Nuclear Instruments and Methods in Physics Research A 825 (2016) 1–5

Contents lists available at ScienceDirect

Nuclear Instruments and Methods in Physics Research A

journal homepage: www.elsevier.com/locate/nima

Sparsity-based shrinkage approach for practicability improvement of H-LBP-based edge extraction

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ARTICLE INFO

Article history:
Received 6 January 2016
Received in revised form
14 March 2016
Accepted 6 April 2016
Available online 7 April 2016

Keywords:
H-LBP
Edge extraction
Shrinkage
Data sparsity
Digital radiography

ABSTRACT

The local binary pattern with H function (H-LBP) technique enables fast and efficient edge extraction in digital radiography. In this paper, we reformulate the model of H-LBP and propose a novel sparsity-based shrinkage approach, in which the threshold can be adapted to the data sparsity. Using this model, we upgrade fast H-LBP framework and apply it to real digital radiography. The experiments show that the method improved using the new shrinkage approach can avoid elaborately artificial modulation of parameters and possess greater robustness in edge extraction compared with the other current methods without increasing processing time.

1. Introduction

As an important imaging postprocessing technique, edge extraction has been widely used in nondestructive testing techniques such as computed tomography (CT) [1,2] and digital radiography (DR) [3]. Because it is required to provide prior visual knowledge of imaged object features [4,5], the speed and efficiency of edge extraction are of primary concerned; however, it is also necessary to reduce the dependence on the parameters to avoid elaborate manual adjustment in real applications.

Benefited from its low computational complexity and high sensitivity to details, local binary pattern (LBP) [6,7] has been used in many applications such as recognition [8,9], estimation [10], detection [11,13] and segmentation [12]. However, these advantages also make LBP unable to avoid the influence of imaging noise. To address this problem, a novel counting scheme with a sigmoid function is introduced into LBP in [14], and an effective edge extraction method, i.e., H-LBP, is presented. Furthermore, [15] verifies that H-LBP is equivalent in function to the point-wise hard-shrinkage operation, where the threshold for each point is determined by the counting scheme of H-LBP. Accordingly, an accelerated method with low computational complexity, i.e., AH-LBP, is provided in [15]. However, when applying either H-LBP or AH-LBP to real 16-bit DCM format images, the related thresholds for hard-shrinkage must be artificially modulated to obtain optimal results for edge extraction, which inevitably affects these methods' feasibility and practicality in real applications.

Motivated by these works, we reformulate H-LBP model and propose a novel sparsity-based shrinkage approach, specifically of which the thresholding operation for each point depends on not only the local count scheme as in [14,15] but also the sparsity of the global area. Consequently, we use the approach to improve and present an upgraded H-LBP-based edge extraction method, herein denoted as SS-LBP. Due to the robustness of the sparsity-based shrinkage approach in real applications, SS-LBP possesses low computational complexity and avoids elaborately artificial modulation of parameters. Experiments on real radiographic images demonstrate its practical performance being superior to that of other H-LBP-based methods.

The remainder of this paper is organized as follows. In Section 2, we shall investigate LBP and present a description of our method and its corresponding algorithm. In Section 3, several experimental results on real radiographic images will be illustrated. Finally, in Section 4, some conclusions will be drawn.

2. Method description

2.1. LBP-based edge extraction methods

As an efficient and powerful tool for texture extraction and classification in digital images, LBP uses a concise method to

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http://dx.doi.org/10.1016/j.nima.2016.04.016
0168-9002/

describe the differences between the center pixel and its neighboring pixels. Here, we consider the neighboring area of a given pixel as an image patch of size 3 × 3 pixels, that is, $U = [u_{i,j}] \in \mathbb{R}^{3\times3}$, ordered lexicographically as a column vector $\mu = \mathbf{Vec}(U) \in \mathbb{R}^{9\times1}$. Let us denote $\mathbf{e}_i$ as a 9 × 1 column vector, of which the i-th element equals 1 and the 5-th element equals −1. Then, we can define a difference matrix $D{:=}[\mathbf{e}_i]_{1\times8}$. Therefore, the LBP value of the centered pixel $u_{2,2}$ can be computed through a scalar product of two vectors as follows:

$$\mathrm{LBP}_{u_{2,2}}{:=}\left\langle B,\kappa\right\rangle, \quad \text{with } B = \mathbf{S}(D^T\mu), \quad \kappa = \left[2^0, 2^1, 2^2, \dots, 2^7\right]^T, \tag{1}$$

where $\langle\cdot,\cdot\rangle$ denotes the scalar product and $\mathbf{S}(\cdot) = [\mathrm{sgn}(\cdot)+1]/2$ is a point-wise binary operator. Here, $\mathrm{sgn}(\cdot)$ is a signum function with assumed $\mathrm{sgn}(0) = 1$. LBP performs well in rapid and efficient texture extraction but lacks noise suppression.

To complement this, H-LBP in [14] proposes an elaborate shrinkage operation with a local threshold achieved via a counting scheme, i.e., $\tau = \langle B, \mathbf{1}\rangle$, where $\mathbf{1}$ is a column vector of all 1 s. In Detail for $u_{2,2}$, the H-LBP value can be computed as

$$\mathrm{H-LBP}_{u_{2,2}}{:=}\mathbf{S}(\mathcal{T}_\tau(\beta)), \quad \text{with } \beta = \left\langle \mathcal{H}_\epsilon(D^T\mu), \kappa\right\rangle. \tag{2}$$

Here, both $\mathcal{T}_\tau(\cdot)$ and $\mathcal{H}_\epsilon(\cdot)$ are hard-shrinkage operators, where $\mathcal{T}_\tau(\beta)$ equals −1 if τ=0 or 8 and β otherwise. In addition, $\mathcal{H}_\epsilon(\cdot)$ is a point-wise operator that satisfies $\mathcal{H}_\epsilon(x) = 1/2 + 1/\pi\cdot\arctan(-x/\epsilon)$ if $x \ge \tau$ and 0 otherwise. By comparing (2) with (1), H-LBP is found to significantly increase mathematical modulation to differentiate features and textures from the extracted details. Nevertheless, some additional computations are found in (2), thereby increasing the computational complexity. By further strengthening the functionality of the hard-shrinkage operation, an acceleration method, called AH-LBP, is presented in [15] as follows:

$$\mathrm{AH-LBP}_{u_{2,2}} = \mathcal{T}^*_{\alpha,\tau}(D^T\mu){:=}\begin{cases}0, & \tau\in\{0,8\} \text{ or } \left\|D^T\mu\right\| < s\tau,\\ 1, & \text{otherwise},\end{cases} \tag{3}$$

where s is an adjustable parameter. As s=1 and the norm of $D^T\mu$ is set as the supremum norm $\|\cdot\|_\infty$, (3) is equivalent to (2).

Based on (3), it can be summarized that AH-LBP is based on the hard-shrinkage operation with respect to s and τ, of which τ is a fundamental parameter and s is used to adjust the scale of τ to obtain globally optimal results. Due to the locality of τ, numerous manual modulations of s continue to be required, which makes both AH-LBP and H-LBP less practical in real applications. As a solution, both globality and locality should be considered in the H-LBP-based edge extraction method.

2.2. Sparsity-based shrinkage approach for SS-LBP

In this subsection, we begin the presentation of the proposed shrinkage approach based on sparsity of the global area. For convenience of discussion, let us introduce some notation. We take all the image patches $\{U_k, k = 1, \dots, p\}$ of size 3 × 3 pixels, ordered lexicographically as column vectors $\mu_k = \mathbf{Vec}(U_k)$ with $k = 1, \dots, p$. Here, we denote $\mathbb{U}{=}[\mu_1, \mu_2, \dots, \mu_p]$.

Aiming at constructing the sparsity-based model Ref. [16], we consider D as a pre-specified dictionary with atoms $\{\mathbf{e}_i, i = 1, \dots, 8\}$. By projecting each μ_k onto D as mentioned in (1), we find that $\alpha_k = D^T\mu_k$ with $k = 1, \dots, p$. Following this, the general form can be provided:

$$\mathbb{Q} = D^T\mathbb{U}, \quad \text{with} \quad \mathbb{Q}{=}[\alpha_k] \in \mathbb{R}^{8\times p}, \tag{4}$$

where each column α_k of $\mathbb{Q}$ provides a sparse representation with respect to the centered pixel and its neighboring area.

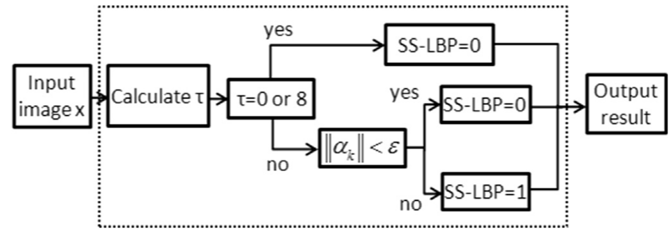

Fig. 1. SS-LBP flow diagram.

By investigating the local sparsity of α_k, H-LBP and AH-LBP implement point-wise edge extraction, several components of which are inherited into our method. Here, let $\mathbb{Q}^*{=}[\alpha_1^*, \dots, \alpha_{p^*}^*]$ where $\left\langle\alpha_k^*, \mathbf{1}\right\rangle \ne 0$ or 8 and $p^* \le p$. Motivated by (3), a global representation can be yielded by a specified column-wise norm as follows:

$$\mathrm{C}(\mathbb{Q}^*) := \left[\left\|\alpha_1^*\right\|, \left\|\alpha_2^*\right\|, \dots, \left\|\alpha_{p^*}^*\right\|\right]. \tag{5}$$

The remaining question is how to find a novel and reasonable threshold ε to constrain the number of nonzero elements in $\mathrm{C}(\mathbb{Q}^*)$, i.e., $\|\mathrm{C}(\mathbb{Q}^*)\|_0 < \varepsilon$ for sparse operations. Following the concepts in [17], a theoretically optimal choice of ε is

$$\varepsilon = \lambda\cdot\mathrm{M}(\mathrm{C}(\mathbb{Q}^*)), \tag{6}$$

where $\mathrm{M}(\mathrm{C}(\mathbb{Q}^*))$ returns the median value of the row vector $\mathrm{C}(\mathbb{Q}^*)$, and λ depends on the noise level. Hence, for a centered pixel u_k with its corresponding α_k, its SS-LBP value can be computed using the following sparsity-based shrinkage:

$$\mathrm{SS-LBP}_{u_k} = \mathcal{T}^S_{\varepsilon,\tau}(\alpha_k){:=}\begin{cases}0, & \tau\in\{0,8\} \text{ or } \|\alpha_k\| < \varepsilon,\\ 1, & \text{otherwise}.\end{cases} \tag{7}$$

As shown in (6), because the threshold ε is driven by the global data sparsity, SS-LBP can be self-adaptive in real applications while avoiding excessive manual modulations. To ensure the speed and efficiency of SS-LBP in real applications, we set the norm used in (5) and (7) as the supremum norm. Especially when λ=1, most cases under weak noise can be well addressed. The SS-LBP flow diagram is shown in Fig. 1. Additionally, SS-LBP is successfully applied to multiple-frame radiographic images. The relevant results will be shown later.

3. Experiments and analysis

All the experiments are performed on a PC equipped with Intel (R) Pentium(R) CPU T4300 2.10 GHz, with 2 GB of memory, and the algorithms were coded in the MATLAB 7.4 environment on Windows 7 32-bit. In this section, we present the results of several experiments on blurry and noisy real digital radiographies (DR) to demonstrate the speed and efficiency superiority of SS-LBP over H-LBP and AH-LBP.

3.1. 8-bit DR images

First, we test on four 8-bit DR images and compare with AH-LBP (equivalent to H-LBP with s=1). The images in Fig. 2, from left to right, are a head CT image, an X-ray computed tomography of hand and two neutron radiographies with low contrast areas. From the comparison of Fig. 2(B) and (C), we find that SS-LBP can successfully extract the full edges, even with the complex backgrounds and low-contrast areas in the images, which almost achieve the parallel results of H-LBP and AH-LBP.