SEGMENTATION OF NOISY IMAGES USING AUTOMATIC UNIFORM LOCAL BINARY PATTERN APPROACH

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ABSTRACT
The process of dividing an image into different segments based on local attributes attained more significance in these days. One of the problems in measuring the local attributes is a small fluctuation or noise may change these attributers drastically. The noisy regions are the major factor that influences the segmentation approaches. These factors confuse or create ambiguity for an efficient segmentation. The noise in images may convert the fundamental local unit information of texture i.e. uniform LBP (ULBP) into non-uniform LBP (NNULBP) and this degrades drastically the overall segmentation process. To address this, the present paper proposes an automatic conversion of noisy-NULBP's into ULBP based on a threshold and conversion factor. To fill the small holes for better visualization and to enhance the contrast of the overall segmentation process a morphological treatment is given in this paper. The proposed approach is compared with the segmentation methods based on ULBP's.

Key words: Local attributes; ULBP; NULBP, noisy local regions;

1. Introduction

Segmentation of an image is a difficult problem because it is difficult to predict and know *a priori*, what types of textures exist in an image, what regions have which textures and how many textures there are. Segmentation is extensively used in image processing. For example, medical image processing, object-based video coding, and surveillance system require precise segmentation results to improve their performance considerably. Image segmentation can be broadly divided into three categories: edge-based segmentation, region-based segmentation and pixel-based segmentation. Segmentation methods also classified in to supervised or unsupervised. Edge-based segmentation or contour detection or edge detection, can find the boundary of an object based on sudden variations in the grey level or color information [1, 2]. Recently advanced edge-based segmentation methods [3, 4] are proposed in the literature. Hierarchical segmentation techniques based on graph- or MS-based approaches are also proposed in the literature and they successively adopted fine-to-coarse pixel aggregation for improving segmentation quality [4, 5]. The only disadvantage of these methods is they entail tremendous computational complexity. The histogram-based methods are simple, efficient, reduce the computational complexity and they are basically pixel-based approaches and that's why they are adopted to segmentation process [7,8]. One of the famous histogram-based methods is Otsu's method [6].The LBP or grey-scale difference operator with statistical measures shown higher performance rates than the existing methods [9]. The LBP, ULBP and other variants of LBP drastically suffers with small noise. The present paper addresses this by transforming the noisy NULBPs into ULBPS.

The present paper is organized as follows. The section 2 describes the related work and the section 3 and 4 describes the methodology and segmentation metrics used respectively. The section 5 and 6 describes the results - discussions and conclusions respectively.

2. DERIVATION OF LBP

A texture primitive is a contiguous set of neighboring pixels with some tonal and/or regional property. The primitives can be described by the average intensity, texture units, maximum or minimum intensity, Local direction patterns (LDP), shape, size, LBP codes, etc. Texture primitive is important in many applications of image processing such as segmentation classification, analysis and synthesis. A successful segmentation, classification or analysis requires an efficient description of image texture. Textures can be efficiently described by its primitives. A texture is not only characterized by the grey level value of a pixel it is mainly influenced by the local information of the pixel surroundings. The LBP is formed based on this. The LBP is one of the significant primitives of texture and it is widely studied recently in age classification [12], face recognition [13], texture classification [14], segmentation [15] etc. and it obtained a good results.

The neighboring pixels of a 3 x 3 window are denoted in the present paper as $\{n_c, n_0, n_1 \ldots n_7\}$, where $n_c$andn_0, $n_1 \ldots n_7$ represents the intensity values of the central and neighboring pixel and $n_i (0 \le i \le 7)$. The LBP categorizes the neighboring pixels in to binary values based on the equation (1)

$$b_i = \begin{cases} 0 & \Delta p_i \ge 0 \\ 1 & \Delta p_i < 0 \end{cases} \tag{1}$$

where $\Delta p_i = n_i - n_c$.

For each 3×3 neighborhood, a unique LBP code is derived from the equation (2)

$$LBP_{P,R} = \sum_{i=0}^{i=7} b_i \times 2^i \tag{2}$$

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 results the LBP code. This LBP code replaces the central pixel. By repeating this on entire image in overlapped manner the image is converted in to a LBP coded image. Thus a single LBP code represents local micro texture information around a pixel by a single integer code LBP. The process of formation of LBP code is shown in the Figure1. The transformation process of LBP code is also shown in the Figure2.

$$\begin{array}{|c|c|c|}\hline n_0 & n_1 & n_2 \\ \hline n_7 & n_c & n_3 \\ \hline n_6 & n_5 & n_4 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline b_0 & b_1 & b_2 \\ \hline b_7 & & b_3 \\ \hline b_6 & b_5 & b_4 \\ \hline \end{array} \times \begin{array}{|c|c|c|}\hline 2^0 & 2^1 & 2^2 \\ \hline 2^7 & & 2^3 \\ \hline 2^6 & 2^5 & 2^4 \\ \hline \end{array} \longrightarrow \text{LBP code}$$

Figure 1: Representation of LBP.

$$\begin{array}{|c|c|c|}\hline 240 & 250 & 199 \\ \hline 100 & 220 & 220 \\ \hline 260 & 194 & 200 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline 1 & 1 & 0 \\ \hline 0 & & 1 \\ \hline 1 & 0 & 0 \\ \hline \end{array} \rightarrow \begin{array}{|c|c|c|}\hline 2^0 & 2^1 & 2^2 \\ \hline 2^7 & & 2^3 \\ \hline 2^6 & 2^5 & 2^4 \\ \hline \end{array} \rightarrow 75$$

(a)The 3x3 neighborhood of the image | (b) Binary neighborhood | (c) Corresponding weights | (d)LBP Code

Figure 2: The process of LBP code generation.

2.1 Morphological Treatment

Mathematical morphology (MM) provides an efficient framework for analyzing object shape characteristics due to its geometry oriented nature. MM provides object shape characteristics like connectivity and size that are not easily accessed by linear approaches. The basic step in morphology is to compare the objects which are to be analyzed with an object of known shape, termed structuring element. Morphology provides an approach to digital image processing based on geometrical shape.

Two basic morphological operations; erosion and dilation are based on Minkowski operations as given in equation (3) and (4). Dilation in general makes objects to grow or dilate in size. Erosion makes objects to shrink. The amount and the way that they expand or shrink depend upon the selection of the structuring element.

$$X \ominus B = \bigcap_{y \in B} X_y \qquad (3)$$

$$X \oplus B = \bigcup_{y \in B} X_y \qquad (4)$$

Where:

$$X_y = \{ x + y \,:\, x \in X \} \qquad (5)$$

$$\hat{B} = \{ b \,:\, -b \in B \} \qquad (6)$$

B and $\hat{B}$ are Structuring elements

Another important pair of morphological operations are closing and opening. They are defined in terms of dilation and erosion, by equations (7) and (8) respectively

$$X \bullet B = (X \oplus B) \ominus B \qquad (7)$$

$$X \circ B = (X \ominus B) \oplus B \qquad (8)$$

The dilation followed by erosion is called closing. The morphological dilation of an image expands the object and fills small gaps. By eroding this image will retain their structure and form, without any change, but tiny holes filled by dilation will disappear. Images merged by the dilation will not be separated again. The image will be smoothed by Closing. This smoothening usually mingles thin breaks and long thin gulfs. This removes or eliminates minute holes, and fills gaps in the contour. This retains the uniformity of a local region. Opening is nothing but erosion followed by dilation. Opening generally smoothens the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions. Opening operation decreases the size of bright, small details with no prominent effect on the darker gray levels.

3. PROPOSED SEGMENTATION APPROACH FOR NOISY IMAGES BASED ON LOCAL ATTRIBUTES

The ULBPs derived from LBP's have become popular and widely used in many computer vision and image processing applications because ULBPs are treated as the fundamental unit of the texture image. The only problem with ULBP is a small noise may predict local primitives differently and it may transform it in to NULBP. The reason for this is the threshold in LBP is based on the intensity levels around center pixel of the window. To overcome this present paper derived a novel scheme that automatically converts the noisy NULBP's in to ULBPS based on a threshold and conversion factor. Once this step is performed accurately then noise will be completely eliminated. Then the remaining steps of segmentation are not affected. The detailed scheme of the proposed method is given in the form of flow chart in Figure3.

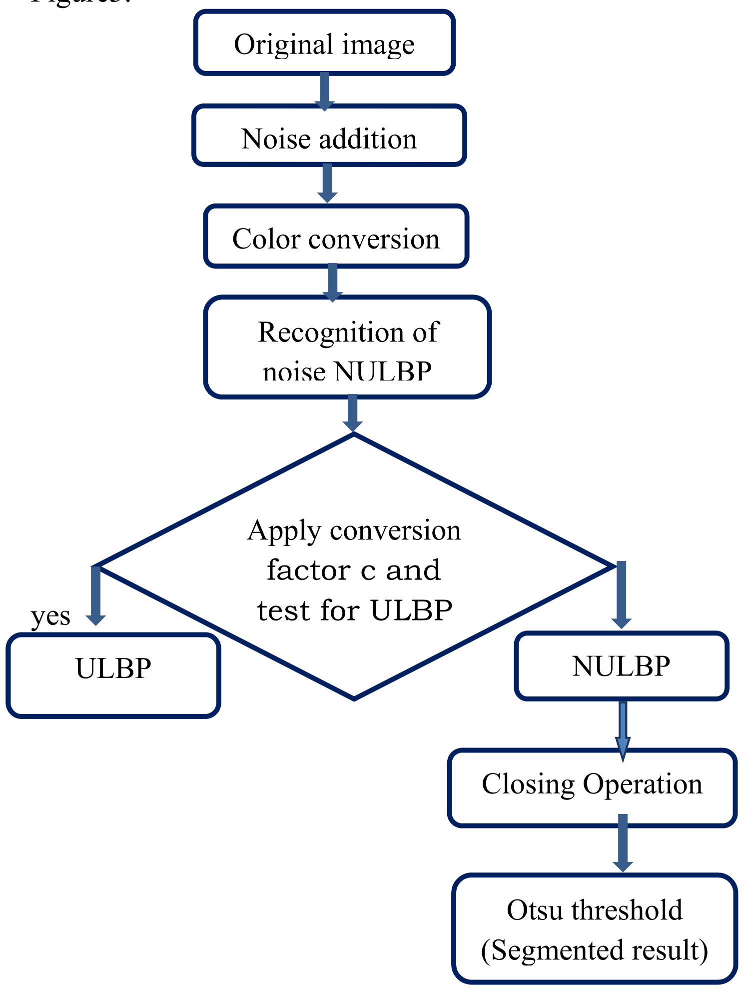


Figure 3: Flow chart of the proposed NNULBP->ULBP segmentation approach.

3.1Automatic Conversion of Noisy-NULBP (NNULBP) into ULBP (NNULBP-> ULBP)

The texture primitive LBP with (8, 1) or (8, 2) derives 2^8= 256 different patterns. Later ULBP are derived on LBP based on the circular transitions from 0 to 1 or 1 to 0. A LBP is called as uniform if it contains a maximum of two transitions from 0 to 1 or 1 to 0 in a circular manner; otherwise they are treated as NULBP's. The uniform patterns are more likely to occur compared with non-uniform patterns in natural images [17, 18]. It is proved in the literature that more than 80% of the texture or human face windows are ULBP's [17, 18]. The major disadvantage of LBP is they are prone to noise and this noise may convert a ULBP into "noisy-non-ULBP (NNULBP)". The reason for this is the LBP and other neighborhood approaches use the sign of pixel differences to compute LBP and its variants and these are vulnerable to noise when they are small. To overcome noise problem in LBP and to measure ULBP's more effectively and precisely the present paper derived a novel scheme called "automatic conversion of NNULBP in to ULBP (NNULBP->ULBP)" based on threshold 't' and conversion **factor 'c'.**

The proposed NNULBP->ULBP method is a two-step method. In the first step it identifies noisy-NULBP (NNULBP). A NULBP window becomes a NNULBP window if the absolute difference of one or more neighboring pixels with central pixel falls within the range of threshold 't' and such neighboring pixels are called as floating pixels as given in equation 9. In the second step NNULBP window may be converted in to a ULBP if it satisfies the limit of conversion factor 'c'. That is if c=k then a maximum of k floating bits can be complemented to convert the NNULBP window in to ULBP. he proposed model transforms one or more floating bits depending on the conversion factor c.

$$|P_n - P_c| \quad <= \qquad (9)$$

Where P_n and P_c are the gray level value of neighboring and central pixel and t is the threshold.

If P_n satisfies the equation 9 then it is treated as a floating pixel. The floating pixels are subject to noise or small fluctuations or variations. The following Figure 4 illustrates the mechanism of automatic conversion of NNULBP->ULBP for t <= 3 with a conversion factor c <= 2.

202	150	203
198	200	199
1	25	75

(a) The 3x3 neighborhood window

1	0	1
0		0
0	0	0

(b) The binary sequence of the LBP with floating pixels (t<=3) shown in red color

Figure4: Recognition of floating bits of NNULB window.

In the above Figure4 (a), the 3x3 window with 8 neighbors i.e. P=8 and R=1 forms a NNULBP because the neighboring pixels n_0, n_2, n_3 and n_7 form the floating pixels for t <= 3. The floating pixels are shown in Figure 4 (b) with red color. This NNULBP window may be transformed in to ULBP window by complementing k number floating pixels (where k <=c) from least significant bit (LSB) so that the LBP code variation is minimum, in our case c=2**.** **T**he above NNULBP window is transformed into ULBP by complementing n_0 floating bit i.e.00000101>00000100. The novel feature of the proposed NNULBP->ULBP model is it complements from LSB of floating bits and verifies for ULBP thus it greatly reduces the LBP code variations between NNULBP and ULBP. The LBP code for NNULBP window is 5 (before conversion) and after conversion the LBP code for ULBP is 4 and the difference of LBP code is minimal. This is the novelty of the proposed method it minimizes the LBP code variation.

4. PERFORMANCE EVALUATION METRICS

The ultimate procedure for assessing the efficacy is subjective evaluation, in which a human visually estimates by comparing the segmentation results for different segmentation approaches. Unsupervised methods does not require ground truth image for matching with the segmentation result. It facilitates the objective testing of various algorithms. In the present study, the segmentation metrics considered are discrepancy, entropy, standard deviation and contrast. Discrepancy is given as

$$Discrepancy = \sum_i^{I_h} \sum_j^{I_w} \left(C_{gl}(i,j) - L(i,j) \right) \quad (10)$$

where $C_{gl}(I, j)$ is the gray level value of pixel $p(I, j)$ on original image and $L(I, j)$ is the gray level value of $p(I, j)$ on the final image. The higher the discrepancy value the better is the segmentation. However very high discrepancy values indicate that there is no relation between original and segmented images.

Entropy of an image is given as

$$Entropy = -\sum_i \sum_j p(i,j) log\big(p(i,j)\big) \quad (11)$$

The value of entropy below *1* is an indication of over segmentation and values above *1.5* is an indication of under segmentation.

Standard deviation of a given vector is expressed as

$$S = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{\frac{1}{2}} \quad (12)$$

Where x_i is the value of vector and $\bar{x}$ is average of all values.

The lower the value of the standard deviation the better is the segmentation.

Internal region contrast is defined as

$$I_j = \frac{1}{S_j}\sum_{s \in R_j} max\{contrast(s,t), t \in W(s) \cap R_j\} \quad (13)$$

Where $W(p)$ is the neighborhood of the p, and contrast(s, t) = $|C_x(s) - C_x(t)|$is the contrast of pixel 's' and 't'. Internal-contrast, I_j, measure the uniformity of each region. $I_j$is defined as the average Max Contrast in that region, where Max Contrast is the largest luminance difference between a pixel and its neighboring pixels in the same region. The low value of internal contrast indicates higher uniformity in the region and hence better segmentation.

5. RESULTS AND DISCUSSIONS

The proposed segmentation approach is tested on four large databases namely WANG [16], Oxford flowers [17], Indian facial expressions [18] and standard images from Google (Lena, Camera man, House, Mandrill, and Ship) [19]. The WANG database consists of 1,000 natural images. The Oxford flower database consists of flowers of 17 categories. The flower images are most suitable for segmentation experiments' because they contain sharp edges with different shapes and different local attributes. In each category there are 80 images. The proposed method is implemented in two modes i.e. mode 1 and mode2. In mode 1 the considered images from the above four databases are the original images (or images without noise). In mode 2 impulse noise of 20% is added in to the data base images. Then the proposed and the existing [21] segmentation approach is applied on the impulse noisy images. The main aim of the present paper is how to deal noise i.e. mode 2.

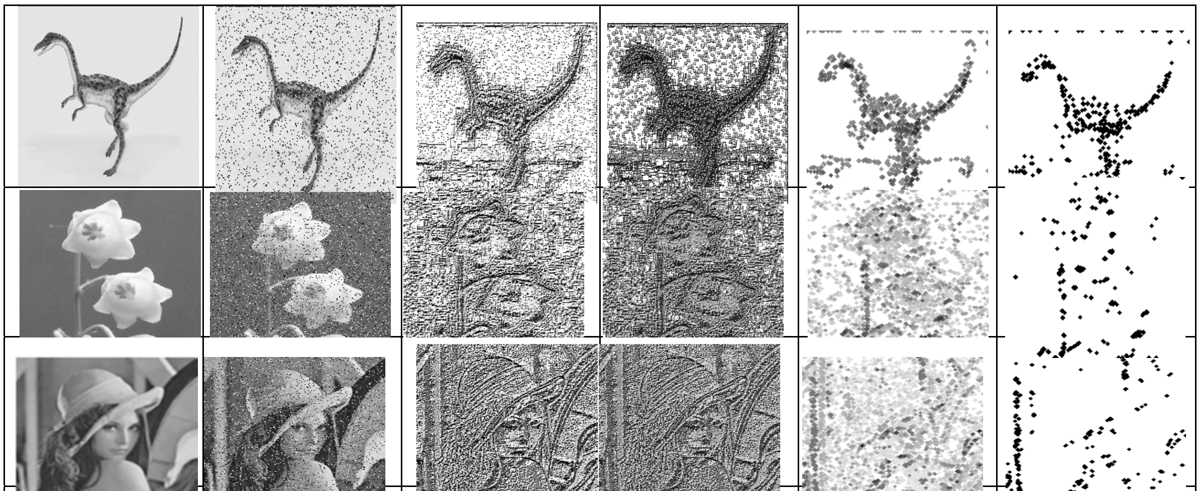
5.1 MODE 1:In mode 1 the proposed method converted approximately 4 to 6 % of NULBPs in to ULBPS and this has led a good segmentation. In mode 1 the present approach and earlier approach [20] has not shown a large variation in the segmented outputs and in the segmented metric values. The proposed approach attained a little bit better results when compared to the existing MULBP method [20]. This is basically due to the images without noise.

5.2 MODE 2: In mode 2 on the original images impulse noise is added. The Figure 5 and 6 shows step wise outputs of the existing MULBP and the proposed NNULBP->ULBP segmentat1ion approach. From the output images of Figure 5 it is clearly evident that the existing MULBP is completely failed in segmenting the noisy images and in most of the cases it has shown partially blanks with white dots. This clearly indicates the deficiency or intolerance of LBP or ULBP in the presence of small noise. The output of Figure 6 of the proposed NNULBP->ULBP approach clearly showed a good segmentation outputs.

The average segmentation metric values of images from the above four databases on mode 1 and mode 2 for the existing and proposed method are plotted in the form of graphs in Figure7, 8, 9 and10 the following are noted down.

1. From Figure5 of the existing MULBP approach, it is clearly evident that though LBP and ULBP operators' are simple, easy to implement , understand, rotationally invariant and out of all describes the local features efficiently in a precise manner but MULBP segmentation approach failed completely in the presence of noise.
2. The very high discrepancy values of the existing MULBP approach in mode 2 clearly indicates a lot variation or no relation among the input and segmented image.
3. The high entropy value of above 2 and 3 indicates over and over segmentation for MULBP in mode 2.

4. The very high standard deviation also indicates a very poor segmentation in mode 2 for the existing MULBP method.
5. The proposed NNULBP->ULBP segmentation approach resulted more or less a value of 1 for entropy, the discrepancy value around 15, standard deviation value around 0.5 to 1.5 and internal contrast around 0.2 to 1.5 for all data base images in both the modes i.e. images with and without noise. The figures (7, 8, 9 and 10) clearly show a little variation of segmented metric values for mode 1 and mode 2 using the present approach. This clearly indicates the present approach reduced the noise effect to great extent.
6. It is observed that there is a large variation between the segmentation metric values of mode 1 and mode 2 for the existing MULBP method. This clearly indicates the noise degrades the overall performance of the MULBP method (Figure 7, 8, 9 and 10).



(a) (b) (c) (d) (e) (f)

Figure 5: (a) The gray scale images (b) Noised image (c) ULBP of noisy images (d) Histogram equalization (e) Closing operation (f) Otsu threshold and final MULBP segmented images.**MODE 2: (For noisy image)**:The step wise performance of the existing MULBP segmentation approach

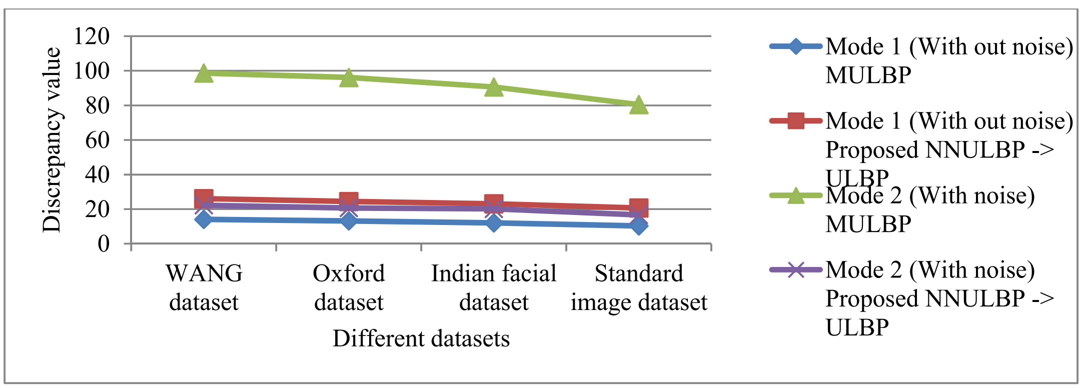


Figure 7: The discrepancy graph for the existing and proposed methods in mode 1 and 2.

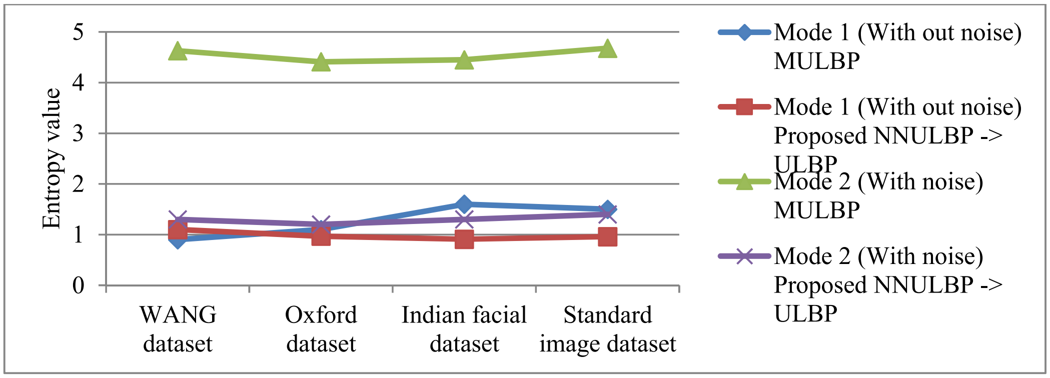


Figure 8: The entropy graph for the existing and proposed methods in mode 1 and 2.

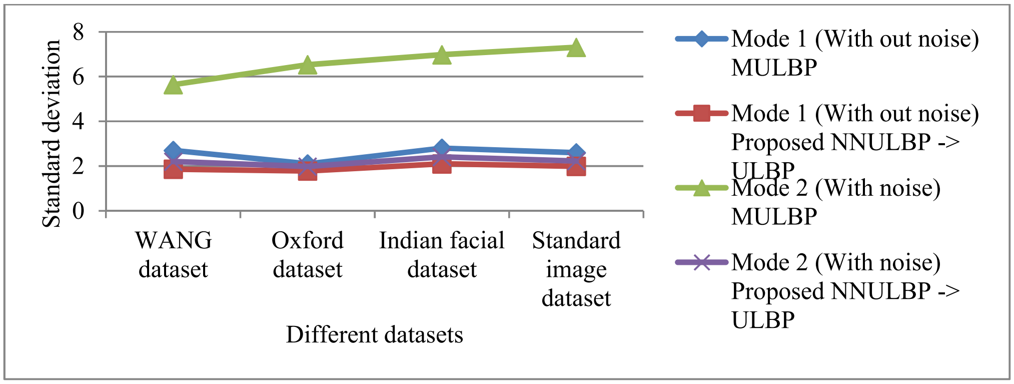


Figure 9: The standard deviation graph for the existing and proposed methods in mode 1 and 2.

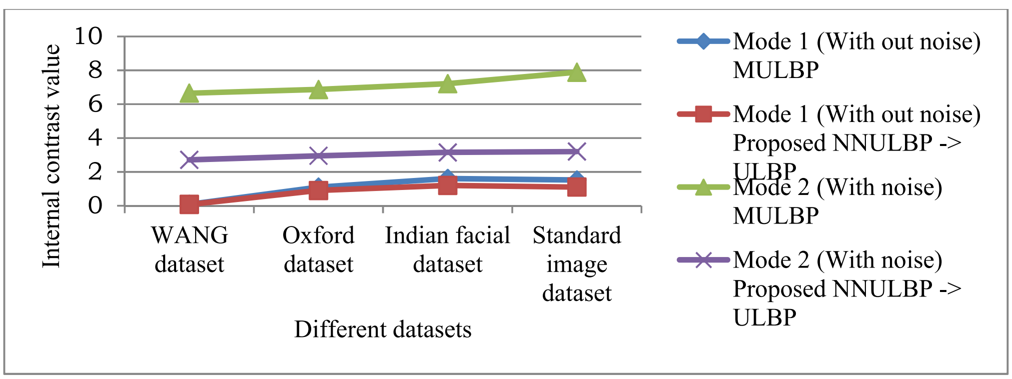


Figure 10: The internal contrast value for the existing and proposed methods in mode 1 and 2.

6. CONCLUSIONS

The proposed approach automatically transforms the NNULBP in to ULBPS based on a threshold and conversion factor. The advantage of considering ULBP is it is rotationally invariant because the ULBP is measured based on the transitions that occur on a circular bit pattern of a 3 x 3 neighbourhood. The morphological treatment filled the small holes and connected borders of regions for a better segmentation. The graphs clearly indicate higher the discrepancy value and a lower value of the standard deviation for the proposed NNULBP->ULBP segmentation approach in both the modes and the noise sustainability of the proposed method. The low value of internal contrast and an entropy value around 1 represent a good segmentation. The proposed segmentation improves the contrast of sharp details in light and dark areas even in the presence of noise. We conclude that the present method is simple, stable in the presence of noise and suitable to real time applications.

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