JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

FACE RECOGNITION IN VIDEO AND EMOTION RECOGNITION

[1]P. Darwin,[2]T. Kalyani,[3]K.S.Geethika Rani,[4]V.Rakesh,[5]D.Ramesh

[1]**AssociateProfessor,** Dept of ECE, Godavari Institute of Engineering and Technology(A),Rajahmundry,AP

[2,3,4,5]**Students,** Dept of ECE, Godavari Institute of Engineering and Technology (A),Rajahmundry,AP

Abstract-Facial recognition research has recently gained traction in the fields of computer vision, neurology, and psychology. Throughout this procedure, a novel color facial recognition (FR) technique is shown. If a face picture has been captured with wildly varying lighting conditions and a poor spatial resolution, color information becomes even more crucial. The recommended strategy consists of 3. The first process involves transforming the source color picture into many different color spaces. The second stage involves extracting eigen values and eigen vectors from the color space models. At last, a closest neighbour classifier is developed to categorise the facial photos according to the retrieved characteristics.

Keywords: Facial Recognition,Facial Features MSU,MFSD,KNN.

1. INTRODUCTION

Forcing a biometric sensor to accept spoofed biometric data as genuine is known as a spoofing attack. An adversary may start a direct assault on the biometric system's sensory input without even knowing the recognition algorithm. As biometric systems are designed to identify identities, rather than verify their usage, they are readily tricked by a fake. Yet, although extremely sophisticated biometric identity and verification technologies are now on the market, anti-spoofing solutions for them are only getting off the ground. The difficulty of creating fake biometric data may increase or decrease depending on the biometric modality that is being exploited. Making a fake finger to fool a fingerprint scanner or contact lenses to mislead an iris scanner requires some talent, but a copy of someone's face is easy to manufacture. Just one user photo is needed, and it may be a stock photo or a remote selfie. To debunk the idea that fake biometric evidence may fool a biometric identity system, the authors of show how to fool a laptop authentication system using only a printed image. Recently, many articles that attack the problem of face spoofing from diverse angles have been published in the field of biometrics. There are a few ways to verify whether or not a real person is in the frame of the camera: (1) using auxiliary equipment; (2) issuing a challenge to the user, such as forcing them to perform a specific gesture; or (3) using a combination of the two. Yet, completely automated solutions are not only more cost-effective, but also more practical, since they don't need any additional gear and don't get in the way of the user's experience. Facial biometrics show promise for use in the vital authentication of users, an integral part of any data security system. The most accessible and unobtrusive kind of biometric identification is facial recognition technology. New studies have proven, sadly, that face biometrics may be fooled using quite simple methods. By adding spatiotemporal (dynamic texture) information to the commonly utilised local binary pattern operator, we provide a novel and promising approach to detecting face faking. The principle behind this technique is to analyse the structure and dynamics of micro-textures to determine if a face is real or fake. We analysed the process using two free datasets (Replay-Attack Database and CASIA Face Anti-Spoofing Database). As compared to state-of-the-art approaches, our approach performs better when evaluated using the criteria stated by each database. The natural and non-intrusive character of the interaction provided by facial information makes identity verification and identification one of the most active and challenging disciplines of computer vision research. Although advances in face recognition technology have been made in recent decades, more research into issues including the effects of multiple viewpoints, the ageing of participants, and the complexities of outside lighting remains a challenge. Discussions centred on the field's recent developments. Unfortunately, little attention has been paid to the problem of determining whether a face shown to a camera is genuine or an attempt to mislead the system (a spoof). Spoofing attacks against face biometric systems have just recently garnered the attention of academics. IJCB 2011 competition on countermeasures to 2-D face spoofing attacks, the first competition meant to investigate best practises for non-intrusive spoofing detection, and the ever-increasing number of openly available datasets are both symptomatic of this trend. To get unauthorised access to restricted resources, spoofing attacks often use forged biometric data. Yet, not just facial biometrics are susceptible to direct attacks. Conclusion According to the study, fingerprint authentication methods suffer from the same problem. Iris recognition systems have been shown to have similar flaws. Finally, we address the problem of spoofing attacks on speaker biometrics. Spoofing attacks may easily trick face biometric identification systems with the use of photos, videos, or masks that seem like the real thing. The most common spoofing mediums are photographs and films, however make-up and plastic surgery are other choices. With to the proliferation of social networking sites like Facebook, Flickr, YouTube, and others, there is a plethora of multimedia content, especially videos and photographs, available online that may be exploited to spoof a face identification system. To lessen the possibility of face authentication systems being hacked, anti-spoofing procedures must be put into place. Micro-texture analysis has been effective in spotting attacks in which just one person is seen in a photograph. Methods of detecting spoofing based on micro-texture analysis have recently seen improvements in both spatial and temporal accuracy. Each paper included spatial and temporal (dynamic texture) extensions to the popular local binary pattern (LBP) approach, and the combined results provided a clear definition of face liveness that took into account both facial appearance and motion. Specifically, we analysed local binary patterns (LBPs) over all three axes. The overall aesthetic and the horizontal and vertical motion patterns may be expressed quite effectively with this version. Several approaches were created to explore the time dimension while LBP-TOP based dynamic texture analysis was examined for face spoofing detection. By the dense sampling of multiresolution method, we were able to obtain the LBP-TOP-based face liveness description from relatively tiny time windows, as opposed to simply averaging LBP-TOP characteristics across greater time periods. In addition, the different approaches to face normalisation among studies resulted in widely varying data sets for analysis. There were many data sets used in the evaluations. In this study, we combine the various methods, identify the important aspects, and explore the efficacy of several LBP-TOP countermeasures in a wide range of settings and data types. Using the same datasets and using the same evaluation metrics, we demonstrate that our principled approach consistently outperforms the state-of-the-art. By providing an open-source base, our work may be duplicated with little effort. In-depth, this research looks at how dynamic texture may be used to describe a person's face vitality. Light field cameras are a special kind of sensor that can record information about the colours and directions of light. This camera may be used for 3D reconstruction as well as face and iris recognition. As part of this study, we offer a novel approach to employing the light field camera to defend against face spoofing attacks, such as those executed using printed 2D facial photographs (henceforth 2D photos) and HD tablet images. By changing our perspective, we can extract two unique features from the raw light field image that would be impossible to capture with a conventional camera. We build libraries of light field images and conduct experiments to prove their efficacy. After putting our proposed fix through its paces against a variety of standard spoofing techniques, we discovered that it maintains an accuracy of at least 94.78% and can achieve up to 99.36% in some circumstances. We provide a novel, effective method for estimating the defocus map from a single natural image. The idea was inspired by the discovery that defocus may significantly modify the spectrum amplitude around the margins of objects in a photograph. We first estimate blur at these edge locations by determining the relationship between the amount of spatially varying defocus blur and spectrum contrast at these edge locations, and then we obtain a complete defocus map by propagating the blur amount at edge locations over the entire image via a nonhomogeneous optimization procedure. The proposed method takes into account both the blur texture of an image and the effect of light refraction. Our testing results demonstrate that our proposed approach provides a more reliable defocus map estimation than existing techniques. Just two of the numerous modern applications of automated face recognition are eliminating identity duplication and verifying mobile payments. Concerns about "facial spoof attacks" arise when a picture or video of a genuine user's face is exploited to trick a face recognition system into providing the intruder access to restricted areas (also known as "biometric sensor presentation attacks"). Whilst several approaches have been presented for detecting face spoofing, their generalizability has not been well explored. We present an efficient and moderately robust face spoof detection system based on Picture Distortion Analysis (IDA). Then, we extract four characteristics to use in building the IDA feature vector: specular reflection, blurriness, chromatic moment, and colour variety. An ensemble classifier is used to identify genuine from phoney facial images. Several SVM classifiers, each trained for a specific kind of face spoofing attack, make up this classifier. In order to identify face spoofing over numerous frames in a video, the suggested approach is extended to use a voting-based system. Our MSU Mobile Face Spoofing Database was built using data from two mobile devices and three spoofing assaults (MSU MFSD). Experiments on three publicly accessible face spoof datasets show that the suggested technique outperforms state-of-the-art technologies in spoof detection (Idiap REPLAY-ATTACK, CASIA FASD, and MSU MFSD). Our research also highlights the difficulty in determining which faces are genuine and which are not, especially when dealing with different devices and databases..

2. PROPOSED SYSTEM

A greater requirement for security will undoubtedly lead to an increase in the prevalence of appropriate technological solutions. It's important for every new idea, business, or technology to be user-friendly and well-received before it can go global. Scientists' attention and research have been drawn into what is termed biometrics because of the high need for user-friendly solutions that can safeguard our assets and preserve our privacy without making us forget who we are in a sea of numbers. Face images are manually categorised using LBP and illustrative Machine Learning techniques.

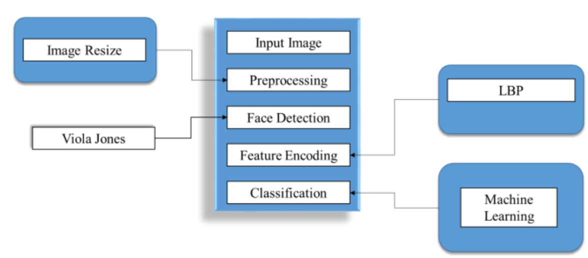


Fig1: System Architecture

3. METHODOLOGY

Input image:

Preprocessing: (Image Resize)

Image scaling is the process of adjusting the size of a digital photo or illustration in fields like computer graphics and digital photography. Upscaling, often called resolution improvement, is a technique used in the video industry to increase the size of digital files.

Scaling a vector graphic involves geometrically transforming the image's graphic primitives, which preserves the image's quality. A new picture with the appropriate amount of pixels is created when a raster graphics image is scaled up or down.

As the number of pixels is reduced (called "scaling down"), the quality of the image often suffers.

Scaling raster images is a good example of sample-rate conversion, the process by which a discrete signal is transformed from one sampling rate (here, the local sampling rate) into another.

Feature Extraction:

The Viola-Jones framework is the first to provide competitive object detection rates in real time. It was inspired by the challenge of face recognition, but it may be taught to recognise other types of objects as well.

Our investigation has led us to conclude that we can effectively extract anti-spoofing characteristics using the diffusion speed model. To be more explicit, our primary characteristics are the diffusion speed values at each pixel location, calculated as

$$\mathbf{F}_{\text{base}} = \{s(x, y) | 0 < x \leq W, 0 < y \leq H\},$$

The face detection zone's dimensions are denoted here by W and H, respectively. We recommend creating local speed patterns when comparing the diffusion speed maps of real and synthetic faces so as to effectively capture even minute variations.

In machine learning, pattern recognition, and image processing, feature extraction is a method used to transform raw measurement data into derived values (features) that are intended to be informative and non-redundant, lightening the load of subsequent learning and generalisation steps and, in some cases, allowing for more accurate human interpretations. There is a tight connection between dimensionality reduction and feature extraction.

When an algorithm's input data is too large and redundant to process (for example, the same measurement reported in feet and metres, or the same image presented in pixels), it may be reduced to a more manageable set of attributes (also named a features vector). This process is referred to as "feature selection" on our end.

Rather of employing the whole set of initial data, a condensed representation including just the characteristics relevant to the task at hand will be used.

Classification:

KNN Classifier:

The k-nearest neighbours algorithm (k-NN) is a nonparametric technique for classification and regression in pattern recognition. For each, the k nearest training samples in the feature space are used as input. If k-NN is utilised for classifying data or predicting outcomes, the results will vary.

When using k-NN classification, the result is a label for a given group. When classifying an item, the k closest neighbours cast a vote and the object is placed in the class that has the most representation (k is a positive integer, typically small). In the simplest case, when k equals 1, an item is simply placed in the category of its closest neighbour.

Outcome in k-NN regression is the value of the object's attribute. This number represents the mean of its k closest neighbours.

Lazy learning, of which k-NN is an example, involves merely making local approximations of the function and saving all computation for the classification stage. A basic example of a machine learning algorithm is the k-NN algorithm.

For both classification and regression, it might be helpful to give greater weight to the contributions of closer neighbours than those farther away. Giving each neighbour a weight of 1/d, where d is the distance to the neighbour, is an example of a popular weighting method.

Performance Analysis

Precision and Recall:

Precision is a measure of the accuracy of the results returned, whereas recall is a measure of the number of relevant results that were returned.

When the area under the curve is large, the recall and precision are both good. When the accuracy is good, the false positive rate is low, and when the recall is good, the false negative rate is low.

A high score for both indicates that the classifier is providing accurate findings (high precision) and producing a majority of positive outcomes (high recall).

Several results are returned by a system with high recall but poor accuracy, however most of the projected labels do not match the right ones from the training labels.

A system with high accuracy but poor recall returns fewer results than usual, yet the majority of its projected labels agree with the actual labels in the training set.

In a perfect world, a system with high accuracy and high recall would return a large number of outcomes, with each of those results accurately categorised.

Equation for Precision:

$$PPV = \frac{TP}{TP + FP}$$

Equation for Recall:

$$R = \frac{T_p}{T_p + F_n}$$

F Measure:

The conventional F-measure (also known as the balanced F-score) is a metric that takes into account both accuracy and recall.

When the two numbers are very near, this value approximates the average of the two; more broadly, it is the harmonic mean, which in the case of two integers corresponds with the square of the geometric mean divided by the arithmetic mean.

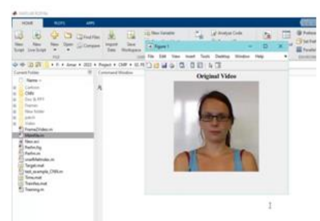
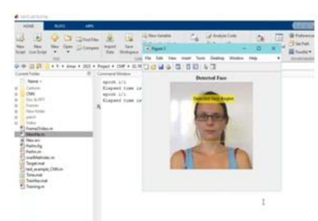
In some contexts, the F-inherent score's bias as an assessment tool might be called into question.

Equation:

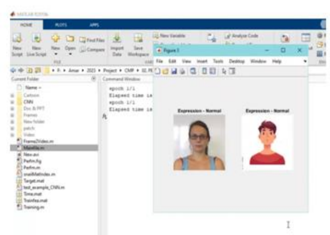
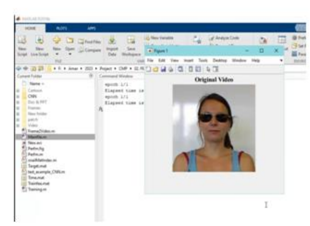
$$F1 = \frac{2TP}{2TP + FP + FN}$$

4. RESULTS

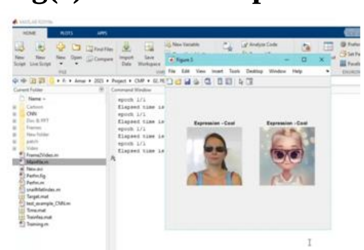
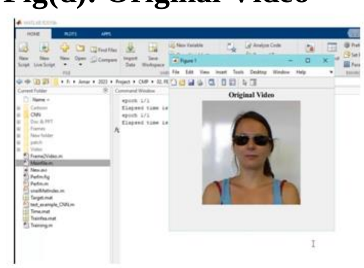
The following images represents the output of this face emotions recognition project with the extracted emotion cartoons according to that emotion of a human in a video sequence

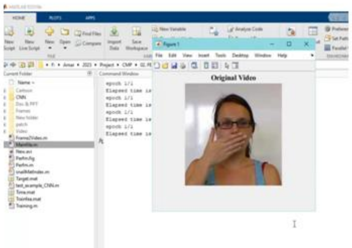
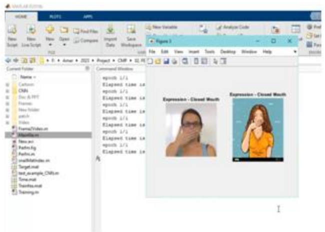
Fig(a): Original Video Fig(b): Detecting face region

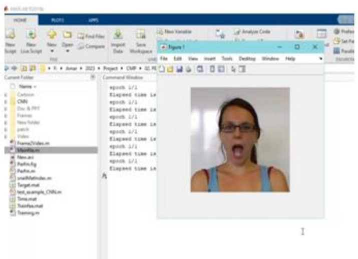
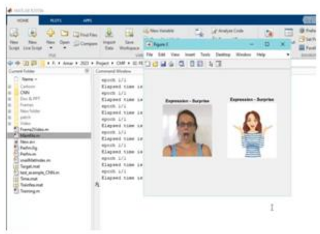
Fig(c): Neutral Expression Fig(d): Original Video

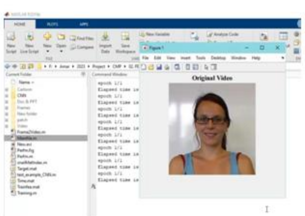
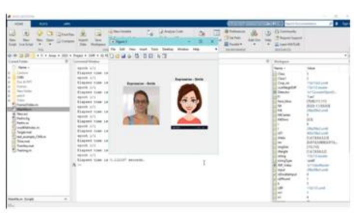
Fig(e): Cool Expression Fig(f): Original Video

Fig(g): Detected Face Region Fig(h): Shocking Expression

Fig(i): Original Video Fig(j): Surprise Expression

Fig(k): Original Video Fig(l): Happy Expression(smile)

5. CONCLUSION AND FUTURE SCOPE

The identification of unconstrained face photos is difficult because of factors such as the deterioration of face image quality and substantial fluctuations in lighting, position, and expression. At least two areas need attention for this issue to be resolved: design of a complete face representation system and an efficient face image descriptor.

REFERENCES

[1] A. K. Jain, S. Prabhakar, L. Hong, and S. Pankanti, “Filterbank-basedfingerprint matching,” IEEE Trans. Image Process. , vol. 9, no. 5,pp. 846–859, May 2000.

[2] Y. Wang, J. Hu, and D. Phillips, “A fingerprint orientation model basedon 2D Fourier expansion (FOMFE) and its application to singular-pointdetection and fingerprint indexing,” IEEE Trans. Pattern Anal. Mach.Intell. , vol. 29, no. 4, pp. 573–585, Apr. 2007.

[3] G. Pan, L. Sun, Z. Wu, and S. Lao, “Eyeblink-based anti-spoofing inface recognition from a generic webcamera,” in Proc. IEEE 11th Int.Conf. Comput. Vis. (ICCV), Oct. 2007, pp. 1–8.

[4] L. Sun, G. Pan, Z. Wu, and S. Lao, “Blinking-based live face detectionusing conditional random fields,” in Proc. Adv. Biometrics , Oct. 2007,pp. 252–260.

[5] K. Kollreider, H. Fronthaler, M. I. Faraj, and J. Bigun, “Real-time facedetection and motion analysis with application in ‘liveness’ assessment,”IEEE Trans. Inf. Forensics Security , vol. 2, no. 3, pp. 548–558,Sep. 2007.

[6] W. Bao, H. Li, N. Li, and W. Jiang, “A liveness detectionmethod for face recognition based on optical flow field,” inProc. IEEE Int. Conf. Image Anal. Signal Process., Apr. 2009,pp. 233–236.

[7] Y. Kim, J. Na, S. Yoon, and J. Yi, “Masked fake face detectionusing radiance measurements,” J. Opt. Soc. Amer. A , vol. 26, no. 4,pp. 760–766, Apr. 2009.

[8] Z. Zhang, D. Yi, Z. Lei, and S. Z. Li, “Face liveness detection by learningmultispectral reflectance distributions,” in Proc. IEEE Int. Conf. Autom.Face Gesture Recognit. (FG) , Mar. 2011, pp. 436–441.

[9] J. Li, Y. Wang, T. Tan, and A. K. Jain, “Live face detection based onthe analysis of Fourier spectra,” Proc. SPIE, Biometric Technol. HumanIdentificat., pp. 296–303, Aug. 2004.

[10] Z. Zhang, J. Yan, S. Liu, Z. Lei, D. Yi, and S. Z. Li, "A face antispoofingdatabase with diverse attacks," in Proc. IEEE 5th IAPR Int. Conf.Biometrics (ICB) , Mar./Apr. 2012, pp. 26–31.

[11] X. Tan, Y. Li, J. Liu, and L. Jiang, "Face liveness detection from a singleimage with sparse low rank bilinear discriminative model," in Proc. 11thEur. Conf. Comput. Vis. (ECCV), 2010, pp. 504–517.

[12] B. Peixoto, C. Michelassi, and A. Rocha, "Face liveness detectionunder bad illumination conditions," in Proc. 18th IEEE Int. Conf. ImageProcess. (ICIP), Sep. 2011, pp. 3557–3560.

[13] J. Maatta, A. Hadid, and M. Pietikainen, "Face spoofing detection fromsingle images using micro-texture analysis," in Proc. IEEE Int. JointConf. Biometrics (IJCB) , Oct. 2011, pp. 1–7.

[14] J. Yang, Z. Lei, S. Liao, and S. Z. Li, "Face liveness detection with com-ponent dependent descriptor," in Proc. IEEE Int. Conf. Biometrics (ICB) ,Jun. 2013, pp. 1–6.

[15] P. Perona and J. Malik, "Scale-space and edge detection usinganisotropic diffusion," IEEE Trans. Pattern Anal. Mach. Intell., vol. 12,no. 7, pp. 629–639, Jul. 1990.

[16] M. Rousson, T. Brox, and R. Deriche, "Active unsupervised texturesegmentation on a diffusion based feature space," in Proc. IEEEComput. Soc. Comput. Vis. Pattern Recognit. (CVPR), vol. 2. Jun. 2003,pp. II-699–II-704.

[17] T. Brox and J. Weickert, "A TV flow based local scale measure fortexture discrimination," in Proc. 8th Eur. Conf. Comput. Vis. (ECCV) ,May 2004, pp. 578–590.

[18] J.Weickert,B.M.T.H.Romeny,andM.A.Viergever,"Efficientandreliable schemes for nonlinear diffusion filtering," IEEE Trans. ImageProcess., vol. 7, no. 3, pp. 398–410, Mar. 1998.

[19] E. H. Land and J. J. McCann, "Lightness and retinex theory," J. Opt.Soc. Amer., vol. 61, no. 1, pp. 1–11, 1971.

[20] W. Kim and C. Kim, "A texture-aware salient edge model for imageretargeting," IEEE Signal Process. Lett., vol. 18, no. 11, pp. 631–634,Nov. 2011.

[21] W. Kim and C. Kim, "Active contours driven by the salient edge energymodel,"IEEE Trans. Image Process. , vol. 22, no. 4, pp. 1667–1673,Apr. 2013.

[22] T. Chen, W. Yin, X. S. Zhou, D. Comaniciu, and T. S. Huang, "Totalvariation models for variable lighting face recognition," IEEE Trans.Pattern Anal. Mach. Intell. , vol. 28, no. 9, pp. 1519–1524, Sep. 2006.

[23] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scaleand rotation invariant texture classification with local binary patterns,"IEEE Trans. Pattern Anal. Mach. Intell. , vol. 24, no. 7, pp. 971–987,Jul. 2002.

[24] P. Viola and M. J. Jones, "Robust real-time face detection," Int. J.Comput. Vis., vol. 57, no. 2, pp. 137–154, 2004.

[25] X. Tan, F. Song, Z.-H. Zhou, and S. Chen, "Enhanced pictorial struc-tures for precise eye localizatio n under uncontrolled conditions," inProc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2009,pp. 1621–1628.

[26] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vectormachines,"ACM Trans. Intell. Syst. Technol. , vol. 2, no. 3, Apr. 2011,Art. ID 27.

[27] I. Chingovska, A. Anjos, and S. Marcel, "On the effectiveness oflocal binary patterns in face anti-

spoofing," in Proc. IEEE Int. Conf.Biometrics Special Interest Group (BioSIG), Darmstadt, Germany,Sep. 2012, pp. 1–7.

[28] I. Chingovska, A. R. D. Anjos, and S. Marcel, "Biometrics evaluationunder spoofing attacks," IEEE Trans. Inf. Forensics Security,vol.9,no. 12, pp. 2264–2276, Dec. 2014.

[29] A. Anjos, M. M. Chakka, a nd S. Marcel, "Motion-basedcounter-measures to photo attacks in face recognition," IET Biometrics,vol. 3, no. 3, pp. 147–158, Sep. 2014.