JOINT WEBER-BASED ROTATION INVARIANT UNIFORM LOCAL TERNARY PATTERN FOR CLASSIFICATION OF PULMONARY EMPHYSEMA IN CT IMAGES

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ABSTRACT

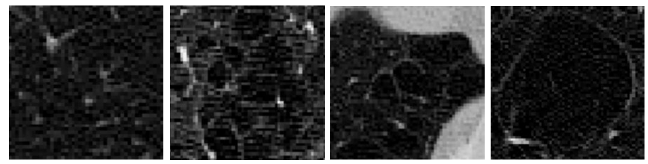
In this paper, we present a novel image representation approach for classifying emphysema in computed tomography (CT) images of the lung. Our proposed method extends rotation invariant uniform local binary pattern (RIULBP) and local ternary pattern (LTP), which are extensively used in a variety of computer vision applications, into rotation invariant uniform local ternary pattern (RIULTP) with a human perception principle: Weber's law. In addition, by integrating the upper pattern and the lower pattern of the Weber-based RIULTP (WRIULTP), we further put forward the joint Weber-based rotation invariant uniform local ternary pattern (JWRIULTP), which allows for a much richer representation and also takes the comprehensive information of the image into account. The proposed methods are tested on the Outex database (texture database) and the Bruijne and Sørensen database (emphysema database). The results show the superiority of the proposed approaches to the state-of-the-art techniques for emphysema classification including rotation invariant local binary pattern (RILBP) and texton-based approach.

***Index Terms*—** Emphysema Classification, Local Ternary Pattern, Rotation Invariance, Weber's Law, Pattern Integration

1. INTRODUCTION

Emphysema is a chronic lung disease, mainly due to excessive expansion of the alveoli, resulting in shortness of breath. The damage of lung tissue involved in gas exchange is the main symptom of emphysema. Known as the main component of chronic obstructive pulmonary disease (COPD), the world's growing health problem[1], emphysema is one of the world's most serious diseases. Therefore, detection and quantification of emphysema is of great significance.

Since the texture of lung tissue is affected by the type of emphysema, texture analysis can be applied to quantitative analysis of different subtypes of emphysema [2]. **Fig.1** shows the examples of different lung tissue patterns. Sørensen et al. [1] proposed to use rotation invariant local binary pattern (RILBP) as texture feature for characterizing emphysema lesions which achieved excellent performance compared with other state-of-the-art techniques. However, RILBP is highly sensitive to noise existing in the processed image due to its threshold scheme. Another state-of-the-art texture representation method for classifying emphysema is to use a texton-based classification system [2].



(a) (b) (c) (d)

Fig.1. (a)Normal tissue(NT). (b)Centrilobular emphysema(CLE). (c)Paraseptal emphysema(PSE). (d)Panlobular emphysema(PLE).

In this paper, with the intention of making it more robust and efficient, we extend the local ternary pattern (LTP) with the same principle as rotation invariant uniform local binary pattern (RIULBP) [3], and present the rotation invariant uniform local ternary pattern (RIULTP). Furthermore, instead of using the pixel value change directly in conventional LTP that violates human perception principle, our proposed Weber-based RIULTP (WRIULTP) depends not only on the absolute value of the stimulus but also on the relative intensity of stimulus [4]. In this way, the magnitude of the center pixel is fully considered, that is to say, if the stimulus has a tiny magnitude, a tiny variation is noticeable. We use the LTP introduced in [5], which has two parts: the upper pattern and the lower pattern. By integrating these two parts of the WRIULTP, we further present the joint Weber-based rotation invariant uniform local ternary pattern (JWRIULTP) which take full consideration of the comprehensive information of the image. With the extracted features, we construct a k-nearest neighbor (KNN) classifier [6] and automatically predict the type of the region of interest (ROI) extracted from emphysema lesions.

2.RELATED WORK

2.1. Local binary pattern (LBP)

Ojala et al. proposed the LBP as a visual descriptor used for characterizing local structure in [7]. Given a central pixel in an image, LBP is calculated by comparing its intensity with those of its local samples [8]

$$LBP(x;R,P)=\sum_{p=0}^{P-1}T(I(x_p)-I(x))2^p \quad T(z)=\begin{cases}1 & if\, z\ \geq\ 0\\ 0 & if\, z\ <0\end{cases} \quad \textbf{(1)}$$

where I is an image, x is the central pixel, $x_p=[-R\sin(2\pi p/P),R\cos(2\pi p/P)]^T+x$ are P neighborhoods calculated at a radius R around x, $T(z)$ is the threshold function[1].

Later, a more general formulation, which allowed for rotation invariance and uniform pattern [3], was presented and given by

$$LBP^{riu2}(x;R,P)=\begin{cases}\sum_{p=0}^{P-1}T(I(x_p)-I(x)) & \text{if } U(LBP(x;R,P))\leq 2\\ P+1 & \text{otherwise}\end{cases} \quad \textbf{(2)}$$

where U is described as the number of spatial transitions (bitwise 0/1 changes) in that pattern [9]:

$$U(LBP(x;R,P))=\left|T(I(x_{P-1})-I(x))-T(I(x_0)-I(x))\right| + \sum_{p=1}^{P-1}\left|T(I(x_p)-I(x))-T(I(x_{p-1})-I(x))\right| \quad \textbf{(3)}$$

2.2. Local ternary pattern (LTP)

The local ternary pattern (LTP) was originally proposed by Tan [5], which is a 3-valued coding. Because of the large dimension of LTP histogram (3^8= 6561), Tan changed the form of original LTP and presented a new form of LTP [5] which was split into the upper pattern and the lower pattern.

$$LTPU(x)=\sum_{p=0}^{7}T_U(I(x_p)-I(x))2^p \quad T_U(z)=\begin{cases}1 & if\ z\geq t\\ 0 & if\ z<t\end{cases}$$

$$LTPL(x)=\sum_{p=0}^{7}T_L(I(x_p)-I(x))2^p \quad T_L(z)=\begin{cases}1 & if\ z\leq -t\\ 0 & if\ z>-t\end{cases} \quad \textbf{(4)}$$

where $T_U(z),T_L(z)$ are the threshold function and t is the threshold for assigning pixel values into different sets.

3.METHODS

In this paper, we make three significant contributions: (1)We extend RIULBP and LTP, which are extensively used in a variety of computer vision applications, into RIULTP. (2)We propose the WRIULTP inspired by the Weber's law, which is a principle of human perception. (3)By integrating the upper pattern and the lower pattern, we further put forward the joint Weber-based rotation invariant uniform local ternary pattern (JWRIULTP).

3.1. Rotation invariant uniform LTP (RIULTP)

LTP is gray-scale invariant, but not rotation invariant. The rotation of the image will result in different LTP values. In order to make it more robust and efficient, we extend the LTP with the same principle as RIULBP , and present the rotation invariant uniform LTP. By varying the radii R and

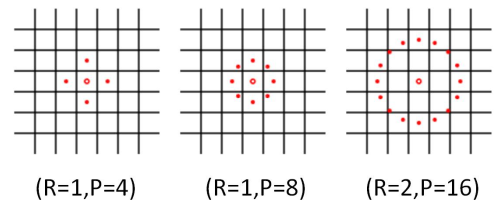


Fig.2. Circularly symmetric neighbor sets for different(R , P)[3]

the number of neighbors P, the RIULTP can be measured at different scales. **Fig.2** shows the circularly symmetric neighbor setting for different (R , P).The RIULTP index at x is formulated as

$$LTPU^{riu2}(x;R,P)=\begin{cases}\sum_{p=0}^{P-1}T_U(I(x_p)-I(x)) & \text{if } U_U(LTP(x;R,P))\leq 2\\ P+1 & \text{otherwise}\end{cases}$$

$$LTPL^{riu2}(x;R,P)=\begin{cases}\sum_{p=0}^{P-1}T_L(I(x_p)-I(x)) & \text{if } U_L(LTP(x;R,P))\leq 2\\ P+1 & \text{otherwise}\end{cases}$$

$$T_U(z)=\begin{cases}1 & if\ z\geq t\\ 0 & if\ z<t\end{cases} \quad T_L(z)=\begin{cases}1 & if\ z\leq -t\\ 0 & if\ z>-t\end{cases} \quad \textbf{(5)}$$

where the U value of the RIULTP is described as the number of spatial transitions(bitwise 0/1 changes) in that pattern [9]:

$$U_U(LTP(x;R,P))=\left|T_U(I(x_{P-1})-I(x))-T_U(I(x_0)-I(x))\right| + \sum_{p=1}^{P-1}\left|T_U(I(x_p)-I(x))-T_U(I(x_{p-1})-I(x))\right|$$

$$U_L(LTP(x;R,P))=\left|T_L(I(x_{P-1})-I(x))-T_L(I(x_0)-I(x))\right| + \sum_{p=1}^{P-1}\left|T_L(I(x_p)-I(x))-T_L(I(x_{p-1})-I(x))\right| \quad \textbf{(6)}$$

3.2. Weber-based RIULTP (WRIULTP)

Weber's law, a psychological law, which states that the perceived change in stimuli is proportional to the initial stimuli [10] , can be defined as

$$\frac{\Delta R}{R}=k(\text{constant}) \quad \textbf{(7)}$$

where ΔR is the change in stimuli, R is initial stimuli and k is referred to as the "Weber fraction" for detecting changes in weight.

According to this law , we refine the RIULTP and propose a novel pattern: Weber-based RIULTP which is given by

$$WLTPU^{riu2}(x;R,P)=\begin{cases}\sum_{p=0}^{P-1}T_U\left(\frac{I(x_p)-I(x)}{I(x)}\right) & \text{if } U_U(LTP(x;R,P))\leq 2\\ P+1 & \text{otherwise}\end{cases}$$

$$WLTPL^{riu2}(x;R,P)=\begin{cases}\sum_{p=0}^{P-1}T_L\left(\frac{I(x_p)-I(x)}{I(x)}\right) & \text{if } U_L(LTP(x;R,P))\leq 2\\ P+1 & \text{otherwise}\end{cases} \quad \textbf{(8)}$$

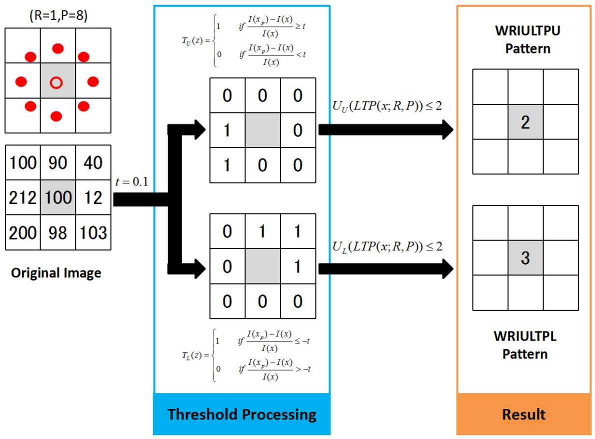
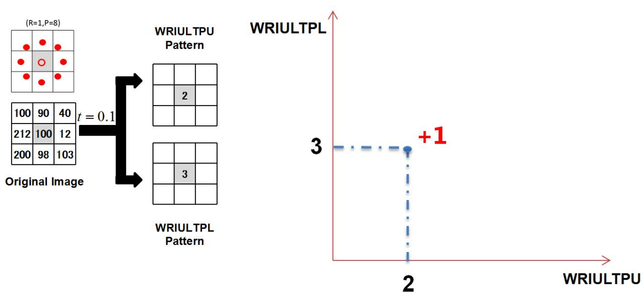


Fig.3. Illustration of calculating the WRIULTP(R =1, P =8)

Instead of using the pixel value change directly in conventional LTP, the Weber-based RIULTP calculates the pixel value change between the neighboring pixels and the center pixel and then divided by the center pixel value to get a ratio. Note that, by comparing the ratio to a specified threshold, the neighboring samples can be interpreted as a P bits binary number. **Fig.3** shows the principle of WRIULTP.

As we know, for the conventional LTP, threshold t is fixed regardless of the magnitude of the central pixel, which violates the principle of human perception. However, our proposed method can effectively solve this problem, since it follows the fact that human perception of a pattern depends not only on the absolute value of the stimulus but also on the relative intensity of the stimulus [4], and takes the information of center pixel into full consideration.

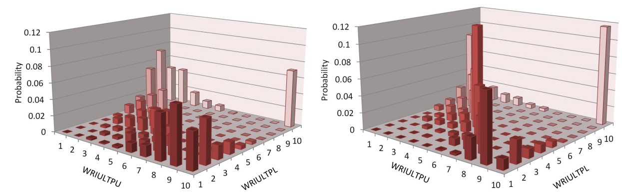
3.3. Joint WRIULTP (JWRIULTP)



(a) (b)

Fig.4. Principle of the JWRIULTP. (a) Diagram of the WRIULTPU pattern and the WRIULTPL pattern (R =1, P =8). (b)After calculating the WRIULTPU pattern and the WRIULTPL pattern of each pixel, we can built a joint histogram to represent the entire image.

As noted previously, each image can generate two WRIULTP images , that is to say, each pixel of the image has two patterns: upper pattern and lower pattern. With the intention of expressing a much richer information of the image , we compute the joint histogram of WRIULTPU image and WRIULTPL image instead of calculating the histogram separately. **Fig.4** illustrates the principle of the joint Weber-based rotation invariant uniform LTP. **Fig.5** shows examples of the joint histogram of CLE (a) and PSE (b).



(a)CLE (b)PSE

Fig.5. Examples of the joint histogram. (a) is computed from the CLE ROI and (b) is calculated from the PSE ROI.

4.EXPERIMENTAL RESULTS

In this section, our proposed approach is compared with LBP,RILBP,RIULBP and LTP on Outex database [3], which is a representative texture database for classification and is public on http://www.outex.oulu.fi/. Furthermore, we also compare our methods with LBP, LTP, and some state-of-the-art approaches for classifying emphysema on a standard public emphysema database [1], provided by Prof. Dr. Bruijne and Dr. Sørensen. Note that, a KNN classifier is used for our experiments.

LTP and RIULTP is computed using the threshold t in the range of (1,10). In the WRIULTP and JWRIULTP, the threshold t ranging from 0.01 to 0.2 is used. Common parameters considered for these methods are as described below: radius R ={1,2}, number of neighbors P = {4,8,16} and number of neighbors in the KNN classifier k ={1,2,…,10}.

4.1. Experimental results on the Outex database

There is a large collection of textures including surface textures and natural scenes in the Outex database. When focusing on a given reference considering illumination, rotation, and spatial resolution, the collection of surface textures reveals well defined variations [11]. We choose the Outex_TC_00010-r set for our experiments. Specifically, it contains 4320 images (128 × 128 pixels) of 24 textures, divided into 480 images for training and 3840 images for testing. The estimated classification accuracies of the seven methods are listed in **Table 1**.

Table 1.

The comparative results of our proposed approaches and a series of LBP-based descriptors on the Outex database.

Methods	Dimension	Classification Accuracy
LBP	256	54.24%
RILBP	36	83.18%
RIULBP	10	84.35%
LTP	512(2×256)	65.70%
RIULTP	20(2×10)	**91.93%**
WRIULTP	20(2×10)	**93.05%**

JWRIULTP	100(10×10)	**95.60%**

For our proposed methods, JWRIULTP performs best, achieving a classification accuracy of 95.60%. Both WRIULTP and RIULTP significantly outperform the LBP-based descriptors and LTP, even though their performance is not as good as JWRIULTP.

4.2. Experimental results on the Bruijne and Sørensen database

In this paper, we concentrate on the two subtypes of pulmonary emphysema, namely, CLE and PSE. For our experimentation, the emphysema database is available for the academic research from the homepage of Sørensen and consists of 168 ROIs (61 × 61 pixels), summarized in **Table 2**.

Table 2.the Bruijne and Sørensen database

Type	NT	CLE	PSE
Number	59	50	59

Six different approaches on the same database are evaluated and compared in **Table 3**. Specifically, rotation invariant LBP (RILBP) is the method used for emphysema classification published in [1].

Table 3.

The comparison between the best results acquired from our method and the results of other approaches on the Bruijne and Sørensen database

Methods	**Dimension**	**Classification Accuracy**
LBP	256	67.11%
LTP	512(2×256)	69.51%
RIULTP	20(2×10)	71.43%
WRIULTP	20(2×10)	76.19%
JWRIULTP	100(10×10)	**82.14%**
RILBP[1]	36	71.43%

From the **Table 3**, we can conclude that JWRIULTP achieves the best performance, with an accuracy of 82.14%.

According to the literature, intensity is a very important factor when processing CT images, where intensities are measurements of a physical property of the tissue displayed [1]. Hence, we take intensity information into account besides texture information. **Table 4** shows the comparison between the results acquired from the our methods and the results of other advanced techniques published in [1] and [2].

1)INT: Intensity histogram(In this work, we use the adaptive binning principle in [7])

2)JINT1: Firstly, we make the joint histograms of intensity and two patterns of WRIULTP respectively, and then connect them directly.

3)JINT2: Joint 3-D WRIULTPU, WRIULTPL and intensity histograms.

4)Texton-based: A texton-based approach for the classification of emphysema published in [2].

5)LBPINT:Joint LBP and intensity histogram for classifying emphysema published in [1].

Table 4.

The comparison between the results acquired from our methods and the results of other advanced techniques on the Bruijne and Sørensen database.

Methods	**Dimension**	**Classification Accuracy**
INT	9	86.90%
JINT1	180(2×9×10)	**95.24%**
JINT2	900(9×10×10)	**95.83%**
Texton-based[2]	30 or 120	90.48%
LBPINT[1]	324(9×36)	92.20%

From the **Table 4**, we can conclude that, for our proposed approaches, JINT2 achieves the best performance.JINT1 also achieves a good result which outperforms other advanced techniques for emphysema classification.

5.CONCLUSIONS

In this work, we presented a novel texture representation approach for classification of the pulmonary emphysema.We extended RIULBP and LTP, which are extensively used in a variety of computer vision applications, into RIULTP, and proposed the WRIULTP on the basis of Weber's law, which is a principle of human perception. Furthermore, we put forward the joint Weber-based rotation invariant uniform local ternary pattern (JWRIULTP) by integrating the upper pattern and the lower pattern. Our experiments on the open Outex database and the public Bruijne and Sørensen database confirmed that our proposed strategy not only increased classification accuracy on the standard texture feature database, but also improved performance on the representative emphysema database compared to other state-of-the-art texture descriptors.

6. ACKNOWLEDGEMENT

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