

DYNAMIC FAST LOCAL LAPLACIAN
COMPLETED LOCAL TERNARY PATTERN
(DYNAMIC FLAPCLTP) FOR FACE
RECOGNITION

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ABSTRACT

Today, face recognition has become one of the typical biometric authentication systems used for high security. Some systems may use face recognition to enhance their security and provide high protection level. Feature extraction is considered to be one of the most important steps in face recognition systems. The important and interesting parts of the image in feature extraction are represented as a compact feature vector. Many features, such as texture, colour and shape, have been proposed in the image processing fields. These features can also be classified globally or locally depending on the image extraction area. Texture descriptors have recently played a crucial role as local descriptors. Different types of texture descriptors, such as local binary pattern (LBP), local ternary pattern (LTP), completed local binary pattern (CLBP) and completed local ternary pattern (CLTP), have been proposed and utilised for face recognition tasks. All these texture features have achieved good performance in terms of recognition accuracy. Although the LBP performed well in different tasks, it has two limitations. LBP is sensitive to noise and occasionally fails to clearly distinguish between two different texture patterns with the same LBP encoding code. Most of the texture descriptors inherited these limitations from LBP. CLTP is proposed to overcome the limitations of LBP. CLTP performed well with different image processing tasks, such as image classification and face recognition. However, CLTP suffers from two limitations that may affect its performance in these tasks: the fixed value of the threshold value that is used during the CLTP extraction process regardless of the type of dataset or system and the longer length of the CLTP histogram than that of previous descriptors. This study focused on handling the first limitation, which is the threshold selection. Firstly, a new texture descriptor is proposed by integrating the fast-local Laplacian filter and the CLTP descriptor, namely, fast-local Laplacian CLTP (FLapCLTP). The fast-local Laplacian filter can help in increasing the performance of the CLTP due to its extensive detail enhancements and tone mapping; this contribution is handled by the constant threshold value used in CLTP. A dynamic FLapCLTP is then proposed to address the aforementioned issue. Instead of using a fixed threshold value with all datasets, a dynamic value is selected based on the image pixel values. Therefore, each different texture pattern has different threshold values to extract FLapCLTP from the pattern. This dynamic value is automatically selected according to the centre value of the texture pattern. Therefore, a dynamic FLapCLTP is proposed in this study. Finally, the proposed FLapCLTP and dynamic FLapCLTP are evaluated for facial recognition systems using ORL Faces, Sheffield Face, Collection Facial Images, Georgia Tech Face, Caltech Pedestrian Faces 1999, JAFFE, FEI Face and YALE datasets. The results showed the priority of the proposed texture compared with previous texture descriptors. The dynamic FLapCLTP achieved the highest recognition accuracy rates with values of 100%, 99.96%, 99.75%, 99.69%, 94.86%, 90.33%, 86.86% and 82.43% using UMIST, Collection Facial Images, JAFFE, ORL, Georgia Tech, YALE, Caltech 1999 and FEI datasets, respectively.

ABSTRAK

Pada masa kini, wajah adalah salah satu biometrik yang telah digunakan untuk meningkatkan keselamatan. Kebanyakan sistem menggunakan muka untuk meningkatkan keselamatan sistem dan memberikan tahap perlindungan yang tinggi. Dalam sistem pengenalan wajah, pengekstrakan ciri adalah salah satu langkah yang penting. Dalam pengekstrakan ciri, bahagian yang paling menarik dalam imej iaitu vektor ciri padat. Banyak ciri telah dicadangkan dalam bidang pemprosesan imej seperti tekstur, warna, dan bentuk. Ciri-ciri ini boleh diklasifikasikan secara global atau secara tempatan bergantung kepada kawasan pengekstrakan dalam imej. Baru-baru ini, deskriptor tekstur memainkan peranan penting sebagai deskriptor tempatan. Jenis deskriptor tekstur yang berbeza telah dicadangkan dan digunakan untuk tugas pengiktirafan muka seperti Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Completed Local Binary Pattern (CLBP) dan Completed Local Ternary Pattern (CLTP). Semua ciri tekstur ini telah mencapai prestasi yang baik dari segi ketepatan pengecaman. Walaupun LBP berfungsi dengan baik dalam tugas yang berbeza, ia mempunyai dua batasan iaitu sensitif terhadap hingar dalam imej dan kadangkala tidak dapat membezakan antara corak tekstur di mana dua corak yang berbeza mungkin mempunyai kod pengekodan yang sama. Kebanyakan deskriptor tekstur mewarisi sekatan-sekatan ini dari LBP. CLTP dicadangkan untuk mengatasi had LBP dan menunjukkan prestasi tinggi dengan tugas pemprosesan imej yang berbeza seperti klasifikasi imej dan pengecaman muka. Bagaimanapun, ia mengalami dua batasan yang mungkin mempengaruhi prestasinya dalam tugas-tugas ini. Pertama, nilai ambang yang tetap digunakan semasa proses penggalan CLTP tanpa mengira jenis dataset atau sistem. Akhir-akhir ini, histogram CLTP lebih panjang daripada deskriptor terdahulu. Kajian ini memberi tumpuan untuk mengatasi batasan pertama iaitu pemilihan ambang. Pertama, deskriptor tekstur baru dicadangkan dengan mengintegrasikan penapis Laplacian tempatan cepat dalam deskriptor CLTP, iaitu Fast Local Laplacian CLTP (FLapCLTP). Penapis Laplacian tempatan boleh membantu meningkatkan prestasi CLTP disebabkan oleh peningkatan terperinci dan pemetaan nada dalam ciri penapisan ini. Sumbangan kedua memberi tumpuan untuk mengatasi masalah nilai ambang dalam CLTP. Untuk menyelesaikannya, Dinamik Fast Local Laplacian CLTP (Dinamik FLapCLTP) dicadangkan. Dinamik nilai ambang akan dipilih berdasarkan nilai pixel imej. Oleh itu, setiap corak tekstur yang berbeza akan mempunyai nilai ambang yang berbeza untuk mengekstrak CLTP. Berdasarkan itu, FLapCLTP yang dinamik dicadangkan dalam kajian ini. FLapCLTP dan dinamik FLapCLTP yang dicadangkan telah dievaluasi dalam sistem pengenalan wajah menggunakan ORL Faces, Sheffield Face, Collection Facial Images, Georgia Tech Face, Caltech Pedestrian Faces 1999, JAFFE, FEI Face dan YALE dataset. Keputusan menunjukkan deskriptor tekstur yang dicadangkan berbanding dengan deskriptor tekstur terdahulu. Dinamik FLapCLTP telah mencapai kadar ketepatan pengecaman tertinggi, ia mencapai 100%, 99.96%, 99.75%, 99.69%, 94.86%, 90.33%, 86.86%, 82.43% menggunakan UMIST, Collection Facial Images, JAFFE, ORL, Georgia Tech, YALE, Caltech 1999, dan FEI dataset masing-masing.

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LIST OF SYMBOLS

α	Alpha
β	Beta
c	Centre pixel
x^2	Distances between two histograms
γ	Gamma
m_p	Mean value of the whole image
μ	Mu
P	Neighbourhood
ω	Omega
ϕ	Phi
π	Pi
R	Radius
σ	Sigma
c_I	The average grey level of the whole image
N	Training image

LIST OF ABBREVIATIONS

2D	Two dimensional
ACC	Accuracy
CLBP	Completed Local Binary Pattern
CLBP_C	Completed Local Binary Pattern_Centre
CLBP_M	Completed Local Binary Pattern_Magnitude
CLBP_S	Completed Local Binary Pattern_Sign
CLTP	Completed Local Ternary Pattern
CLTP_C	Completed Local Ternary Pattern_Centre
CLTP_M	Completed Local Ternary Pattern_Magnitude
CLTP_S	Completed Local Ternary Pattern_Sign
Dynamic FLapCLTP	Dynamic Fast Local Laplacian Completed Local Ternary Pattern
FEI	FEI Face Dataset
FLapCLTP	Fast Local Laplacian Completed Local Ternary Pattern
JAFFE	Japanese Female Facial Expression
KNN	K-Nearest Neighbour
LBP	Local Binary Pattern
LDTP	Local Directional Ternary Pattern
LTP	Local Ternary Pattern
MRELBP	Median Robust Extended Local Binary Pattern
ORL	ORL Dataset
SVM	Support Vector Machine
UMIST	Sheffield Face Dataset
YALE	Yale Face Dataset

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