

NOVEL METHODOLOGIES FOR ROBUST FACE RECOGNITION

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by

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ABSTRACT

The thesis presents methodologies to address some of the limitations of a face recognition system due to changes in face caused by makeup, variations in pose, changing lighting conditions and expressions. It also presents the development of methods for identifying the age group of a person through facial image.

Automated age group estimation based on texture classification using Gaussian non-additive entropy feature has been proposed. The method is primarily founded upon the features representing the information from texture changes occurring in the face of a person as age progresses.

The extraction of the above features is followed by a classifier which is based on the minimization of error between the training and test features by emphasizing a margin between them. The feature error is based on the triangular norms or the t-norms such that an aggregate of the training set of features and their subsequent fusion of errors produces the classifying margin between the categories.

A variant of Features from Accelerated Segment Test is created using Gaussian non-additive entropy in ID3 algorithm to maintain the invariance of interest points and also the discriminatory power of the algorithms using the same.

In order to design a robust face recognition system, Kernel Entropy Component Analysis based on Gaussian non-additive entropy is examined for dealing with various changes in face due to variations in illumination, pose and expressions. The approach is combined with Gabor Wavelet Transform for achieving illumination invariance with some degree of expression and pose invariance, and Discrete Cosine Transform for significant robustness towards illumination changes in the face.

To accomplish makeup invariance in face recognition, a methodology developed using Gaussian non-additive entropy based Features from Accelerated Segment Test and Eigen Vectors is discussed. For pose invariant face recognition, a method based on Gabor Jets combined with Inner Product Classifier is suggested. Illumination invariance issue can also be addressed by using Features from Accelerated Segment Test based on Gaussian non-additive entropy and the aforementioned classifier based on t-norms. To achieve invariance to expressions, robust clustering methods like partitioning around medoids and possibilistic fuzzy c-medoids are used. Another technique examined for expression invariant face recognition uses Topographic ICA to extract features from the face followed by the Inner Product Classifier for the subsequent classification. The proposed techniques are also computationally more efficient than the other methods compared and they also address the speed-accuracy trade-off.

The techniques presented in this thesis have been evaluated on the standard databases such as JAFFE, Yale, VMU, FERET databases etc. and their effectiveness has been ascertained using the proposed features and the classifier.

सार

यह शोध प्रबंध श्रृंगार, चेहरे की मुद्रा, प्रकाश की स्थिति और अभिव्यक्ति बदलने के कारण चेहरे में उत्पन्न परिवर्तन की वजह से चेहरे की मान्यता प्रणाली की सीमाओं को संबोधित करने के तरीकों को प्रस्तुत करता है। यह चेहरे की छवि के माध्यम से किसी व्यक्ति के आयु वर्ग की पहचान करने के तरीकों के विकास को भी प्रस्तुत करता है।

गॉसियन नॉन-एडेटीटिव एंट्रोपी का उपयोग करते हुए संरचना वर्गीकरण के आधार पर स्वचालित आयु समूह अनुमान प्रस्तावित किया गया है। विधि मुख्य रूप से उन विशेषताओं पर आधारित है जो उम्र की प्रगति की वजह से एक व्यक्ति के चेहरे में होने वाली संरचना परिवर्तनों की जानकारी का उपयोग करती है।

उपरोक्त विशेषताओं का निष्कर्षण एक क्लासिफायर द्वारा किया जाता है जो उनके बीच एक मार्जिन पर बल देकर प्रशिक्षण और परीक्षण विशेषताओं के बीच न्यूनतम त्रुटि पर आधारित है। विशेषता त्रुटि त्रिकोणीय मानदंडों या टी-मानदंडों पर आधारित है, जो कि विशेषताओं के प्रशिक्षण सेटों का एक कुल और त्रुटियों के संलयन श्रेणियों के बीच वर्गीकरण मार्जिन पैदा करता है।

त्वरित सेगमेंट टेस्ट से विशेषताओं के एक प्रस्तावित संस्करण में, आईडी 3 एल्गोरिथम में गॉसियन नॉन-एडेटीटिव एंट्रोपी का उपयोग करने से इनटूस्ट पाइन्ट की अचूकता एवं एल्गोरिदम की भेदभावपूर्ण शक्ति में वृद्धि प्राप्त हुई है।

एक मजबूत मुख पहचान प्रणाली को डिजाइन करने के लिए, गॉसियन नॉन-एडेटीटिव एंट्रोपी के आधार पर कर्नेल एंट्रोपी घटक विश्लेषण की जांच की गई है क्योंकि रोशनी, मुद्रा और अभिव्यक्ति में भिन्नता के कारण चेहरे में विभिन्न परिवर्तन आते हैं। यह कार्यप्रणाली गैबोर वेवलेट

परिवर्तन के साथ मिलाई गई है जिसके माध्यम से अभिव्यक्ति और मुद्रा के अचूकरण को प्राप्त किया गया है, साथ ही असतत कोसाइन परिवर्तन के माध्यम से रोशनी के अचूकरण को प्राप्त किया गया है।

चेहरे की पहचान में श्रृंगार अपरिवर्तनीयता को पूरा करने के लिए, गॉसियन नॉन-एडिटिव एन्ट्रापी पर आधारित तकनीक का उपयोग कर विकसित की गई एक पद्धति त्वरित सेगमेंट टेस्ट से विशेषताएं और ईगेन वैक्टर की चर्चा की गई है। मुद्रा अपरिवर्तनीयता के लिए, इनर प्रोडक्ट क्लासिफायर के साथ संयुक्त गैबोर्स जेट्स पर आधारित एक विधि का सुझाव दिया गया है। प्रकाश अपरिवर्तनीयता मुद्दे को गॉसियन नॉन-एडिटिव एन्ट्रापी पर आधारित त्वरित सेगमेंट टेस्ट से विशेषताओं और टी-मानदंडों के आधार पर पूर्ववर्ती क्लासिफायर का उपयोग करके भी संबोधित किया जा सकता है। अभिव्यक्ति अपरिवर्तनीयता प्राप्त करने के लिए, मिडोइड्स के विभाजन के साथ-साथ संभावित फजी सी-मिडोइड्स जैसे शक्तिशाली क्लस्टरिंग विधियों का इस्तेमाल किया गया है। अभिव्यक्ति अपरिवर्तनीयता के लिए टॉपोग्राफिक आईसीए के द्वारा चेहरे में से विशेषताओं का निष्कर्षण और वर्गीकरण के लिए इनर प्रोडक्ट क्लासिफायर का उपयोग किया गया है। प्रस्तावित तरीके अन्य तरीकों की तुलना में कम्प्यूटेशनल रूप से अधिक कुशल और गति-सटीक हैं।

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Acronyms

DCT	Discrete Cosine Transform
EBGM	Elastic Bunch Graph Matching
EER	Equal Error Rate
FAR	False Acceptance Rate
FAST	Features from Accelerated Segment Test
FBG	Face Bunch Graph
FCM	Fuzzy C-Means
FCMdd	Fuzzy C-Medoids
FRR	False Rejection Rate
GAR	Genuine Acceptance Rate
GLCM	Grey Level Co-occurrence Matrix
GLCP	Grey Level Co-occurrence Probabilities
GWT	Gabor Wavelet Transformation
ICA	Independent Component Analysis
KECA	Kernel Entropy Component Analysis
KPCA	Kernel Principal Component Analysis
LBP	Local Binary Pattern

LDA	Linear Discriminant Analysis
NN	Neural Network
NNS	Nearest Neighbour Search
PAM	Partitioning Around Medoids
PCA	Principal Component Analysis
PCM	Possibilistic C-Means
PCMdd	Possibilistic C-Medoids
PFCM	Possibilistic Fuzzy C-Means
PFCMdd	Possibilistic Fuzzy C-Medoids
PIE	Pose Illumination Expression
ROC	Receiver Operating Characteristics
ROI	Region of Interest
SIFT	Scale Invariant Feature Transform
SURF	Speeded Up Robust Features
SVM	Support Vector Machine
TICA	Topographic Independent Component Analysis