A NEW FEATURE-BASED WAVELET COMPLETED LOCAL TERNARY PATTERN (FEAT-WCLTP) FOR TEXTURE AND MEDICAL IMAGE CLASSIFICATION

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Pada masa kini, pemerihal imej berdasarkan tekstur diguna pakai dalam pelbagai aplikasi nyata yang penting. Penggunaan analisis tekstur dalam pengelasan imej perubatan dan tekstur telah menarik perhatian ramai pihak. Corak Perduaan Tempatan (LBP) salah satu yang paling mudah namun berkesan tekstur pemerihal. Tetapi ia mempunyai beberapa batasan yang boleh menjejaskan ketepatannya. Oleh itu, kebanyakan pemerihal berasaskan LBP telah dicadangkan untuk menangani kekurangan ini dan meningkatkan ketepatan mereka. Corak Pertigaan Tempatan Lengkap (CLTP) adalah salah satu pemerihal berasaskan LBP yang penting. Walau bagaimanapun, CLTP menderita dari dua batasan utama: pemilihan nilai ambang berasaskan secara manual dan keamatan yang tinggi yang memberi kesan negatif kepada prestasi deskriptor dan membawa kepada pengiraan yang tinggi. Kajian ini bertujuan untuk meningkatkan ketepatan klasifikasi CLTP dan mengatasi had komputasi dengan mencadangkan pemerihal baru yang diilhamkan oleh CLTP. Oleh itu, penyelidikan ini memperkenalkan dua sumbangan: Yang pertama adalah pemerihal baru yang dicadangkan yang menggabungkan transformasi wavelet diskrit yang berlebihan (RDWT) dengan CLTP asal, iaitu, wavelet menyelesaikan pola ternary tempatan (WCLTP). Mengeluarkan CLTP dalam bentuk jelmaan gelombang kecil dapat meningkatkan ketepatan pengelasan disebabkan oleh sifat peralihan tak varian dalam RDWT. Pertamanya, imej diuraikan kepada empat sub-kumpulan (LL, LH, HL dan HH) dengan menggunakan RDWT. Kemudian, CLTP dikeluarkan berdasarkan kepada koefisien gelombang kecil LL. Sumbangan kedua pula ialah pengurangan daya kedimensian WCLTP dengan mengurangkan saiz dan mencadangkan pemerihal tekstur baru, iaitu Corak Pertigaan Tempatan Lengkap Gelombang Kecil Berdasarkan Fitur (Feat-WCLTP). Pemerihal cadangan ini dapat meningkatkan prestasi CLTP dan mengurangkan kedimensian tinggi. Oleh itu, Feat-WCLTP merupakan gabungan antara bahagian isyarat, fitur dan pusat. Prestasi kaedah WCLTP dan Feat-WCLTP yang dicadangkan telah dinilai menggunakan empat set data tekstur (Outex, CURet, UIUC dan Kylberg) dan dua set data perubatan (2D HeLa dan Breast Cancer) dan kemudian dibandingkan dengan beberapa varian LBP yang terkenal. WCLTP berjaya mengatasi pemerihal lain dan mencapai ketepatan pengelasan tertinggi dalam semua eksperimen. Keputusan kaedah cadangan ini bagi set data tekstur ialah 99.35% dalam OuTex, 96.57% dalam CUReT, 94.80% dalam UIUC dan 99.88% dalam Kylberg. Manakala, keputusan WCLTP dalam set data perubatan ialah 84.19% dalam 2D HeLa and 92.14% dalam set data Breast Cancer. Feat-WCLTP pula bukan sahaja dapat mengatasi masalah kedimensian, malah meningkatkan daya ketepatan pengelasan. Keputusan Feat-WCLTP dalam set data tekstur ialah 99.66% dalam OuTex, 96.89% dalam CUReT, 95.23% dalam UIUC dan 99.92% dalam Kylberg. Manakala, keputusannya dalam set data perubatan ialah 84.42% dalam set daha 2D HeLa dataset and 89.12% dalam set data Breast Cancer. Di samping itu, kaedah cadangan Feat-WCLTP dapat mengurangkan saiz fitur bagi corak tekstur (1,8) daripada 400 bin kepada 160 bin dalam WCLTP. Kedua-dua kaedah WCLTP dan Feat-WCLTP mempunyai daya ketepatan dan kedimensian yang lebih baik berbanding kaedah CLTP asal.

ABSTRACT

Nowadays, texture image descriptors are used in many important real-life applications. The use of texture analysis in texture and medical image classification has attracted considerable attention. Local Binary Patterns (LBP) is one of the simplest yet eff ective texture descriptors. But it has some limitations that may affect its accuracy. Hence, different variants of LBP were proposed to overcome LBP's drawbacks and enhance its classification accuracy. Completed local ternary pattern (CLTP) is one of the significant LBP variants. However, CLTP suffers from two main limitations: the selection of the threshold value is manually based and the high dimensionality which is negatively affected the descriptor performance and leads to high computations. This research aims to improve the classification accuracy of CLTP and overcome the computational limitation by proposing new descriptors inspired by CLTP. Therefore, this research introduces two contributions: The first one is a proposed new descriptor that integrates redundant discrete wavelet transform (RDWT) with the original CLTP, namely, wavelet completed local ternary pattern (WCLTP). Extracting CLTP in wavelet transform will help increase the classification accuracy due to the shift invariant property of RDWT. Firstly, the image is decomposed into four sub-bands (LL, LH, HL, HH) by using RDWT. Then, CLTP is extracted based on the LL wavelet coefficients. The latter one is the reduction in the dimensionality of WCLTP by reducing its size and a proposed new texture descriptor, namely, feature-based wavelet completed local ternary pattern (Feat-WCLTP). The proposed Feat-WCLTP can enhance CLTP's performance and reduce high dimensionality. The mean and variance of the values of the selected texture pattern are used instead of the normal magnitude texture descriptor of CLTP. The performance of the proposed WCLTP and Feat-WCLTP was evaluated using four textures (i.e. OuTex, CUReT, UIUC and Kylberg) and two medical (i.e. 2D HeLa and Breast Cancer) datasets then compared with several well-known LBP variants. The proposed WCLTP outperformed the previous descriptors and achieved the highest classification accuracy in all experiments. The results for the texture dataset are 99.35% in OuTex, 96.57% in CUReT, 94.80% in UIUC and 99.88% in the Kylberg dataset. The results for the medical dataset are 84.19% in the 2D HeLa dataset and 92.14% in the Breast Cancer dataset. The proposed Feat-WCLTP not only overcomes the dimensionality problem but also considerably improves the classification accuracy. The results for Feat-WCLTP for texture dataset are 99.66% in OuTex, 96.89% in CUReT, 95.23% in UIUC and 99.92% in the Kylberg dataset. The results for the medical dataset are 84.42% in the 2D HeLa dataset and 89.12% in the Breast Cancer dataset. Moreover, the proposed Feat-WCLTP reduces the size of the feature vector for texture pattern (1,8) to 160 bins instead of 400 bins in WCLTP. The proposed WCLTP and Feat-WCLTP have better classification accuracy and dimensionality than the original CLTP.

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LIST OF SYMBOLS

R	The radius of symmetric neighbourhood circle
p	The number of neighbourhood pixels
i_c	The grey value of the centre pixel
i_p	The grey value neighbour pixel
U	Uniformity
u2	Uniform patterns
riu2	Rotation invariant uniform pattern
t	Threshold value
s_p	Sign component
m_p	Magnitude component
c_I	The average grey level of the whole image
μ_m	Mean of the magnitude vector
σ_m^2	Variance of the magnitude vector
t_μ	Local threshold value for mean
t_σ	Local threshold value for variance
t_c	Local threshold value for centre
Ψ	Mother wavelet function
$*$	Convolution operator
$\downarrow$	Downsampling operator
cj	Output coefficients of highpass filter
dj	Output coefficients of lowpass filter
N	Number of training images
x^2	Distance between two histograms
H	Histogram

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network techniques
AR	Autoregression
BRINT	Binary Rotation Invariant and Noise Tolerant
CLBC	Completed Local Binary Count
CNN	Convolutional Neural Network
CLBP	Completed Local Binary Pattern
CLTP	Completed Local Ternary Pattern
CuReT	Columbia-Utrecht Reflectance and Texture Database
CWT	Continuous Wavelet Transforms
WT	Wavelet Transform
DRLBP	Dominant Rotated Local Binary Patterns
DWT	Discrete Wavelet Transform
FbLBP	Feature-based Local binary pattern
Feat-WCLTP	Feature-based Completed Local Ternary Pattern
GLCM	Gray Level Co-occurrence Matrix
HH	High-High
HL	High-Low
K-NN	K-Nearest Neighbor
LBC	Local Binary Count
LBP	Local Binary Patterns
LH	Low-High
LL	Low-Low
LTP	Local Ternary Pattern
MRF	Markov Random Field
MLP	Multi-Layer Perceptron
NRLBP	Noise Resistant Local Binary Pattern
PET	Positron Emission Tomography
RDWT	Redundant Discrete Wavelet Transform
RBF	Radial Basis Function
RGB	Red, Green and Blue
RLBP	Robust Local Binary Pattern

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