International Journal of Scientific Research

Listed in International ISSN Directory, Paris

Volume 1 | Issue 1 | June 2012

ISSN No. 2277 – 8179

A Multi-Subject Journal

Journal for All Subjects

ISSN No. 2277 – 8179

International Journal of Scientific Research

Journal for All Subjects

Editor,
INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH
3, SUHANA, Nr. Rubi Apartment, B/H NID, Rajnagar Road,
Paldi – 380007. Ahmedabad-Gujarat. (INDIA)
Contact: +91 98247 02127, +91 88660 03636
Www.theglobaljournals.com | ijsr@theglobaljournals.com

Index

ISSN : 2277 – 8179

June, 2012

Study on Texture Descriptors in Super Resolution

* Kiran .P Patel

Abstract

The local geometry of an image is conveyed by image features such as edges, corners and curves. In this paper, I present study & overview of state-of-the-art Texture Descriptors , namely local binary pattern, uniform local binary pattern, local ternary pattern & noise tolerant local ternary pattern operator. We can encode these features with these operators .A new learning based technique to super-resolve a low resolution image using these Operators and a database of low resolution (LR) images and corresponding high resolution (HR) versions. The missing high resolution features of the low resolution observation are learnt in the form of discrete cosine transform coefficients from high resolution images in the training database.

Keywords : Index terms: Local Binary Pattern Operator , Uniform Local Binary Pattern operator , Local Ternary Pattern operator & Noise Tolerant Ternary Pattern operator

Binary Pattern Operator

Local Binary Pattern (LBP) [3] is an n-bit binary code at a pixel, c, in a gray scale image is generated by Equation (1), which compares c's intensity with that of its n neighbours. These neighbours are located at uniform distances on a circle centered at c with radius r:

$$LBP_{n,r}(x_c,y_c)= \sum^{n-1}_{l=0} q(g_1-g_c)2^l,$$

$$q(a)=\begin{cases} 1 & \text{if } a\geq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where (x_c,y_c) is the pixel co-ordinate of c,g_c, and g_l are the intensities of *c* and the i^{th} neighbouring pixel, respectively.

77	85	29
52	52	38
54	11	68

Threshold →

1	1	0
0	(i,j)	0
0	0	1

Binary code:11001000

(a) The LBP operator

The LBP codes can represent texlets such as edge, corner and line-end. The basic local binary pattern operator, introduced by Ojala et al. [6], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength. In that work, the LBP was proposed as a two-level version of the texture unit to describe the local textural patterns. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholded by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighbourhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighbourhood. It has gained popularity for its computational simplicity and robustness against monotonic changes in illumination. It has already shown its capabilities in several image processing applications such as face detection, face recognition, facial expression detection, moving object detection, finger biometric recognition and many others. However, LBP is very noise sensitive, especially in near uniform regions. Small changes in intensities due to noises in near uniform regions may lead to erroneous LBP codes. Even for small intensity fluctuations, which are very common in digital images, LBP and most of its variants fail to generate the same code for the same type of texture structures. Keeping this in mind, Tan and Triggs proposed Local Ternary Pattern (LTP) [14], which uses three-value encoding and shows tolerance to noise up to a certain level as they assume noises in an image usually vary within a fixed threshold (±5).

Local structural variations of an image are reflected by image features in the form of edges, corners, junctions and curves. The next step in the algorithm is to model these image features with the help of local binary pattern (LBP) operator.LBP was originally proposed for texture classification by Ojalaet al. [7]. The original LBP operator and its variants were then employed for various applications such as face recognition [21], object detection [23], license plate recognition [28] and smoke detection [22]. It is an effective descriptor to capture local structural variations. LBP code of a pixel is obtained by comparing its intensity with that of the neighboring pixels.

B. Uniform Local Binary Pattern Operator

An LBP is defined as uniform local binary pattern (ULBP) if there are at most two bit transitions in its binary equivalent.

$$U(LBP_{n,r}(x_c,y_c)) = |q(g_{n-1}-g_c) - q(g_0-g_c)| + \sum_{l=0}^{n-1} |q(g_l-g_c) - q(g_{l-1}-g_c)| \qquad (2)$$

For example, 11100011 is a uniform pattern, while 11101011 is not. When uniformity is taken into consideration, all the non-uniform patterns are accumulated in a single bin during histogram formation.

* Master of Engineering, L.D. College of Engineering, Ahmedabad

C. **Local Binary Pattern Operator**

Local Ternary Pattern (LTP) [14] mainly follows the same spirit of Local Binary Pattern(LBP). The key difference is that it introduces a new bit to manage the intensity fluctuations. Thus, LTP becomes a ternary code at a pixel c, which is generated by Equation (1): The LocalTeinary Pattern (LTP)[6] at a point c is defined by:

$$LTP_{n,r}(x_c,y_c) = \sum_{l=0}^{n-1} h(g_l - g_c)3^l$$

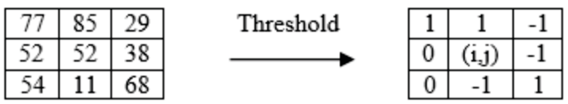
$$h(u,i) = \begin{cases} -1, & (u-i) < -t \\ 1, & (u-i) > t \\ 0, & \text{else} \end{cases} \quad (3)$$

We create a ternary pattern instead of a binary pattern where a 1 is stored if the neighboring pixel is greater than the center pixel, a −1 is stored if it is less and 0 is stored if they are almost the same. Sameness is defined w.r.t. to a threshold t Then, the LTP vector is the vector of these ternary values over a given neighborhood (fig.1(b)). Thus, the ith bit of the LTP

vector for the point c is given by:

$LTP_C(i)=z(I_{ki,}I_c)$ (4)

Where ki is the ith neighborhood point for c.



Ternary code:11-1-11-100

(b) LTP operator

Tan and Triggs[1] create ternary patterns in the above way but while matching, they split the pattern into two binary codes, combining −1 with 0 (termed as Up LTP code(fig.2(c(1))))and 1 with 0(termed as Down LTP codefig.2(c(2))) in the two binary patterns (Fig. 2 ©).

.However, as mentioned in the introduction, the method is susceptible to small Gaussian noise or intensity changes in homogenous regions.An adaptive noise band (ANB) can be defined to approximate the amount of noise contamination around a pixel up to a certain extent. Based on this ANB,we generate reliable codes named noise tolerant ternary pattern (NTTP) to represent the textures in an image.[19]

D. Adaptive Noise Band

An adaptive noise band[10] defines the maximum possible extent of noise that can be contaminated with the observed intensity, i, of a pixel, and can be approximated by the square root of that intensity. When the difference between two neighboring pixel values is within the ANB, we consider that the difference is due to noise. In some pixels, the ANB may results in inclusion of orignial texture patterns into the noise band. However, this may not casuse much harm to the classification; rather this helps to distinguish prominent and less prominent patterns, which results in improved classification.the noise characteristics do not remain same for different intensity region. For low intensity region (R1), the dominant noises are independent of signal and remain constant. Another point here is that this PTC curve is calculated in the sensor domain (light space), but our focus is to deal with noises in the given image (image space). This problem is addressed by Faraji et al. in [17], where it is shown that this constant behavior is also observed in the image space. Since the gray levels at this region are low, the noises are usually higher than the square root of the observed intensity. We, therefore, slightly modify the ANB at intensity I as:

$$ANB_i = \begin{cases} \pm\tau \text{ if } i < R \\ \pm\sqrt{i} \text{ otherwise} \end{cases} \quad (5)$$

where R is the boundary point separating the low-intensity region in image space that corresponds to the R1 region in Figure 2, and is a constant to be set empirically. The value of R can be found in different ways. According to the method in [17], the value of R can be picked from the plot of intensity vs. noise standard deviation.

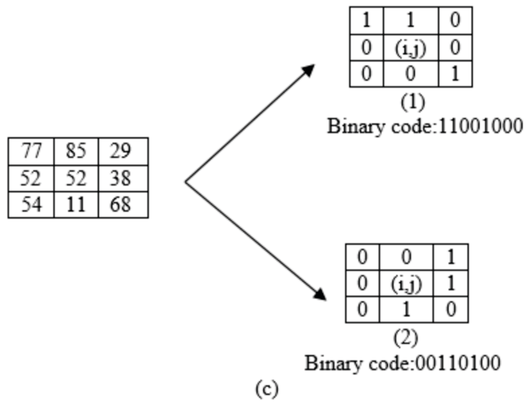
E. Noise Tolerant Ternary Pattern Texture Descriptor

The proposed NTTP[10] uses the aforementioned ANB to encode the texture pattern for a given pixel, where the NTTP code at a pixel *c*, coordinated at (x_c, y_c) is generated by comparing its intensity g_c with its neighbors according to Equation

$$NTTP_{n,r}(x_c,y_c) = \sum_{l=0}^{n-1} h(g_l - g_c)3^l$$

$$h(u,i) = \begin{cases} -1, & (u-i) < -ANB \\ 1, & (u-i) > ANB \\ 0, & else \end{cases} \quad \mathbf{(6)}$$

the remaing part is as LTP.



(c) The Tan and Triggs[14] LTP operator.

C. Searching similar features

F. Impementing Textures discriptors

Using appropriate algorithm , the algorithm searches the training database to find LR training images with similar features to that of the test image. For this we can divide the encoded test image using these pattern operarors and LR training images into 8×8 image patches. We compare 8×8 = 64 pixels in each patch of the test image with the corresponding image patches of all the LR training images in the database and select the LR training image with maximum number of matching pixels in the patch under consideration as the best match for that patch. This indicates that there are maximum matching features such as edges, corners and curves in the patch of the test image and the best matching image patch of the LR training image. Thus we have a matching LR training image with similar features corresponding to all the 8×8 image patches of the test image.

Let P_T (x; y) and P_{LRp}(x; y), 1≤ (x; y)≤ 8 be the image patches of the test image and pth LR training image respectively. We search the best matching patch from the database by maximizing,

$$\hat{c} = \text{argmax} \sum_{x,y=1}^{8} d(x,y) \quad (7)$$

with respect to c, where c is the index of the training image pair in the database and ĉ is the index of the best matching training image. Here, d(x; y) is the distance measure defined as,

$$f(x,y) = \begin{cases} 1, & if\ P_T(x,y) = P_{LRm}(x,y) \\ 0, & otherwise \end{cases} \quad (8)$$

I apply this procedure to each image patch in the test image and find best matching LR training image for the corresponding patch.

IV. Conclusion

I have presented a study & overview on various texture descriptors , namely local binary pattern, uniform local binary pattern, local ternary pattern & noise tolerant local ternary pattern operator to super-resolve an image using single observation. Image features are recovered by representing them with these pattern operators that encodes the local structural variations into corresponding codes. It is understood that NTTP gives best results , then comes LTP , then Uniform LBP & LBP is least advisable in these four texture descriptors

References

[1] Jing Tian and Kai-Kuang Ma , 'A survey on super-resolution imaging ,signal ,Image and Video processing' ,(5)(3) (2010) 329-342.|[2] S.C.Park,M.K.Park and M.G.Kang , 'Super-Resolution Image Rcognition: A Technical Overview' , IEEE Signal Processing Magazine,(20)(3)(2003) 21-36.|[3]S.Borman and R.L. Stevension, 'Spatial Resolution Enhancement of Low- Resolution Image Sequences:A Comprehensive Review with Directions for Future Research,Technical Report', University of Notre Dame,1998.|[4]Z.Wang and A.C.Bovik and H.R.Sheikh and E.P.Simoncelli 'Image quality assessment : From error visibility to structural similarity',IEEE Transaction on Image Processing,(13) (4)(2004) 600-11|[5] Z.Wang and A.C.Bovik,' Mean squared error: love it or leave it ?',IEEE Signal Processing Magazine, (2009) 98-117|[6] T. Ojala and M . Pietikainen and T. T. Maenpaa ,' Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local BinaryPatterns', IEEE transactions on pattern analysis and machine intelligence.(24)(7) (2002) 971-987 |[7] Changhyun Kim, Kyuha Choi, Ho-young Lee, Kyuyoung Hwang and Jong Beom Ra, 'Robust learning-based super-resolution', IEEE International Conference on Image Processing (ICIP), (2010) 2017 - 2020|[8] W. T. Freeman and T. R. Jones and E. C. Pasztor', Example based superresolution' ,IEEE Computer Graphics and Applications. (22)(2) (2002)56 – 65.| [9].S. Rajaram and M. D. Gupta and N. Petrovic and T. S. Huang, 'Learning based nonparametric image super resolution', EURASIP Journal of Appllied Signal Processing. (2006)(2) (2006) 1 – 11.| [10]T. A. Stephenson and T. Chen, 'Adaptive markov random fields for example-based super-resolution of faces', EURASIP Journal of Appllied Signal Processing. (2006)(2) (2006) 1-11.|[11]C. V. Jiji and M. V. Joshi and S. Chaudhuri, 'Single-frame image superresolution using learned wavelet coefficients', International Journal of Imaging Systems and Technology. (14)(3) (2004) 105-112.|[12] W. T. Freeman and E. C. Pasztor and O. T. Carmichael, 'Learning lowlevel vision', International Journal of Computer Vision.(40) (1) (2000)25-47.|[13] P.V.Pithadia,P.P.Gajjar ,J.G.Dave 'Super Resolution using DCT based Learning with LBP as Feature Model'.IEEE International conference on Computing, Communication & Networking Technologies(ICCC NT 2012).|[14] X.Tan and B.Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," in IEEE InternationalWorkshop on Analysis and Modeling of Faces and Gestures, 2007, pp.168–182.|[15]Saeed Dabbaghchian, Masoumeh P. Ghaemmaghami and Ali Aghagolzadeh,' Feature extraction using discrete cosine transform and discrimination power analysis with a face recognition technology', Pattern Recognition, (43)(4) (2010) 14311440.| [16] Nuno Roma and Leonel Sousa, A tutorial overview on the properties of the discrete cosine transform for encoded image and video processing, Signal Processing, (91)(11) (2011) 24432464.|[17] P. P. Gajjar and M. V. Joshi, 'New Learning based Super-Resolution: Use of DWT and IGMRF Prior', IEEE Transactions on Image Processing. (19)(5) (2010) 1201-1213|[18] Z. Lin, J. He, X. Tang, and C. K. Tang,' Limits of learning-based superresolution algorithms', in Proc. of IEEE Int. Conf. Comput. Vis., (2007) 1-8. [19]Mohammad Shoyaib 1, M. Abdullah-Al-Wadud 2 and Oksam Chae 1A Noise-Aware Coding Scheme for Texture Classification Sensors 2011, 11, 8028-8044; doi:10.3390/s110808028

Sara Publishing Academy
INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH
Journal for All Subjects

Editor,
INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH
3, SUHANA, Nr. Rubi Apartment, B/H NID, Rajnagar Road,
Paldi – 380007. Ahmedabad-Gujarat. (INDIA)
Contact: +91 98247 02127, +91 88660 03636
Www.theglobaljournals.com | ijsr@theglobaljournals.com

Printed at Unique Offset, Novatsing Rupam Estate, Opp. Abhay Estate, Tavdipura, Shahibaug, Ahmedabad