

(An ISO 3297: 2007 Certified Organization)

Website: <u>www.ijirset.com</u> Vol. 6, Issue 2, February 2017

# Discriminating Fake Faces From Genuine Ones by Using Color Texture Analysis

A. Reeta Joldrine<sup>1</sup>, D. Elavarasi<sup>2</sup>

M.E. Computer Science and Engineering, Mount Zion College of Engineering and Technology, Lena Vilakku,

Thirumayam Tk, Pudukkottai, Tamil Nadu 622507, India.

Assistant Professor, Department of Computer Science and Engineering, Mount Zion College of Engineering and

Technology, Lena Vilakku, Thirumayam Tk, Pudukkottai, Tamil Nadu 622507, India.

**ABSTRACT:** Inquire about on non-nosy programming based face caricaturing identification plans has been essentially centered around the examination of the luminance data of the face pictures, thus disposing of the chroma part, which can be exceptionally valuable for segregating fake countenances from real ones. This paper presents a novel and engaging methodology for identifying face satirizing utilizing a shading surface examination. We misuse the joint shading surface data from the luminance and the chrominance channels by extricating corresponding low-level element depictions from various shading spaces. All the more particularly, the component histograms are figured over every picture band independently. All the more significantly, not at all like the vast majority of the strategies proposed in the writing, our proposed approach can accomplish stable execution over all the three benchmark informational indexes. The promising consequences of our cross-database assessment propose that the facial shading surface representation is more steady in obscure conditions contrasted and its dark scale partners.

**KEYWORDS:** Facial Features Extraction, Face identification, Spoofing Detection, Attack Finding, Presentation Attack, Color and texture Analysis.

### I. INTRODUCTION

Image processing is a process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image. The most common type of image processing is photography. For instance, in [1], researches inspected the threat of the OSNFD against the latest version of face authentication system. In this process, an image is captured or scans using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology. In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image.

### **Grayscale Images**

A grayscale image is made up of pixels, each of which holds a single number corresponding to the gray level of the image at a particular location. Assuming 256 gray levels, each black and white pixel can be stored in a single byte (8 bits) of memory. The key idea is that an image of a fake face passes through two different camera systems and a printing system or a display device, thus it can be referred to in fact as a recaptured image. As a consequence, the observed fake face image is likely to have lower image quality compared to a genuine one captured in the same conditions due to e.g. lack of high frequency information [2]–[6]. Furthermore, the recaptured images may suffer from other quality issues, such as content-independent printing artefacts or video noise signatures [7]–[12].

### Image Representation and Description

The output of the segmentation types usually in pixel data, constituting either the boundary of a region or all the points in the region itself. In either case converting the data to a suitable form for computer processing. The decision must be



(An ISO 3297: 2007 Certified Organization)

### Website: <u>www.ijirset.com</u>

#### Vol. 6, Issue 2, February 2017

made, whether the data should be represented as a boundary or as a complete region. Regional representation is appropriate when the focus is on internal properties, of skeletal shape.

In some applications, however, these representations coexist. This situation occurs in character recognition applications, which often require algorithms based on boundary shape as well as skeletons and other internal properties.

### **II. IMAGE SEGMENTATION**

The next stage deals with segmentation. Segmentation partitions an input image into its small constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing.

A segmentation procedure brings the process a long way towards the successful solution of an imaging problem. On the other hand, weak or erratic segmentation algorithms almost guarantee eventual failure. In terms of character recognition, the key role of segmentation is to extract individual characters and words from the background.



Fig.1 Color images

#### **Image Recognition**

Recognition is the process the label to an object based on the information provided by its descriptors. Pure image quality assessment based features have shown comparable performance to texture analysis based algorithms [5]. However, as expected, they are robust in detecting fake faces presented on mobile phone displays, whereas high-definition face spoofs caused problems [5]. In addition, the spoofing detection performance of the proposed feature set was highly dependent on the used imaging quality, i.e. the method performed well on high quality input images, whereas the results degraded dramatically at lower acquisition qualities [5]. Interpretation involves assigning meaning to an ensemble of recognized objects. For example, identifying a character as, say, c requires associating the descriptors for that character with the label c. Interpretation attempts to assign meaning to a set of labeled entities.



Fig.2. System Architecture Design



(An ISO 3297: 2007 Certified Organization)

### Website: www.ijirset.com

Vol. 6, Issue 2, February 2017

#### Input Image

In this module, the test image is used for automatic extraction of the region of interest by calculating the mean of each row (column) and compared to the threshold as follows.



Fig.3. Input Image

Analog cameras are cameras that generate a video signal in analog format. The analog signal is digitized by an image acquisition device.

A digital image is a representation of a two-dimensional image as a finite set of digital values, called picture elements or pixels. The inputs should be only the authorized face of the user. Only the face is accepted as input Video signals and mobile images or not accepted as input. The face that doesn't accept the recognition.

#### Image space conversion

The different color channels can be more discriminative for detecting recapturing artifacts, i.e. providing higher contrast for different visual cues from natural skin tones. To gain insight into which colour spaces are most suitable for discriminating genuine faces from fake ones, the previous works on face spoofing detection are based on analyzing only the luminance (i.e. gray-scale) information of the face images, we introduce a novel and appealing approach using color texture analysis and demonstrate that the chroma component can be very useful in discriminating fake faces from genuine ones. A color space is a specific organization of colors. In combination with physical device profiling, it allows for reproducible representations of color, in both analog and digital representations.



Fig.4. Test Images



(An ISO 3297: 2007 Certified Organization)

### Website: <u>www.ijirset.com</u>

#### Vol. 6, Issue 2, February 2017

#### **III. HISTOGRAM ANALYSIS**

The different facial colour texture representations are extracting from the different local descriptors from the individual image channels in the different colour spaces. Then, holistic texture descriptions are extracted from each colour channel and the resulting feature vectors are concatenated into an enhanced feature vector in order to get an overall representation of the facial colour texture.



Fig.5. Histogram Analysis

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. Improvements in picture brightness and contrast can thus be obtained. E.g. facial motion patterns and sudden characteristic reflections of planar spoofing media [11] and content-independent video noise signatures [12].



### **Face Validation**

The final feature vector is fed to a binary classifier and the output score value validates whether person is fake or genuine one. Face validity is the extent to which a test is subjectively viewed as covering the concept it purports to measure.



Fig.7. Face Validation

It refers to the transparency or relevance of a test as it appears to test participants. In other words, a test can be said to have face validity if it "looks like" it is going to measure what it is supposed to measure. Binary classifier defines the classification of real face and fake user of that particular application. It distinguish the patches of faceand help us to find the histogram.



(An ISO 3297: 2007 Certified Organization)

Website: <u>www.ijirset.com</u>

Vol. 6, Issue 2, February 2017



### **IV. EXISTING SYSTEM**

Typical non-intrusive software-based countermeasure to face spoofing is liveness detection that aims at detecting physiological signs of life, such as eye blinking, facial expression changes, mouth movements and even small color and motion. In addition to facial motion used in liveness detection, other motion cues can also be exploited for face anti-spoofing. The main problem of liveness detection and motion analysis based anti-spoofing techniques is that the verification process takes some time or the user needs to be still very cooperative in practice. One can assume that fake faces are usually smaller in size or they would contain fewer high frequency components compared to genuine ones, thus countermeasures based on analyzing the high frequency content have been proposed. Such an approach may work well for down sampled photos or crude face masks but is likely to fail for higher-quality spoof samples. One can assume that fake faces are usually smaller in size or they would contain fewer high frequency components compared to genuine ones, thus countermeasures based on analysing the high frequency content have been proposed. Such an approach may work well for down sampled photos or crude face masks but is likely to fail for higher-quality spoof samples. One can assume that fake faces are usually smaller in size or they would contain fewer high frequency components compared to genuine ones, thus countermeasures based on analysing the high frequency content have been proposed [2]–[4].

### Disadvantages

- Accuracy is less
- Time consuming
- The verification process takes some time .

• The main problem of liveness detection and motion analysis based anti-spoofing techniques is that the verification process takes some time or the user needs to be still very cooperative in practice.

• In particular, a face authentication system prompts a user for a specific action (challenge), such as a facial expression, mouth movement or head rotation (3D information), and then analyses the user activity in order to check whether the required action was actually performed (response) or not.

• The drawback of the challenge-response approach is that it requires user cooperation, thus making the authentication process a time-consuming and unpleasant experience.



(An ISO 3297: 2007 Certified Organization)

### Website: <u>www.ijirset.com</u>

### Vol. 6, Issue 2, February 2017

• Another disadvantage of challenge-response based countermeasures is that it is rather easy to deduce which liveness cues need to be fooled.

### V. PROPOSED METHODOLOGY

The novel and appealing approach for detecting face spoofing using a colour texture analysis is proposed. Introducing a novel and appealing approach using colour texture analysis and demonstrate that the Chroma component can be very useful in discriminating fake faces from genuine ones. In general, the gamut mapping algorithms focus on preserving the spatially local luminance variations in the original images at the cost of the chrominance information because the human eye is more sensitive to luminance than to chroma [14]. We exploit the joint colour-texture information from the luminance and the chrominance channels by computing low-level features using different descriptors extracted from different colour spaces. Fortunately, the colour reproduction (gamut) of different display media, e.g. photographs, video displays and masks, is limited compared to genuine faces. Thus, the presented fake faces suffer from spoofing medium dependent colour.Gamut mapping functions are typically required in order to preserve colour perception properties across different output devices, e.g. printer or video display, which can alter the (colour) texture of the original image.

#### Advantages:

- Higher accuracy of authorized user
- Less time consumption
- Our proposed approach is able to achieve stable performance
- Texture analysis of gray-scale face images can provide sufficient means to reveal the recapturing artifacts of fake faces.
- The image resolution (quality) is good enough to capture the fine details of the observed face.
- The final feature vector is fed to a binary classifier and the output score value describes whether there is a live person or a fake one in front of the camera.

• The YCbCr space separates the RGB components into luminance(Y), chrominance blue (Cb) and chrominance red (Cr). It is worth noting that the representation of chroma components in HSV and YCbCr spaces is different, thus they can provide complementary facial colour texture descriptions for spoofing detection.

### Algorithm 1: Color texture Analysis

Input: Query image q, Output: Validated image y, Validation status Colour texture analysis: Step 1: Initial face  $(q_x)^*(q_y)$  is detected, cropped and normalized into an M×N pixel image. Step 2: RGB image is extracted q<sub>RGB</sub> Step 3: Compute YCbCr Image space conversion ;  $yc_bc_r \leftarrow q_{RGB}$ Step 4: The colour texture features of the image I represented in the space S can be defined by:  $Hs = [H(1)s \dots H(L)s]$ . Step 5: Compute color-texture histogram for YCbCr; For each pixel in an image, a binary code is computed by thresholding a circularly symmetric neighborhood with the value of the central pixel.  $LBP_{P,R}(x, y) = \sum_{n=1}^{P} \delta(rn - rc) \times 2^{n-1},$ Step 6: Extract the concatenated histogram LBP(x, y)The similarity is measured using the Chi-square distance:  $d\chi^2 (Hx, Hy) = {}^N \sum_{i=1} (Hx(i) - Hy(i))^2 / (Hx(i) + Hy(i)),$ Where *Hx* and *Hy* are two LBP histograms with *N* bins. Step 7: Resulted feature vectors;



(An ISO 3297: 2007 Certified Organization)

### Website: <u>www.ijirset.com</u>

### Vol. 6, Issue 2, February 2017

More specifically, we computed mean LBP histograms for both real and fake face images in the training set and used these two models to compute a Chi-square distance based score value for each sample in the test set as follows:  $d(Hx, Hr, Hf) = d\gamma 2 (Hx, Hr) - d\gamma 2 (Hx, Hf)$ 

where Hx is the LBP histogram of the test sample, and Hr and Hf are the reference histograms for real and fake faces, respectively

Step 8: Output validates Real/Fake

### VI. LITERATURE SURVEY

In the year of 2014 the authors "J. Galbally and S. Marcel" described into their paper titled "Face Anti-Spoofing Based on General Image Quality Assessment" such as a new face anti-spoofing method based on general image quality assessment is presented. The proposed approach presents a very low degree of complexity which makes it suitable for real-time applications, using 14 image quality features extracted from one image (i.e., the same acquired for face recognition purposes) to distinguish between legitimate and impostor samples.[5]

The experimental results, obtained on two publicly available datasets, show very competitive results compared to other state-of-the-art methods tested on the same benchmarks. The findings presented in the work clearly suggest that the analysis of the general image quality of real face samples reveals highly valuable information that may be very efficiently used to discriminate them from fake images.

In the year of 2015 the authors "D. Wen, H. Han, and A. K. Jain" described into their paper titled "Face Spoof Detection with Image Distortion Analysis", IEEE Trans. Inf. Forensics Security" such as Automatic face recognition is now widely used in applications ranging from de-duplication of identity to authentication of mobile payment.[6] This popularity of face recognition has raised concerns about face spoof attacks (also known as biometric sensor presentation attacks), where a photo or video of an authorized person's face could be used to gain access to facilities or services.

We propose an efficient and rather robust face spoof detection algorithm based on Image Distortion Analysis (IDA). Four different features (specular reflection, blurriness, chromatic moment, and color diversity) are extracted to form the IDA feature vector. An ensemble classifier, consisting of multiple SVM classifiers trained for different face spoof attacks (e.g., printed photo and replayed video), is used to distinguish between genuine and spoof faces. The proposed approach is extended to multi-frame face spoof detection in videos using a voting based scheme.

In the year of 2010 the authors "J. Y. Choi, K. Plataniotis and Y. M. Ro" described into their paper titled "Using Color Local Binary Pattern Features for Face Recognition" such as We propose a novel feature representation based on color-based Local Binary Pattern (LBP) texture analysis for face recognition (FR). The proposed method exploits both color and texture discriminative features of a face image for FR purpose. [16]

We evaluate the proposed feature using three public face databases: CMU-PIE, Color FERET, and XM2VTSDB. Experimental results show that the results of the proposed feature impressively better than the results of grayscale LBP and color features. In particular, it is shown that the proposed feature is highly robust against severe variations in illumination and spatial resolution.



(An ISO 3297: 2007 Certified Organization)

Website: <u>www.ijirset.com</u>

Vol. 6, Issue 2, February 2017

VII. EXPERIMENTAL RESULTS



### **Fig.9 Authroized User Identification**

- M 1	pcasifttool	
RE Sy	(2)	Face Spoofing Detection using Color Texture Analysis
Sy Gc Sh 2.0 R i		Process facet
SH 1.1 GG Fil	63	Process Face2
Sh Sh Sh 10.		Match
SH 1.2		

Fig.10 User Histogram processing



Fig. 11 User Matching Points



(An ISO 3297: 2007 Certified Organization)

Website: <u>www.ijirset.com</u>

Vol. 6, Issue 2, February 2017

D pcasifttool			م 🍋
	Face Spoofing De	tection using Color Texture Analysis	10
	Process Face1		
62	Process Face2	Distance	
	Match	FAKE USER	

Fig.12 Histogram of Unauthorized User

#### VIII. CONCLUSION AND FUTURE SCOPE

To approach the problem of face anti-spoofing from the colour texture analysis point of view is proposed. We investigated how well different colour image representations (RGB, HSV and YCbCr) can be used for describing the intrinsic disparities in the colour texture between genuine faces and fake ones and if they provide complementary representations. Fortunately, the colour reproduction (gamut) of different display media, e.g. photographs, video displays and masks, is limited compared to genuine faces. Thus, the presented fake faces suffer from spoofing medium dependent colour.

The YCbCr space separates the RGB components into luminance (Y), chrominance blue (Cb) and chrominance red (Cr). It is worth noting that the representation of chroma components in HSV and YCbCr spaces is different, thus they can provide complementary facial colour texture descriptions for spoofing detection. The effectiveness of the different facial colour texture representations was studied by extracting different local descriptors from the individual image channels in the different colour spaces.

#### REFERENCES

[1] Y. Li, K. Xu, Q. Yan, Y. Li, and R. H. Deng, "Understanding OSN-based facial disclosure against face authentication systems," in Proc. 9th ACM Symp. Inf., Comput. Commun. Secur. (ASIA CCS), 2014, pp. 413–424.

[2] J. Li, Y. Wang, T. Tan, and A. K. Jain, "Live face detection based on the analysis of Fourier spectra," Proc. SPIE, vol. 5404, pp. 296–303, Aug. 2004.

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

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

[5] J. Galbally and S. Marcel, "Face anti-spoofing based on general image quality assessment," in Proc. IAPR/IEEE Int. Conf. Pattern Recognit. (ICPR), Aug. 2014, pp. 1173–1178.

[6] D. Wen, H. Han, and A. K. Jain, "Face spoof detection with image distortion analysis," IEEE Trans. Inf. Forensics Security, vol. 10, no. 4, pp. 746–761, Apr. 2015.

[7] J. Bai, T.-T. Ng, X. Gao, and Y.-Q. Shi, "Is physics-based liveness detection truly possible with a single image?" in Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), May/Jun. 2010, pp. 3425–3428.

[8] J. Määttä, A. Hadid, and M. Pietikäinen, "Face spoofing detection from single images using micro-texture analysis," in Proc. Int. Joint Conf. Biometrics (IJCB), Oct. 2011, pp. 1–7.

[9] J. Maatta, A. Hadid, and M. Pietikäinen, "Face spoofing detection from single images using texture and local shape analysis," IET Biometrics, vol. 1, no. 1, pp. 3–10, Mar. 2012.

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

[11] T. de Freitas Pereira et al., "Face liveness detection using dynamic texture," EURASIP J. Image Video Process., vol. 2014, no. 1, pp. 1–15, Dec. 2014.



(An ISO 3297: 2007 Certified Organization)

### Website: www.ijirset.com

#### Vol. 6, Issue 2, February 2017

[12] A. Pinto, H. Pedrini, W. R. Schwartz, and A. Rocha, "Face spoofing detection through visual codebooks of spectral temporal cubes," IEEE Trans. Image Process., vol. 24, no. 12, pp. 4726–4740, Dec. 2015.

[13] Digital Photography Review, accessed on Nov. 1, 2015. [Online]. Available: http://www.dpreview.com/forums/thread/3861133

[14] N. Bonnier, "Contribution to spatial gamut mapping algorithms," M.S. thesis, Lab. Commun. Process. Inf. (LTCI), Télécom ParisTech, Paris, France, Sep. 2008.

[15] Z. Boulkenafet, J. Komulainen, and A. Hadid, "Face anti-spoofing based on color texture analysis," in Proc. IEEE Int. Conf. Image Process. (ICIP), Sep. 2015, pp. 2636–2640. [16] J. Y. Choi, K. Plataniotis, and Y. M. Ro, "Using colour local binary pattern features for face recognition," in Proc. IEEE Int. Conf. Image Process. (ICIP), Sep. 2010, pp. 4541–4544. [17] D. Gragnaniello, G. Poggi, C. Sansone, and L. Verdoliva, "An investigation of local descriptors for biometric spoofing detection," IEEE Trans. Inf. Forensics Security, vol. 10, no. 4, pp. 849–863, Apr. 2015. [18] N. Erdogmus and S. Marcel, "Spoofing 2D face recognition systems with 3D masks," in Proc. IEEE Int. Conf. Biometrics Special Interest

[18] N. Erdognus and S. Marcel, Spooling 2D face recognition systems with 3D masks, in Proc. IEEE Int. Com. Biometrics Special Interest Group, Sep. 2013, pp. 1–8.
[19] I. Pavlidis and P. Symosek, "The imaging issue in an automatic face/disguise detection system," in Proc. IEEE Workshop Comput. Vis. Beyond

[19] I. Pavlidis and P. Symosek, "The imaging issue in an automatic face/disguise detection system," in Proc. IEEE Workshop Comput. Vis. Beyond Visible Spectrum, Methods Appl. (CVBVS), 2000, pp. 15–24.

[20] Z. Zhang, D. Yi, Z. Lei, and S. Z. Li, "Face liveness detection by learning multispectral reflectance distributions," in Proc. IEEE Int. Conf. Autom. Face Gesture Recognit. Workshops, Mar. 2011, pp. 436–441

### BIOGRAPHY



**Ms. Reeta joldrine. A**. Studying M.E. Computer Science and Engineering in Mount Zion College of Engineering and Technology, which is located in Lena Vilakku, Pudukkottai, Tamil Nadu, India.