistance compared with other approaches. We inject Gaussian noise and uniform noise of different noise levels on the AR database for face recognition and the Outex-13 dataset for texture recognition. Compared with FLBP, the proposed approaches are much faster and achieve comparable or slightly better performance. They consistently achieve better performance than all other approaches. We further compare the proposed NRLBP and ENRLBP with others for face recognition on the extended Yale B database and the O2FN database, protein cellular classification on the 2D Hela database, as well as image segmentation. The proposed approaches demonstrate superior performance on these applications

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