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Full Length Article

Directional local ternary quantized extrema pattern: A new descriptor for biomedical image indexing and retrieval

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ABSTRACT

This paper proposes a new pattern descriptor called directional local ternary quantized extrema pattern (*DLTerQEP*) for biomedical image indexing and retrieval. The standard local binary patterns (*LBPs*) and local ternary patterns (*LTPs*) encode the gray scale relationship between the center pixel and its surrounding neighbors in two dimensional (2*D*) local region of an image whereas the proposed method encodes the spatial relation between any pair of neighbors in a local region along the given directions (i.e., 0°, 45°, 90° and 135°) for a given center pixel in an image. The novelty of the proposed method is it uses ternary patterns from horizontal–vertical–diagonal–antidiagonal ($HVDA_7$) structure of directional local extrema values of an image to encode more spatial structure information which lead to better retrieval. *DLTerQEP* also provides a significant increase in discriminative power by allowing larger local pattern neighborhoods. The experiments have been carried out for proving the worth of proposed algorithm on three different types of benchmark biomedical databases; (i) computed tomography (*CT*) scanned lung image databases named as *LIDC-IDRI-CT* and *VIA/I-ELCAP-CT*, (ii) brain magnetic resonance imaging (*MRI*) database named as *OASIS-MRI*. The results demonstrate the superiority of the proposed method in terms of average retrieval precision (*ARP*) and average retrieval rate (*ARR*) over state-of-the-art feature extraction techniques like *LBP*, *LTP* and *LQEP* etc.

1. Introduction

1.1. Motivation

Healthcare services today rely heavily on diverse biomedical imaging data which have been expanded exponentially in quantity – as there is rapid increase in the number of medical check-up per day; because of the use of diverse range of imaging modalities such as magnetic resonance imaging (*MRI*), ultrasound (*US*), computed tomography (*CT*), *X-ray*, etc. for different clinical studies. As we know that medical imaging is made up of dissimilar minor structures, there has been much interest of researchers in the development of well structured techniques to work on huge image databases of biomedical images for efficient access, search and retrieval. To sort out the problem of medical images, the knowledge of the content based image retrieval (*CBIR*) approach is disseminated to develop content based medical image retrieval (*CBMIR*). Some comprehensive and extensive literature survey on *CBIR* systems is presented in Antani et al. [2], Jing and Allinson [21] and Yue et al. [69]. *CBIR* uses the visual content features such as color, texture, shape, and spatial layout etc. of regions or objects to represent and index the biomedical image database for efficient retrieval. These features are arranged as multi-dimensional feature vectors and stored in the feature database. The main step of the *CBIR* is feature extraction, the effectiveness of which rests upon the method derived for extracting features from given images. The selection of feature descriptors affects on image retrieval performance.

Nowadays, texture based features play an important role as powerful discriminating visual features. They are extensively used in the image processing applications to identify the visual patterns. Some of texture feature extraction methods are proposed by Haralick et al. [16], Tamura et al. [57] and Haralick [15]. *WLD* and *BGP* texture descriptors have proposed by Chen et al. [5] and Zhang et al. [72], respectively. Siqueira et al. [54] have proposed extended GLCM texture descriptors to multiple scales on benchmark texture data sets. Verma et al. [61] proposed local extrema co-occurrence

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patterns (*LECoP*) in which *GLCM* is used to find a co-occurrence of the mapped pixels. Parida and Bhoi [50] used texture features to extract the objects from gray scale images. For the directional features based on texture retrieval, Do and Vetterli [6] have suggested the discrete wavelet transform (*DWT*) which extracts the features in three directions (horizontal, vertical and diagonal). Kokare et al. [27] have used rotated wavelet filters for image retrieval by collecting various image features in various directions. Kokare et al. [25], Kokare et al. [26] and Kokare et al. [27] advocated the amalgamation of the *DT-CWF*, *DT-RCWF* and also rotational invariant *DT-RCWF* to have some other directional features that are not present in *DWT*. Hussain and Triggs [18] have proposed the local quantized patterns (*LQP*) which collects the directional geometric features in horizontal, vertical, diagonal and anti-diagonal strips of pixels; combinations of horizontal–vertical, diagonal–antidiagonal and horizontal–vertical–diagonal–antidiagonal; and traditional circular and disk-shaped regions for visual recognition. Most of biomedical images represented in gray scale are extensively textured in common. Hence, in clinical exams, the appearance of organ/tissue/lesion in the images is due to intensity variations that laid on various texture characteristics. Thereafter, texture became very popular in biomedical image retrieval because of eminent significance of acquired texture. For example, Gibbs and Turnbull [11] got significant differences between benign and malignant lesions for a number of textural features on breast imaging. Felipe et al. [10] worked on retrieval of medical *CT* and *MRI* images in varied tissues using co-occurrence matrix. Traina et al. [59] proposed medical image retrieval system using wavelet transformations. Jhanwara et al. [20] have suggested content based image retrieval system using motif co-occurrence matrix (*MCM*) to delineate texture properties. Hajek et al. [14] have used the concept of texture analysis for magnetic resonance imaging and possible clinical application in that modality. Scott and Shyu [53] have utilized the concept of entropy balanced statistical (*EBS*) *k-d* tree on high-resolution computed tomography (*HRCT*) lung images for biomedical media retrieval system. Liu et al. [31] have described texture information using the technique of multi-scale complexity and multi-scale fractal dimension for medical image retrieval. Kassner and Thornhill [23] have shown texture analysis as valuable tool on neuro-*MR* imaging (brain tumors dataset). Ramamurthy et al. [51] explored intensity, texture features using fusion method from large scale of dental images. Nanni et al. [42] have proposed the texture descriptors by extending the *GLCM* to multi-scale based on Gaussian filtering and by extracting features which were tested on biomedical image classification problems, not only from the entire co-occurrence matrix but also from subwindows. Yadav et al. [67] have proposed a new approach with compressive sampling which extracts the texture features of large medical databases for retrieval. Vaidehi and Subashini [60] have proposed texture features for content-based mammogram retrieval. Irmak et al. [19] have worked on brain tumor images using medical image processing.

However, the computation complexity of the texture features calculated from *co-occurrence matrix* [10], *MCM* [20], *multi-scale fractal dimension* [31], *Multi-scale* texture descriptors [42], *compressive sampling* [67], etc., is more expensive. To address the same, the local binary pattern (*LBP*) by Ojala et al. [46] is proposed. *LBP* being having low computational complexity and capacity of coding minute specifications, Ojala et al. [47] advocated some more moderations in *LBP* for texture classifications. Takala et al. [56] proposed the block-based texture features using the *LBP* texture features for image retrieval. Heikkila et al. [17] used the combination of *LBP* features and scale invariant feature transform (*SIFT*) to introduce texture pattern method i.e., center symmetric local binary pattern (*CS-LBP*). *LBPs* have encoded using five discrete levels by Nanni et al. [43] and Nanni et al. [44]. Guo et al. [12] and Liu et al. [30] proposed the local configuration pattern (*LCP*) and binary

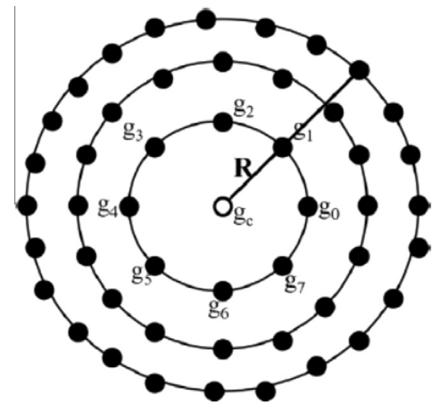

Fig. 1. Circular neighborhood sets for different (*P*, *R*).

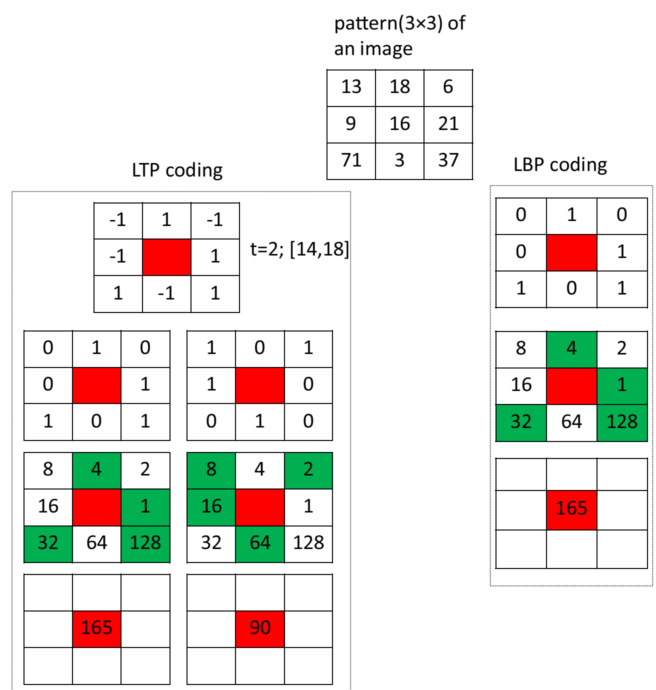

Fig. 2. Calculation of LBP and LTP operators.

rotation invariant and noise tolerant (*BRINT*) texture descriptors respectively using *LBPs*. Some of other *LBP* variants for texture image retrieval applications are proposed by Vipparthi and Nagar [65], Vipparthi and Nagar [66], Vipparthi et al. [64] and Bala and Kaur [3]. In the field of medicine, Oliver et al. [48] used *LBP* descriptor for mammogram images. Keramidas et al. [24] have given texture representation on thyroid ultrasound images. In (2008b, 2008c), Nanni and Lumini [40,41] used *LBP* to automate the cell phenotype image classification. In the area of face classification, Nanni and Lumini [38], Ahonen et al. [1] and Chen et al. [4] have extensively worked on *LBP*. Guo et al. [13] have proposed rotational invariant *LBP* variance operator for texture classification. Some important papers of Nanni and Lumini [39] and Zenghai et al. [70] have also successfully experimented *LBP* in other useful applications. More on *LBP* can be explored at http://www.ee.oulu.fi/mvg/page/lbp_bibliography#biomedical.

In the literature, Murala et al. [35], Murala et al. [36], Murala et al. [37], Murala and Jonathan [33], Murala and Jonathan [34], Dubey et al. [7], Dubey et al. [8], Dubey et al. [9] and Vipparthi et al. [63] have proposed many extended versions of *LBP* to obtain new image features for biomedical image indexing. As we know

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