Face spoofing detection using surface and sub-surface reflections analysis

Azim Zaliha Abd Aziz¹, Mohd Rizon Mohamed Juhari²

¹Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin (UniSZA), Terengganu, Malaysia ²Faculty of Engineering, Technology and Built Environment, UCSI University, Kuala Lumpur, Malaysia

Article Info

Article history:

Received Dec 20, 2020 Revised Aug 9, 2021 Accepted Aug 20, 2021

Keywords:

Face biometrics Face spoofing detection Polarized imaging system Sub-surface reflection Surface reflection

ABSTRACT

Reflection based analysis has been used in previous research for various objectives. Materials classification is one of them. Basically, each material consists of two types of reflections: surface and sub-surface. To separate these two reflections, polarized light could be applied. Previously, multireflections characteristics were analyzed using polarized light to classify objects such as between metals and non-metals. However, no trial has been done using the same method to distinguish real and fake faces that could be used to combat spoofing attempts in face biometric system. Since human skin is multi layers structure, it also produces multi reflections. In this paper, driven by the theory, surface and sub-surface reflections of both genuine human face and paper face mask were statistically examined. In addition, iPad displayed face images were also used as spoofing attempts. Images of genuine and spoofing faces were captured using polarized light under two different polarization angles: 0 and 90 degrees. Each angle captured images with surface and sub-surface reflections, accordingly. Those reflections were analyzed based on the mean, standard deviation, skewness and kurtosis. Modality distribution of each image was also studied using another method called the bimodality coefficient (BC). From the results, it is not possible to distinguish between genuine face and printed photos because of the multi reflections' similarities. However, iPad displayed face images have been successfully identified as spoofing trials.

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Corresponding Author:

Azim Zaliha Abd Aziz Faculty of Informatics and Computing Universiti Sultan Zainal Abidin (UniSZA) Besut Campus, 22200, Terengganu, Malaysia Email: azimzaliha@unisza.edu.my

1. INTRODUCTION

Biometric is an authentication technique that rely on measureable physical characteristics that can be automatically detected. There are several types of biometric identification schemes such as individual's unique fingerprints, iris analysis, the analysis of facial characteristics and also the analysis of a person's voice. The selection of any biometric trait depends on the purpose of the application. As in face authentication system, the main purpose of the development is to identify valid users for security reasons. Implementation of face biometric system can be widely seen in airports all around the world. However, the system could be easily spoofed by an impostor with no difficulty. The impostor can obtain a photo of an authorized person, plays a video, or display a 3D model such as a face mask which mimics a valid individual, in front of the sensor to gain access [1]. This vulnerability of face-based security system has encouraged various studies and preventive measures among biometric community. Spoofing face countermeasure that relies on liveness and motion-based analysis is no longer relevant. liveness-based anti-spoofing detection which detect eyes and lips movements have been tricked with perforated mask in the eyes and mouth. While for motion-based countermeasure, it can be easily challenged by placing a recorded video in front of the camera. Another face anti-spoofing method which is based on reflectance properties has driven more studies towards this analysis. Since face masks are made of various types of materials, characteristics of each material which provide vital information can be used as classification parameters. As in [2], a reflectance-based analysis on texture images from a 2D+3D face mask was introduced. Images of 3D face mask were decomposed into illumination and reflectance components. The results reported that 3D face mask reflectance component is higher than the real face.

Another study presents multispectral reflectance using multispectral lighting to discriminate between a genuine face, a photo face and variety of face masks made of plastic, silica gel, paper, plaster and sponge [3]. Different wavelengths were tested on each material and from the analysis, both wavelengths of 850nm and 1450 nm produced the most discriminative values. In another study [4], two discriminative wavelengths (685 and 850 nm) were selected after examining the albedo curves of the forehead region of facial skin and mask materials. At these two light wavelengths, greater reflectance contrast has been achieved between a genuine facial skin and 2D images. In oder to find the presence of human skin, a method based on spectroscopy was employed [5]. The processing method was divided into two regions known as visible light (VIS) and near-infrared (NIR). In VIS, YCbCr colour space was used to specify pixel whose colour is similar to skin. While in NIR, the reflectance difference in two different wavelengths of each image was used to determine human skin.

Over the last 20 years, classifying materials have already been done by using polarized light. Various experiments were done to proof that reflection properties of each object may be used as classification method [6]. In addition, diffuse and specular reflections can be separated using polarized light by adjusting the polarization angles. A year later, a polarization based method was introduced to discriminate between metal and dielectric surfaces based upon Fresnel reflectance theory [7]. According to this theory, the specular component of reflection is assumed to be higher than the diffuse reflection component.

Popularity of polarization-based techniques has increased since then, notably in differentiating materials. In 2011, an image sensor called complementary metal-oxide-semiconductor (CMOS) was developed to identify metal and dielectric surfaces [8]. Degree of polarization for plastic surface was higher compared to aluminium surface. Another study using polarized light has been done to classify among transparent and opaque objects [9]. Methodologies such as Stokes degree of polarization and polarization Fresnel ratio were presented. The results showed that the degree of polarization of transparent object was higher than opaque objects for most of incident angles.

In oder to differentiate genuine human skin and other materials, property of human real skin can be manipulated. For instance, human skin texture consists of three layers structure which are known as the epidermis layer, the dermis layer and the fat layer [10]. Therefore, skin produces more than one reflection which are named as surface and sub-surface reflections. Theoritically, these could be used as a classification feature between human skin and fake face. Thus, polarized light could be used for this purpose. Previously, a study using polarized light was implemented to compare between visible light images and polarized images of human skin with multiple diseases [11]. Based on the study, polarization images visualized the disruption on skin surface such as skin cancer based on the surface and sub-surface reflections analysis.

A polarization imaging device was demonstrated to monitor lights transmitting through healthy breast tissue and breast tissue with cancer [12]. In another study, Stokes values of images obtained under parallel polarized light are related to human skin characteristics [13]. Thus, the finding was used to evaluate dermatologic diseases. In 2012, the advantages of polarized light were manipulated to classify skin into several age groups [14]. As the results, surface reflection of younger skin is higher compared with older skin.

In view of several previous works that has been mentioned so far, it is undeniable that polarizationbased technique can be implemented as one of anti-spoofing techniques in face recognition systems. Thus, in this paper, multi-reflections of real face, printed photo and iPad displayed images were separated and statistically analysed. This paper is organized in several sections. Section 2 lists several theories that drive toward this research. In section 3, research method is presented. In section 4, experimental results are discussed. Finally, conclusion and future work are provided in section 5.

2. RESEARCH THEORY

2.1. Human skin's structure

To detect fake faces in a face biometric system, it is vital to understand the characteristics of genuine human skin. One of them is skin surface reflections. Basically, human skin structure has three layers which are epidermis, dermis and fat layers [15]. The outmost layer is called the epidermis that contains melanin which act as absorption and scattering agents. Skin colour contributes to the amount of melanin.

Dark skin has more amount of melanin compared to fair skin colour [16]. Dermis, the second layer is a thick layer underneath the epidermis. The deepest layer is made of fat and connective tissues. Figure 1 illustrates the structure of skin layers which was depicted from [17].



Figure 1. Human skin's structure

As can be seen in Figure 1, skin contains of multilayers structures. Because of this, skin produces more than one reflection. When normal light beam strikes on skin surface, part of the incidence light is reflected at the air-skin surface. This happens due to the different in index of refraction of each medium. Figure 2 shows the reflections of normal light beam when it strikes on skin surface. From Figure 2, it can be seen that particles like melanin, collagen and haemoglobin act as scattering and absorption agents on the light wave that penetrates through the layers.



Figure 2. Reflections when lights hit human skin surface

2.2. Printed photo paper's structure

Photo attacks are usually happened when a photograph of a legitimate user is presented in front of a face biometric system as attempts to gain access. Imposters used paper mask as spoofing attacks because of some basic reasons. First, it is easy to get a photo of any legitimate users either by downloading from related social media websites or applications. Next, photos can also be taken by an impostor using digital or video camera. Those photos can be easily printed and used as spoofing attempts. Because of low cost and affordable, paper mask is actually a popular choice as spoofing attacks among imposters.

Similar as other materials, paper also has its own physical properties. It is necessary to study the properties of a piece of paper before proceeding in examination of polarized reflection between real face and photo attacks. Basically, paper is made of cellulose fibres, a complex carbohydrate consisting of more than 3,000 glucose units [18]. Paper has four important optical properties which are brightness, colour, opacity, and gloss [19]. According to [20], matte paper has low reflection property. Most of lights that hit matte paper is absorbed, only a small amount is reflected. The absorbed light is diffused by the paper before re-emerged

to the air. Amount of the reflected light is also affected by the inks printed on the paper. In an investigation, light which strikes on the black dots is absorbed while the remaining is diffused by the paper [21].

Generally, it seems that human skin and coloured printed paper have similar reflection properties. Both produce more than one reflection: surface and subsurface (diffuse) reflections. Because of this, it can be assumed that the analysis to differentiate between real face and printed photo will experience a more intense challenge.

2.3. iPad screen displayed image

iPad screen is a flat display panel or basically known as a liquid-crystal display (LCD). Liquid crystal does not emit light directly, instead it use backlight or reflector to produce images in color or monochrome. The backlight emitted from the screen is polarized. Light waves interference might occur if two or more light waves meet. Polarized light emitted from iPad screen should be perpendicular to the polarization axis of light source. Thus, the traveling perpendicular light wave is stopped by a polarizer from transmitting through. The camera captured image at 90^{0} polarization angle without any light transmitted. This is a significant positive correlation between lights emitted from iPad screen and the polarization angle. The differences between real face and iPad displayed image at 90^{0} polarization angle can be used to discriminate real face and the iPad attack.

3. RESEARCH METHOD

3.1. The polarization imaging system

Since there is no polarized images dataset that is publicly available, polarized images of human faces and printed photos used in this research were self-collected. The data were collected using own-developed imaging system similar to an imaging system introduced in [22]-[24]. Figure 3 illustrates the experimental setup used in to capture images in this study.



Figure 3. The polarization imaging setup

In Figure 3, two table lights were placed 80cm each to the right and left of the camera. The lights were placed to light up the experimental subjects at an angle of 45° . Each of them was coupled with a linear polarizer sheet, labelled as P₂ and P₃. Both polarizers were aligned in parallel position to each other at the same polarization axis. This setup will let the table lights wave travelled in the same direction towards the subject. The camera used in this experiment was Samsung Full HD camera, placed 80cm in front of the subject. A linear polarizer made of glass, P₁, coupled with an angle rotator, was placed in front of the camera lens. An angle rotator was used to adjust the polarization angles during the dataset recording process.

3.2. Surface and sub-surface images' dataset

Polarized image captured under parallel polarization consists both surface and subsurface reflections [14]. Image with only subsurface reflection can be recorded under 90⁰ polarization angle. For this, polarized image under 90⁰ polarization angle is subtracted from polarized image recorded under parallel polarization. In this study, polarized image captured under 90⁰ polarization angle is denoted as Img₉₀ while polarized image captured under parallel polarization is labelled as Img₉₀. Any image with surface reflection is known as S₁ which is one of the Stokes components. Figure 4 listed samples of Img₉₀ and S₁ of the real and fake faces available in the self-collected dataset. There are two new datasets, namely as face-photo-spoof (FaPs) dataset and Face-iPad dataset. In FaPs dataset, there are 37 genuine faces were recorded randomly selected among the faculty members. They were then generally classified into three groups: 26 Asian; 4 Black; and 7 Caucasian. Meanwhile, printed photos of each subject were added to the FaPs dataset. In

another dataset called Face-iPad dataset, there are five females and three males of two skin colours: Asian and Caucasian. Images of each subject were captured and digitally stored to be later displayed as spoofing attempt.

As shown in Figure 4, it is quite clear that S_1 images between real face, printed photo and iPad displayed images are significantly different. However, the subsurface images represented by Img₉₀ are relatively similar between the real face and printed photo. For Img₉₀ of the iPad displayed face shows total different compared to Img₉₀ of the genuine face. These images were then statistically analysed.



Figure 4. The surface (S1) and subsurface (Img90) images

4. **RESULTS AND DISCUSSION**

Results of this research is presented and discussed in several sub sections. Since the main objective is to study surface reflection properties by using statistical measures, each measure is explained in details in sub section accordingly.

4.1. Mean, standard deviation, skewness and kurtosis

In this section, reflection properties for both S_1 and Img_{90} images of each genuine and fake faces were statistically analysed. Figures 5 and 6 present the statistical results of S_1 and Img_{90} images of each subject, respectively. As can be seen in Figure 5, there is a significant difference between real faces and iPad displayed faces, measured by the mean and standard deviation. In contrast, skewness and kurtosis of these two subjects are similar to each other. Surprisingly, none of these measures shows significant different between real faces and printed photo faces. Data in Figure 5 can be compared with statistical data of subsurface images in Figure 6.





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From Figure 6, it can be seen that mean and standard deviation scores between real faces and iPad faces are significantly different. Despite a slight mean intensity difference of Img_{90} between real and photo faces, no other differences were found in the standard deviation, skewness and kurtosis measures. To further examine the distribution of S₁ and Img_{90} for the real faces and the two fake faces, histograms of each subject was plotted and presented in Figure 7. As displayed in Figure 7, S₁ images for the real face and printed photo face are assumed to have unimodal distributions whereas iPad displayed face images has bimodal distribution. In contrast, Img_{90} for the iPad face shows unimodal distribution while the real and photo faces indicate bimodal distributions.



Figure 6. Subsurface image, Img90 of real and fake faces' statistical analysis



Figure 7. Histograms of the S1 and Img90 images

4.2. The bimodality coefficient (BC)

To measure modality of a distribution, the bimodality coefficient (BC) was used as the second emasure in this study. Values of the BC ranged from 0 to 1. Any empirical values that us more than 0.555 suggesting bimodal distribution [SAS Institute, (1989)]. Otherwise, the modality of distribution is classified

as unimodal. The bimodality coefficient algorithm was measured using (1) as proposed by [25]. Modality of distributions for all S_1 and Img_{90} images in the FaPs and Face-iPad datasets were measured and the results are compared in Figure 8.

$$BC = \frac{m_3^2 + 1}{m_4 + 3\left(\frac{(n-1)^2}{(n-2)(n-3)}\right)}$$
(1)

Where m_3 = skewness (x,0); m_4 = kurtosis (x,0) – 3; and n = sample size.

<i>n</i> = 82	Predicted: Real face	Predicted: Fake face		<i>n</i> = 82	Predicted: Real face	Predicted: Fake face	
Actual: Real face	34	3	37	Actual: Real face	33	4	37
Actual: Fake face	28	17	45	Actual: Fake face	27	18	45
	62	20			60	22	
	Surface image, S ₁				Subsurface image. Img₀		

Figure 8. S1 and Img90 prediction scores based on the BC

From the data in Figure 8, total number of fake faces were 45 consisting of 37 printed photos and 8 iPad displayed faces. Overall, majority of the fake faces were shown to have unimodal distributions and have been identified as genuine faces. True positive rate (TPR) and false positive rate (FPR) were calculated by using (2) and the accuracy rate was measured using (3). Table 1 provides the detection rates of the BC algorithm for both S_1 and Img_{90} distributions. As shown in Table 1, the accuracy rates of the BC for both S_1 and Img_{90} distributions are 62.20% in which more than half of the fake faces' distributions were labelled as unimodal. Based on the analysis results, surface and subsurface distributions modality using the BC algorithm, seem not possible to be used as one of the face spoofing detection parameters.

True positive rate (TPR) =
$$\sum$$
 True positive (TP) / \sum real face
False positive rate (FPR) = \sum False positive (FP) / \sum fake face (2)

$$Accuracy (AC) = \frac{TP+TN}{TP+FN+FP+TN}$$
(3)

Table 1. Detection rates of the BC for S1 and Img90

	TPR	FPR	Accuracy (AC)			
	in percentage (%)					
S_1	91.89	62.22	62.20			
Img ₉₀	89.19	60.00	62.20			

5. CONCLUSION

As stated in the Introduction, multi reflections properties of real face and fake faces could be manipulated as one classification method in spoofing face detection. Surface and sub-surface reflection of each material were differentiated using polarized light. However, the findings showed that real faces and printed photo faces consist similar reflections properties. Due to these similarities, it is difficult to distinguish between real faces and printed photo faces based on S₁ and Img₉₀ images. On the other hand, iPad attacks can be easily detected only by the mean values of S₁ and Img₉₀. Moreover, density of the iPad distributions mode was also significantly different from the genuine faces. The results of this study will now be compared to the findings of previous works: classification between plastic and aluminium object; and classification between transparent and opaque objects. Both results measured the degree of polarization (DOP) values of the materials. Several possible explanations can be listed for these results. The polarization of the reflected light depends on the properties of the object surface. In accordance to the surface properties, the difference between transparent and opaque objects is physically obvious. Transparent object such as glass not only allows light to transmit but also reflects light. The reflections from a transparent object have been reported to be mostly specular while an

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opaque object's reflections are diffused. As been discussed in section 2, the iPad screen was made of glass which is an insulator. Printed photos were obviously insulators. Apart from that, the three materials were opaque objects although the iPad screen was made of glass. Another similarity between the real face and printed photo is that both of them produce two types of reflections: specular and diffuse. In contrast, iPad does not reflect light but emits its own light. Despite these similarities, statistically, printed photos were unable to be distinguished from the genuine faces by using both surface and sub-surface reflection.

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BIOGRAPHIES OF AUTHORS



Azim Zaliha Abd Aziz is currently a lecturer in Faculty of Informatics & Computing, Universiti Sultan Zainal Abidin (UniSZA), Terengganu Malaysia. She received her PhD (Computer Science) from University of Reading, United Kingdom in 2017. She did her first degree in Computer Science in 2000 at Faculty of Computer Science, Universiti Teknologi Malaysia.



Prof. Mohd Rizon Juhari graduated Doctor of Engineering at Department of Computer Science and Intelligence System in Oita University, Japan. He was a Professor of Biomedical Technology in King Saud University, Saudi Arabia in 2010. He served at MIEC, Fuzhou University, China in 2019. Currently, he is a Professor at Department of Electrical and Electronics, UCSI University, Malaysia. MIET, MIEM member.