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Fuzzy and Entropy based approach for Feature Extraction from Digital Image

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ABSTRACT

This paper presents texture feature extraction scheme with the help of extended version of Fuzzy local binary pattern (FLBP) to get more efficient feature from the input image. The proposed scheme extends (FLBP) technique employing Intuitionistic fuzzy set and it is known as Intuitionistic fuzzy local binary pattern (IFLBP). Moreover, IFLBP provides additional bin in the distribution of IFLBP values. Additionally, it can be used as the feature vector of the image and can be apply in diverse fields of image processing. The proposed algorithm has used various medical as well as image processing images of different sizes for result analysis. It clearly shows that the obtained results are better than the existing techniques and its extracted feature are more informative than the reported methods.

Keywords: Entropy, fuzzy local binary pattern, feature extraction, intuitionistic fuzzy local binary pattern, histogram, intuitionistic fuzzy sets

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INTRODUCTION

There are diverse research areas of image processing where features extraction is the primary step. Most of the researchers employed their algorithm after extracting features from the image because it reduces the dimension as well as time. Further, it is a process of extracting the compact as well as crucial information against an image. Moreover, the prime purpose of feature

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extraction is to locate the most important information against original as well as raw data. Additionally, when the input image and raw data of an algorithm are terribly huge to be handled also it is hypothetical to be redundant (diminutive information, bulky data). The input data is going to be converted into a drastically compact dimension demonstration as well as a set of features (acknowledged as features vector). Furhter, these extracted feature vectors are going to represent the complete image. Moreover, if extracted features are vigilantly chosen then it is likely to get the features set which will excerpt important informative data in order to carry out the chosen task with this compact demonstration in the place of input image as well as full data. Lastly, the excerpt features vectors have been employed in diverse area of image processing as well as signal processing namely image forensics, remote sensing, bio medical image processing, visual inspection, image classification, character recognition, document verification, terrain delimitation, script recognition, pattern recognition, reading bank deposit slips and object discrimination. (Ansari & Ghrera, 2016; 2017; 2018a; 2018b; Castellano et al., 2004; Tsymbal et al., 2005; Li et al., 2003; Wang et al., 2008; Chow et al., 2007; Kumar et al., 2013; Kaur et al., 2018; Singh & Gupta, 2018; Ansari et al. 2014; 2016; 2017).

The main features are existing in the image consist of color, texture as well as shape. Further, feature extraction is primarily reliant on these kind of features. Additionally, performance of every preferred task is also reliant on these extracted features. In general, feature illustration techniques are classified into three types namely global based, block-based and region-based, features (Tian, 2013; Chow et al., 2007). Further, a smaller amount work been done in the field of feature extraction interconnected to a significant research on annotation as well as retrieval model itself designed. This article mainly facus on texture feature extraction methods. Lastly, developed technique is applied on diverse medical images such as X-Ray, Thyroid, Brain CT scan, image processing images namely Lena image as well as JUIT logo.

Various techniques are developed for textural feature extraction method (Wagner, 1999; Petrou & Sevilla, 2006). The local binary pattern (LBP) technique (Ojala et al., 1996) is giving his efforts on the concept of binary patterns for demonstration of texture. Further, it is comprehensively accepted because LBP is simple and effectual in depicting the local spatial construction of an image. Morever, the LBP technique were intensified as well as accompanied with diverse methods. In outcome, the extensive variety of texture revelation idea is suitable for various image analysis tasks. The classic examples consist of LBP extensions rotation invariance (Fehr, 2007), fusion of micro LBP and macro Gabor features (Li & Staunton, 2008) merger of inter as well as intra spatial structure of the LBP patterns (Wu et al., 2008) and featuring scale invariance (Chan et al., 2007).

BACKGROUND

The primary research on visual inspection (Iivarinen, 2000) has indicated with the aim of the LBP features was proficiently applied in surface defect detection. Additionally, BP based features are also applied in wood quality discrimination (Silven et al., 2003). Lately, such features have been used in automatic defect detection (Hadizadeh et al., 2008) as well as in remote sensing (Grabner et al., 2008). Various investigation have indicated with the purpose of the BP based feature eradication techniques are advisable for content based image retrieval (CBIR) (Jiang et al., 2004) while currently the LBP based techniques have been utilized in discriminative model for image ranking againts text queries (Grangier & Bengio, 2008). Furthermore, in the field of face recognition LBP is identified as a highly proficient texture illustration technique. Additionally, it is efficiently applied in invariant face recognition (Li et al., 2007; Zhang et al., 2008), recognition of facial expressions (Shan et al., 2009) and face authentication (Destrero et al., 2009). Fantastic outcomes are accomplished from its diverse application of biomedical imaging together with classification of protein images (Nanni & Lumini, 2008), video endoscopy (Iakovidis et al. 2006), computer aided neuroblastoma prognosis system (Sertel et al., 2009).

Finally, it is also fruitfully employed in diverse field of motion analysis namely underwater image matching (Garcia et al., 2001), object tracking (Petrovic et al., 2008), modeling and detection of moving objects (Heikkila & Pietikainen, 2006).

The research society has a lot of attention on LBP texture demonstration, various techniques have been developed based on the BP model. Futher, the approach was designed for the estimation of local contrast measure (Ojala et al., 1996). Afterward, the LBP/C technique was developed with the help of joint distribution of LBP codes and local contrast measures. Moreover, it is also applied to get better discrimination ability of the original LBP technique (Ojala et al., 1996) . Additionally, other edition of LBP is local edge patterns (LEP) approach which was proposed for image segmentation (Yao et al., 2003). This method depicts the spatial formation of local texture throughout the spatial orientation of edge pixels. identical technique median binary pattern (MBP) was designed by Hafiane et al., (2007).

Fuzzy sets offer a compliant structure for handling indeterminacy characterizing real world systems, originating primarily from the imprecise as well as imperfect nature of information. Moreover, the fuzzy sets do not cope the hesitancy (intuitionistic index) in a images originated out of diverse aspects, in which the preponderance are caused by inherent weaknesses of the acquirement as well as imaging mechanisms. Further, distortions occur as a result of the limitations of acquirement chain, like quantization noise, the suppression of dynamic range, or the non-linear behavior of mapping system, affect our certainty regarding the “brightness” or “edginess” of a pixel and therefore introduce a degree of hesitancy associated with the corresponding pixel.

Fuzzy sets theory introduced by Zadeh, (1965) on the extraction of texture spectrum features (Barcelo et al., 2007) and their competent successors. Furthermore, the LBP features are capable to enhance their robustness to noise (Ahonen & Pietikäinen, 2007; Iakovidis et al., 2008; Keramidas et al., 2008; Keramidas et al., 2011). Though, the above studies can only be considered as elementary since they incorporate only a constrained experimental estimation. Keramidas et al. (2011) and Iakovidis et al. (2008) proposed a generic, uncertainty aware approach for the derivation of fuzzy local binary pattern (FLBP) texture replicas. Furthermore, intuitionistic fuzzy set theory developed by Atanassov (1986; 1989) provides a compliant mathematical structure to cope uncertainty with the hesitancy arising from imperfect as well as imprecise information. Additionally, a prominent characteristic of IFS is that it appoints to every element a membership degree as well as a non membership degree with assertive amount of hesitation degree. Finally, this manuscript presents intuitionistic fuzzy local binary pattern (IFLBP) for texture demonstration with the help of the Atanassov's intuitionistic fuzzy sets.

PROPOSED METHOD AND ALGORITHM

To simplify the FLBP approach, this method is capable of managing the uncertainty through hesitancy arising as of either imperfect as well as imprecise information. Moreover, this segment describes the proposed Intuitionistic fuzzy local binary pattern (IF-LBP) for texture representation by using IFSs as follows:

Let V= {0, 1……, n-1} be the universal set for n-pixels neighborhood. Then a IFSs R on the universe of discourse V is defined as given below:

$$R = \left\{ \left\langle p_x, \mu_R(p_x), \nu_R(p_x) \right\rangle \mid p_x \in V \right\}, \tag{1}$$

such that μ_R belong to U[0,1] and p_x belong to U [0,1] are membership and non-membership function of IFS R to which a member p_x has less grey or greater than I_c in R, respectively, under 0≤ p_x +(p_x)+ ν_R (μ_R) ≤ 1. The indeterminacy degree μ_R (μ_R) = 1 - μ_R (p_x) - p_x(p_x), p_x $p_x \in$ U, where 0≤ p_x (p_x)≤1 is measurement of ambiguity such that p_x belongs to R or not $\forall$ $p_x \in V$, where 0≤ μ_R (p_x)≤1 is measurement of ambiguity such that p_x belongs to R or not.

The membership and non-membership functions of IFS R are defined as follows:

$$\mu_R(x) = \begin{cases} 0, \quad \text{if} \quad I_x < I_c - S, \\ 0.5(1+\hbar)\left(1+\dfrac{I_x - I_c}{S}\right), \text{ if } I_x \in [I_c - S, I_c], \ S \neq 0, \\ 0.5\left[\left(1+\dfrac{I_x - I_c}{S}\right) + h\left(\dfrac{I_x - I_c}{S} - 1\right)\right], \text{ if } I_x \in \left]I_c, I_c + S\right], S \neq 0, \\ 1, \text{ if } \quad I_x \geq I_c + S. \end{cases} \tag{2}$$

$$\nu_R(x)=\begin{cases}1, \text{ if } I_x < I_c - S,\\ 0.5\left[\left(1-\frac{I_x-I_c}{S}\right)-\hbar\left(1+\frac{I_x-I_c}{S}\right)\right], \text{ if } I_x \in [I_c-S, I_c], S\neq 0,\\ 0.5(1+\hbar)\left(1-\frac{I_x-I_c}{S}\right), \text{ if } I_x \in]I_c, I_c+S], S\neq 0,\\ 0, \text{ if } I_x \geq I_c+S.\end{cases} \tag{3}$$

For neighbourhood pixel (n×n), in a single bin of IFLBP histogram, the contribution $IFLBP_C$ of each pattern code is given by

$$IFLBP_C(\alpha,\beta,j)=\prod_{\ell=0}^{\xi-1}\left[b_\ell(j)(\alpha)+\left(1-b_\ell(j)\right)\nu_R(\alpha)\right], \tag{4}$$

where $\xi \in [0,n]$, (α, β) and $b_l(j) \in \{0,1\}$ represent the number of neighbouring pixels, the coordinates of a pixel and calculated value of l^{th} bit of binary representation of bin j, respectively, and complete IFLBP histogram is given by

$$IFLBP_H(j)=\sum_{\alpha,\beta} IFLBP_C(\alpha,\beta,j), \quad j=0,1,...,2^{\xi}-1. \tag{5}$$

We can examine that employing the crisp LBP operator, in which each n×n pixel adjacent invariably gives one bin of the histogram. Moreover, FLBP as well as IF-LBP histogram of each n×n pixel adjacent mostly provides more than one bin of the histogram. Though, the sum of contribution of each n×n pixel adjacent (IF-LBP) to the bins of IF-LBP histogram is equal to 1, given as follows:

$$\sum_{j=0}^{2^{\xi}-1} IFLBP_C(\alpha,\beta,j)=1. \tag{6}$$

An example of IF-LBP computation scheme for 3×3 pixel surroundings is shown in Figure 1.

We proposed a new technique for texture feature extraction from the image as shown in Figure 2. These extracted features can be used in various image processing areas. Firstly, the image is taken as input and converted into grey scale which is resized to 512×512. Furthermore, 3×3 Local neighbourhoods have chosen for each pixel from input image and then fix the threshold (Ts) to get the IFLBP code of each block. Additionally the IFLBP code of each block is combined. Lastly the histograms have been plotted for FLBP code as shown in Figure 3-7. To measure the information in the image, the entropy value has been calculated depicted in Table 1-5.

Remarks 1: When S≠0, $\hbar$=0, the resulting Intuitionistic fuzzy membership and non-membership functions given by the Equation 2 and 3 are almost equivalent to the fuzzy membership function $\mu_A(x)$, the distinctness being that $\mu_R(x) = \nu_R(x) = 0.5$ where as $\mu_A(x)=1$ when $I_i=I_c$.

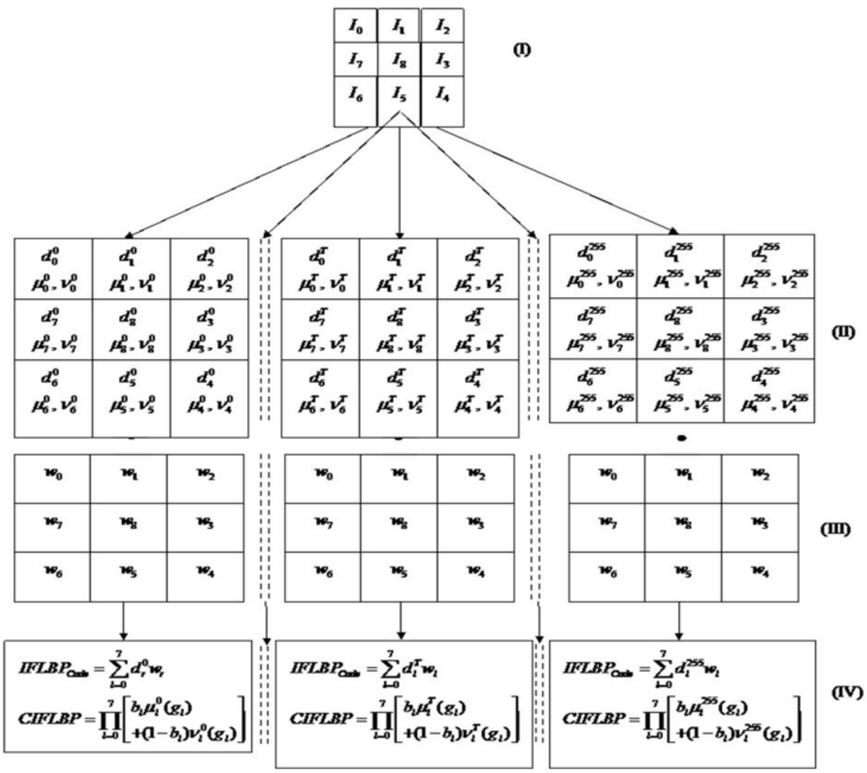


Figure 1. IFLBP computation design for a 3×3 pixel surrounding. (I) Grey- levels of a 3×3 pixels surrounding. (II) Intuitionistic fuzzy threshold values along with membership and non-membership values. (III) Binomial weights matrix. (IV) IFLBP codes and CIFLBP.

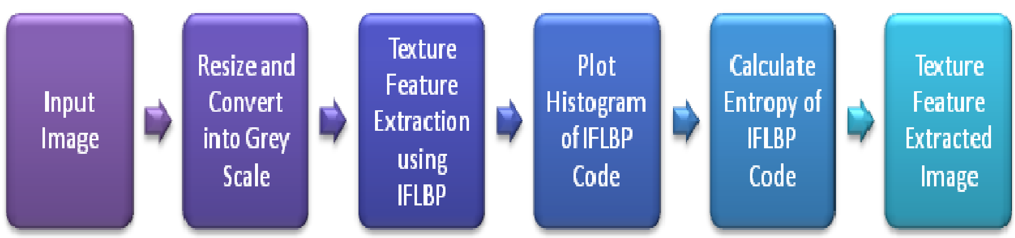


Figure 2. Proposed Model

Remarks 2: When S=0, the resulting Intuitionistic fuzzy membership and non-membership functions are equivalent to the crisp thresholding function $X_A(x)$.

PERFORMANCE METRICS: ENTROPY OF IFLBP FEATURES

The information content of an image is frequently computed by calculating the uncertainty or entropy of an image. Moreover, as the amount of entropy increases, more information is associated with the image. Furthermore, the entropy measures the average as well as the global information content of an image in terms of average bits per pixel.

The entropy measure for probability distribution is defined as:

$$e = -\sum_{j=0}^{255} x_j \log_2 x_j \tag{7}$$

This is Shannon entropy (Shannon, 1948) and where x_j is jth pattern probability.

It is worthiness to comment that the logarithmic entropic measure (7) that as x_j tend to 0 its analogous self-information of this event, $I(x_j)= -\log(x_j)$ tends to infinity $I(x_j= 1)= \log x_j$ tends to 0. Thus, we see that information gain for an event is neither bounded at both ends nor defined at all points. In practice, the gain in information for an event, either highly probable or uncertain, is estimated to lie between two definite limits. i.e., as maximum pixels of an image are analyzed, the information gain increases such that all the pixels are examined the gain achieves its maximum value, irrespective of the essence of an image.

In Shannon's entropy, which is vastly acclaim, the self-information of an event with x_j is chosen as $\log x_j$ which is a decreasing function of x_j The similar characteristic may be preserved by considering it as a function of $(1- x_j)$ instead of $1/x_j$. These deliberations imply the self-information as an exponential function of $(1- x_j)$ rather of logarithmic behavior. This is also suitable while taking into account the idea of information gain in an image. Lastly, Pal and Pal entropy (Pal & Pal, 1989) is defined by

$$e_p = \sum_{j=0}^{255} x_j \exp\left(1 - x_j\right) \tag{8}$$

RESULT AND DISCUSSION

It is recognized that Keramidas's method (Keramidas et al., 2011) and Ansari's method (Ansari & Ghrera, 2018) have zero values for some bins out of 255 bins. Though, developed technique histograms do not have bins with zero values and there are more spikes, though limited in magnitude. This indicates that Ansari's method is more informative than Keramidas method and proposed method is more informative than existing techniques.

The more diversified signal illustrates the higher entropy and more actual information gain. Normally, if all the bins of histogram are having equal possibility, then the maximum entropy will be obtained. Ostensibly, for the fixed threshold S, developed technique's histograms always provide better entropy than existing method's histograms. However, Ansari's method, histograms for the same threshold and using hesitation threshold values $\hbar \in [0, 1]$ gives greater entropy than

Keramidas's technique histograms. Hence, IFLBP histogram gains more information than other reported methods histograms.

Furthermore, we have employed IFLBP approach on diverse images as depicted in Figures 3-7 of size 256×256 to determine the histograms feature vector for various threshold values as well as varying hesitation ($\hbar \in [0,1]$) and measure the entropies from these histograms, lastly the results are depicted in Tables 1 to 5. Moreover, we can observe from these tables that the maximum entropy achieved in Table 1 for the S=6, S=10 are at S=0.3, for S=2, S=14, S=20, S=12 are at $\hbar$=0.1. Similarly, we have followed the same process for other images; the results are depicted in Tables 2-5 and Figures 3-7 correspondingly. Thus, the entropies achieved by developed technique are invariably better than the entropies achieved by existing techniques. Further, we have plotted the histograms of IFLBP codes of each image where we have obtained the highest entropy as depicted in Figures 3-7. With these histograms we can examine that the IFLBP histograms do not have bins with zero values. Additionally, the IFLBP features of all images are more informative than existing features.

Table 1

The entropy values at diverse threshold and hesitation for x-ray image

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Keramidas et al., 2011	0.0	1.90	1.68	0.87	0.58	0.38
Ansari & Ghrera, 2018	0.1	1.85	1.66	0.85	0.59	0.38
	0.3	1.77	1.61	1.02	0.59	0.49
	0.5	1.79	1.65	1.27	0.86	0.57
	0.7	1.75	**1.69**	**1.43**	1.05	0.82
	1.0	1.67	1.66	1.42	**1.32**	**1.32**
Proposed Method	0.1	**2.68**	2.69	2.69	**2.70**	**2.70**
	0.3	2.68	**2.70**	**2.70**	2.70	2.70
	0.5	2.68	2.69	2.70	2.70	2.70
	0.7	2.67	2.69	2.69	2.69	2.69
	1.0	2.61	2.64	2.65	2.65	2.65

Table 2

The entropy values at diverse threshold and hesitation for thyroid image

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Keramidas et al., 2011	0.0	1.68	**1.90**	1.65	0.81	0.58
Ansari & Ghrera, 2018	0.1	1.74	1.87	1.63	1.03	0.55
	0.3	**1.83**	1.84	1.65	1.11	0.58

Table 2 *(Continue)*

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Ansari & Ghrera, 2018	0.5	1.74	1.85	1.62	1.49	0.66
	0.7	1.69	1.82	**1.70**	1.45	0.81
	1.0	1.35	1.64	1.61	1.36	**0.87**
Proposed Method	0.1	**2.68**	2.69	2.69	2.70	**2.70**
	0.3	2.68	**2.69**	**2.70**	**2.70**	2.70
	0.5	2.68	2.69	2.69	2.70	2.70
	0.7	2.66	2.68	2.69	2.69	2.69
	1.0	2.56	2.59	2.61	2.61	2.61

Table 3
The entropy values at diverse threshold and hesitation for Brain CT Scan image

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Keramidas et al., 2011	0.0	1.61	1.45	0.87	0.77	0.57
Ansari & Ghrera, 2018	0.1	1.61	1.50	1.17	1.00	0.63
	0.3	1.76	1.72	1.72	1.58	1.20
	0.5	1.77	1.80	1.79	1.71	1.62
	0.7	1.49	1.48	1.51	1.55	1.61
	1.0	1.10	1.15	1.11	1.16	1.13
Proposed Method	0.1	**2.69**	**2.69**	**2.70**	**2.70**	2.70
	0.3	2.69	2.69	2.69	2.70	**2.71**
	0.5	2.67	2.68	2.68	2.69	2.69
	0.7	2.62	2.63	2.64	2.65	2.65
	1.0	2.22	2.24	2.68	2.29	2.29

Table 4
The entropy values at diverse threshold and hesitation for Lena image

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Keramidas et al., 2011	0.0	1.77	1.68	1.13	0.60	0.49
	0.1	1.77	1.68	0.91	0.57	0.48
	0.3	1.77	1.60	0.76	0.57	0.45

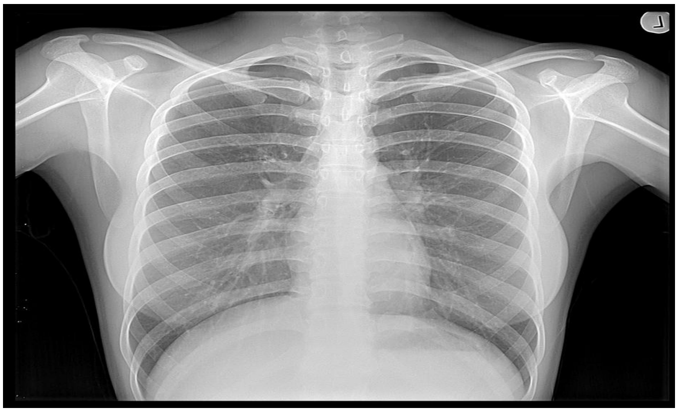
Table 4 *(Continue)*

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Ansari & Ghrera, 2018	0.5	1.79	1.55	0.91	0.65	0.53
	0.7	1.79	1.59	1.20	0.85	0.73
	1.0	1.80	1.59	**1.46**	**1.40**	**1.46**
Proposed Method	0.1	2.67	2.69	2.69	2.70	2.70
	0.3	2.66	2.69	2.70	2.70	**2.70**
	0.5	**2.67**	2.69	2.70	**2.70**	2.70
	0.7	2.66	**2.69**	**2.70**	2.70	2.70
	1.0	2.67	2.69	2.70	2.70	2.70

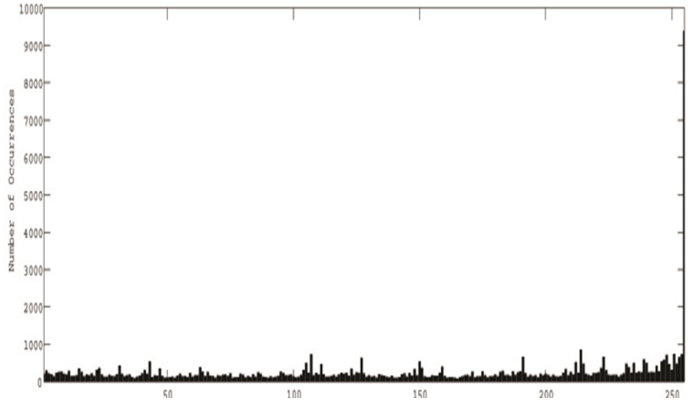
Table 5

The entropy values at diverse threshold and hesitation for JUIT Logo

Techniques	Hesitancy degree ($\hbar$)	Threshold (S)				
		2	6	10	14	20
Keramidas et al., 2011	0.0	0.74	0.70	0.68	0.67	0.62
Ansari & Ghrera, 2018	0.1	0.93	0.62	0.60	0.56	0.52
	0.3	1.79	1.74	1.71	1.64	1.56
	0.5	1.84	1.81	1.79	1.78	1.77
	0.7	1.50	1.56	1.58	1.56	1.60
	1.0	1.12	1.04	1.03	1.04	1.05
Proposed Method	0.1	2.70	2.70	2.70	2.70	2.70
	0.3	2.69	2.69	2.70	2.70	2.70
	0.5	2.68	2.68	2.68	2.68	2.68
	0.7	2.63	2.63	2.63	2.63	2.63
	1.0	2.18	2.16	2.14	2.13	2.12

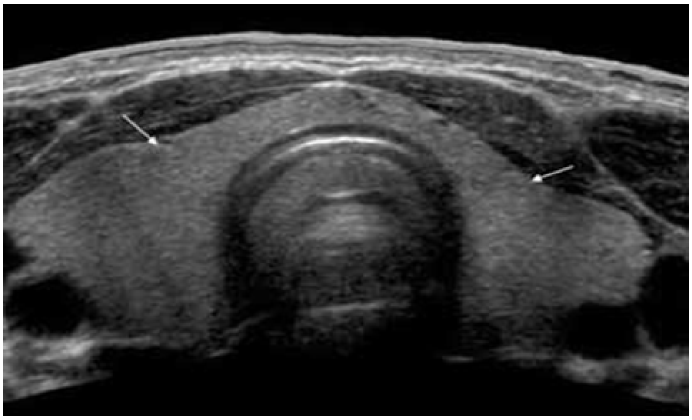


(a)



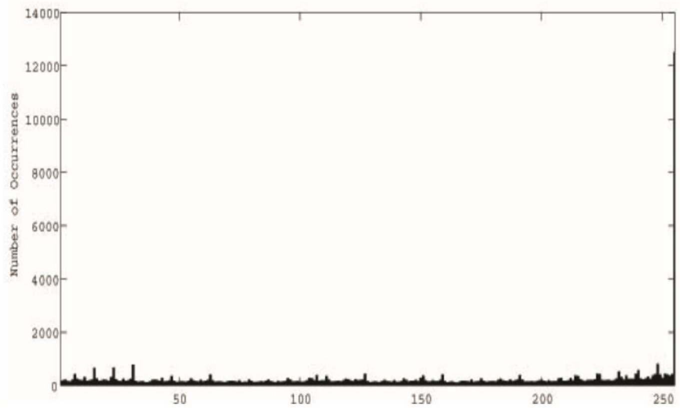
(b)

Figure 3. (a) Original image (b) Histogram Plot of IFLBP Code for X-Ray Image



(a)

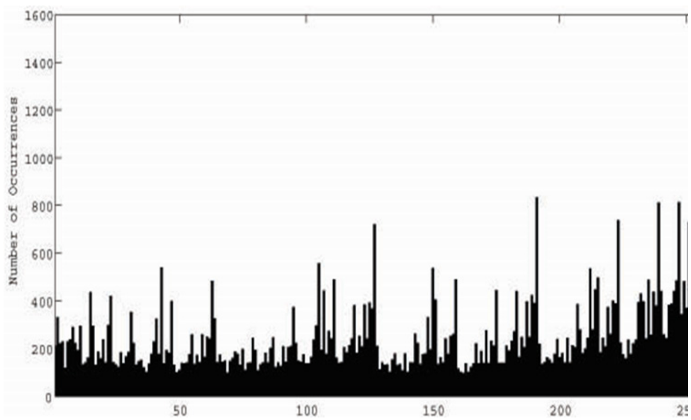
Figure 4. (a) Original image of IFLBP Code for Thyroid Image



(b)

Figure 4. (b) Histogram Plot of IFLBP Code for Thyroid Image

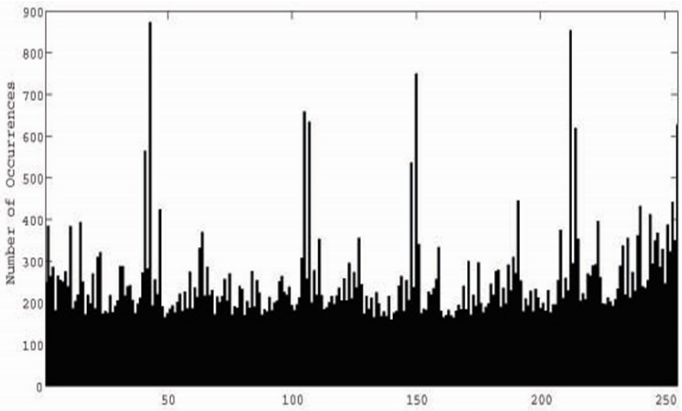
(a)



(b)

Figure 5. (a) Original image (b) Histogram Plot of IFLBP Code for Brain CT Scan Image

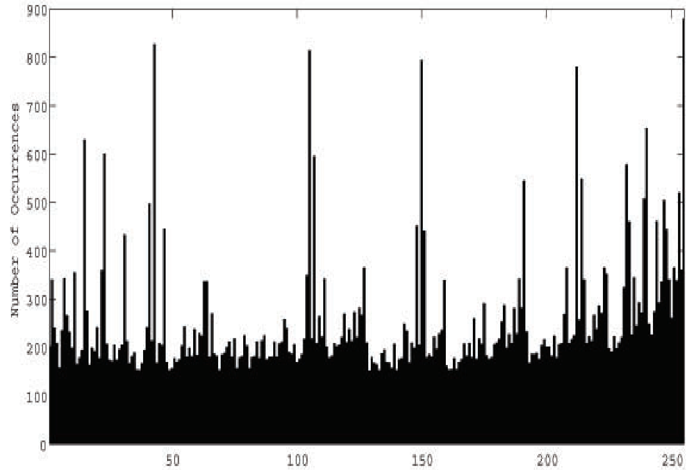
(a)



(b)

Figure 6. (a) Original image (b) Histogram Plot of IFLBP Code for Lena Image

(a)



(b)

Figure 7. (b) Histogram Plot of IFLBP Code for JUIT Image

CONCLUSION AND FUTURE WORK

A novel and efficient technique for extracting texture features from digital images have been developed using Intuitionistic fuzzy local binary pattern with the help Intuitionistic fuzzy set theory. The proposed scheme extends (FLBP) technique employing Intuitionistic fuzzy set theory and it is known as Intuitionistic fuzzy local binary pattern (IFLBP). Moreover, IFLBP provides additional bin in the distribution of IFLBP values. Further, it can be used as the feature vector of the image and can be apply in diverse fields of image processing. The developed method is experimentally executed on various medical as well as image processing images of different sizes. Moreover, the obtained result (Tables 1-5) clearly shows that the entropy value of developed technique is always greater than the reported methods. The extracted features are more informative than the existing ones. Additionally, IFLBP features can be employed in different research fields of image processing as well as medical image processing like face recognition, pattern recognition, image de-noising, image segmentation, image forgery detection, image and pattern classifications etc.

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