Novel local bit-plane dissimilarity pattern for computed tomography image retrieval

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The performance of any image retrieval system relies over the image descriptor used for matching. The recently proposed descriptors mainly suffer due to the "less discriminative power" and "curse of dimensionality". In this letter, we introduced a novel image descriptor using Local Bit-plane Dissimilarity Pattern (LBDISP). The descriptor is computed by finding the dissimilarity map between the center pixel and its neighbors over each Bit-plane. The relation between the center pixel and dissimilarity map is then encoded to form the LBDISP descriptor. The dimension of the descriptor depends upon the number of neighbors only. A retrieval experiment over NEMA-CT database confirms the superiority and efficiency of the LBDISP descriptor.

Introduction: Nowadays, the images such as X-Ray, Magnetic Resonance Imaging, Computed Tomography, etc. are the most important source of information for medical analysis [1]. One possible way to analyze the captured medical image is to find the most similar images from a database with known characteristics on the basis of some important features using Content Based Image Retrieval (CBIR). The Local Binary Pattern (LBP) introduced by Ojala et al. is the most widely adopted feature descriptor [2]. The LBP has also shown very promising performance in medical image analysis [3]. Various variants of LBP are available in the literature [4-6]. Extensive research over the effective LBP variant descriptor is also being done for the medical image retrieval [7-10]. The existing local descriptors have at least one of the two main downsides: less discriminative and high dimensionality.

In this letter, we have designed a more discriminative and low dimensional local descriptor. The introduced method first decomposes the local neighborhood into bit-planes, then finds the dissimilarity map by computing the dissimilarity between the center and its neighbors at each bit-plane and finally finds the Local Bit-plane Dissimilarity Pattern (LBDISP) by exploiting the relationship of center with dissimilarity map.

Local Bit-plane Dissimilarity Pattern: Let $M^{i,j}$ is a pixel with intensity value $I^{i,j}$ in i^{th} row and j^{th} column of any image M (having B bit-depth) of dimension $m_1 \times m_2$. The N neighbors of pixel $M^{i,j}$ equally spaced at a radius of R is represented by $M_k^{i,j}$ with intensity values $I_k^{i,j}$ for $k \in [1, N]$. The center pixel $M^{i,j}$ along with its N neighbors $M_k^{i,j}$ are decomposed into the B number of binary bits. The B bits of center pixel and its neighbors can be visualized as the B bit-planes of a cylinder as depicted in the Fig. 1(a-b). The $I^{i,j,t}$ is the binary bit in t^{th} bit-plane corresponding to the raw intensity value $I^{i,j}$, and similarly $I_k^{i,j,t}$ is the binary bit in t^{th} bit-plane corresponding to the $I_k^{i,j}$ (i.e. k^{th} neighbor of center pixel) for $t \in [1, B]$.

The local bit-plane dissimilarity encoding utilizes the information at the bit-level to enhance the discriminative ability of the descriptor. It basically encodes the difference between the center and its neighbors at each bit-plane as depicted in Fig. 1(c). Let, $D_k^{i,j,t}$ is the binary value obtained after local bit-plane dissimilarity encoding in t^{th} bit-plane for a k^{th} neighbor of the center pixel. The $D_k^{i,j,t}$ is computed as:

$$D_k^{i,j,t}|_{t\in[1,B]\,\&\,k\in[1,N]} = \begin{cases} 0, & if\ I_k^{i,j,t} = I^{i,j,t} \\ 1, & otherwise \end{cases} \quad (1)$$

Note that this step does not affect the binary values $I^{i,j,t}$. In other words, $D^{i,j,t} = I^{i,j,t}$ for $t \in [1, B]$ or $D^{i,j} = I^{i,j}$.

The N neighboring values in local bit-plane dissimilarity map is represented with $D_k^{i,j}$ (see Fig. 1(d)) and computed as:

$$D_k^{i,j}|_{k\in[1,N]} = \sum_{t=1}^{B} 2^{t-1} \times D_k^{i,j,t} \quad (2)$$

We encoded the relationship between the center pixel and its neighbors from the local bit-plane dissimilarity map and finally taken its histogram to compute the final descriptor. The LBDISP histogram based descriptor is calculated as follows,

$$H(\gamma) = \sum_{i=R+1}^{m_1-R} \sum_{j=R+1}^{m_2-R} \begin{cases} 1, & if\ \gamma = \sum_{k=1}^{N} 2^{k-1} \times LBDISP_k^{i,j} \\ 0, & Otherwise \end{cases} \quad (3)$$

for $\forall\, \gamma \in [0, 2^N - 1]$, where $LBDISP_k^{i,j}$ is the k^{th} element of $LBDISP^{i,j}$ and represents the relationship between the center and k^{th} neighbor of the dissimilarity map.

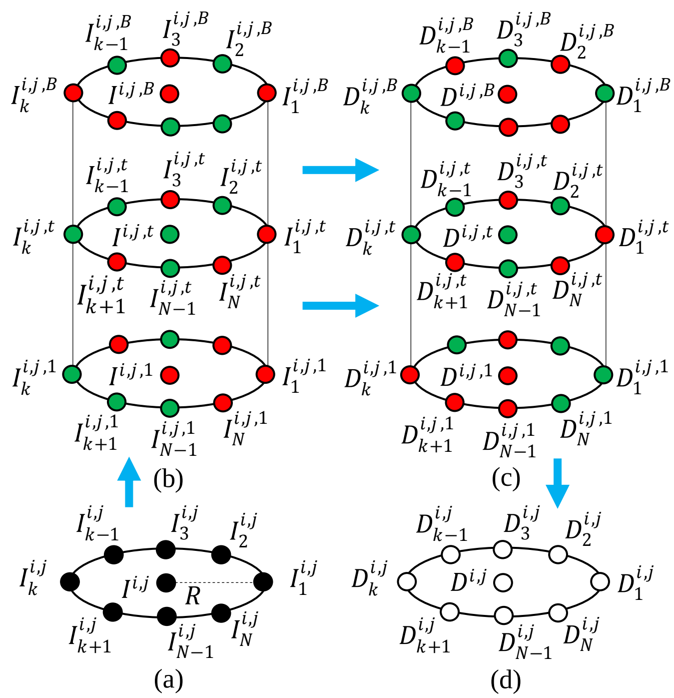

Fig. 1. The local bit-plane decomposition and dissimilarity map generation, (a) a center pixel $M^{i,j}$ having intensity value $I^{i,j}$ and its N neighbors $M_k^{i,j}$ with intensity values $I_k^{i,j}|_{k\in[1,N]}$ situated at a radius of R at equal intervals, (b) the B bit-planes obtained after the local bit-plane decomposition, (c) the dissimilarity values of the neighbors at each bit-plane (the dissimilarity values for the center is unchanged), and (d) the local bit-plane dissimilarity map obtained by converting the bit-planes into the decimal. Note that 'Black' circles denotes the raw intensity values, 'Red' and 'Green' circles represent the binary bit '1' and '0' respectively, and 'White' circles signifies the dissimilarity values in decimal.

Mathematically, $LBDISP_k^{i,j}$ is computed from $D^{i,j}$ and $D_k^{i,j}$ as follows,

$$LBDISP_k^{i,j}|_{k\in[1,N]} = \begin{cases} 1, & if\ D_k^{i,j} \geq D^{i,j} \\ 0, & otherwise \end{cases} \quad (4)$$

Experimental Results: This section is devoted to the image retrieval experiments and analysis over the NEMA-CT database [11]. The 499 CT images of resolution 512×512 are considered from CT0001, CT0003, CT0020, CT0057, CT0060, CT0080, CT0082, and CT0083 cases. We manually categorized into 8 categories on the basis of the different body part with the number of images are 104, 46, 29, 71, 108, 39, 33 and 69 respectively. The example images of this database are shown in Fig. 2. The same NEMA-CT database is used in [9-10]. The LBDISP is compared with the Local Binary Pattern (LBP) [2], Local Ternary Pattern (LTP) [4], Local Derivative Pattern (LDP) [5], Local Tetra Pattern (LTrP) [6], Local Ternary Co-occurrence Pattern (LTCoP) [7], Local Mesh Pattern (LMeP) [8], Local Diagonal Extrema Pattern (LDEP) [9], and Local Bit-plane Decoded Pattern (LBDP) [10]. The values of radius of local neighborhood (R), number of local neighbors (N), and bit-depth of the image (B) are considered as 1, 8, and 8 respectively. The similarity measure used is D_1 distance which is used in most of existing methods [7]. We have turned each image of the NEMA-CT database as the query image and retrieved the top matching images. The retrieved image which is from the same category as of the query image is the correct match otherwise it is a false match. The performance of the retrieval system is judged on the basis of the average retrieval precision (ARP) [10] and average normalized modified retrieval rank (ANMRR) [12]. High value of ARP and low value of ANMRR signifies the better retrieval performance and vice-versa.

The retrieval results for each descriptor over NEMA-CT database is demonstrated in Fig. 3. The ARP and ANMRR curves are plotted against number of top matches. Very promising results using LBDISP descriptor can be seen in Fig. 3 as compared to the other descriptors. It can be noticed that the ARP values are highest and the ANMRR values are lowest for the LBDISP. The LBDISP is also better as compared to the LBDP over NEMA-CT database because this database is having the images from different body parts and LBDISP is encoding the local dissimilarity of the image. The dimension of LBDISP depends only upon the number of neighbors considered. The LBP, LTP, LDP, LTrP, LTCoP, LMeP, LDEP, LBDP, and LBDISP descriptors are having the dimensions of 256, 2×256, 4×256, 13×256, 2×256, 3×256, 24, 256, and 256. The retrieval complexity of LBDISP is generally better except LDEP.

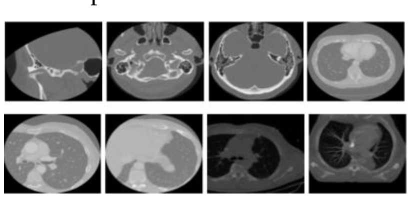

Fig. 2. Sample images of the NEMA-CT database with one image per category.

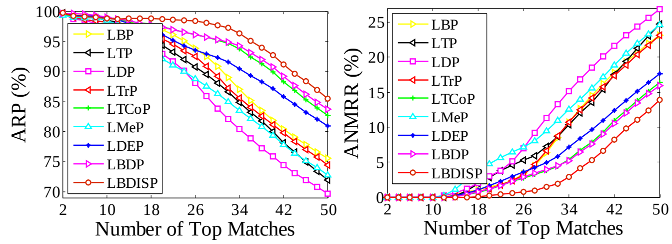

Fig. 3. The experimental results over NEMA-CT database for each descriptor using ARP and ANMRR.

Conclusion: A novel local bit-plane dissimilarity pattern (LBDISP) is proposed to tackle the less discriminative and high dimensionality problem by encoding the dissimilarity between a center pixel and its surrounding neighbors at bit-level. The dimension of LBDISP is very reasonable and only depends upon the number of neighbors. From the retrieval experiments over NEMA-CT database, it is concluded that the LBDISP outperforms the recent descriptors.

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References

1. D.L. Rubin, H. Greenspan, and J.F. Brinkley, "Biomedical Imaging Informatics," *Biomedical Informatics*, pp. 285-327, 2014.
2. T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 971-987, 2002.
3. S. He, J.J. Soraghan, B.F. O'Reilly, and D. Xing, "Quantitative analysis of facial paralysis using local binary patterns in biomedical videos," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 7, pp. 1864-1870, 2009.
4. X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1635-1650, 2010.
5. B. Zhang, Y. Gao, S. Zhao, and J. Liu, "Local derivative pattern versus local binary pattern: face recognition with high-order local pattern descriptor", *IEEE Trans. Image Process.*, vol. 19, no. 2, pp. 533-544, 2010.
6. S. Murala, R.P. Maheshwari, and R. Balasubramanian, "Local tetra patterns: a new feature descriptor for content-based image retrieval", *IEEE Trans. Image Process.*, vol. 21, no. 5, pp. 2874-2886, 2012.
7. S. Murala and Q. M. J. Wu, "Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval," *Neurocomputing*, vol. 119, pp. 399-412, 2013.
8. S. Murala and Q. M. J. Wu, "Local Mesh Patterns Versus Local Binary Patterns: Biomedical Image Indexing and Retrieval," *IEEE Journal of Biomedical and Health Informatics*, vol.18, no.3, pp. 929-938, 2014.
9. S.R. Dubey, S.K. Singh, and R.K. Singh, "Local diagonal extrema pattern: a new and efficient feature descriptor for CT image retrieval", *IEEE Signal Processing Letters*, vol. 22, no. 9, pp. 1215-1219, 2015.
10. S.R. Dubey, S.K. Singh, and R.K. Singh, "Local Bit-plane Decoded Pattern: A Novel Feature Descriptor for Biomedical Image Retrieval," *IEEE Journal of Biomedical and Health Informatics*, 2015.
11. NEMA–CT image database, Available from [Online]: ⟨ftp://medical.nema.org/ medical/Dicom/Multiframe/⟩.
12. K. Lu, N. He, J. Xue, J. Dong, and L. Shao, "Learning View-Model Joint Relevance for 3D Object Retrieval", *IEEE Transactions on Image Processing*, vol. 24, no. 5, pp. 1449-1459, 2015.