A Novel Colour Texture Based Face Spoofing Detection using Machine Learning

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Abstract- *A study on non-invasive software based on face spoofing detection schemes has mainly been given focus on the analysis of the luminance information of the face images, hence removing the chroma component can be very much useful for discriminating photo faces from genuine faces. This technique provides us an appealing way for identifying face spoofing using colour texture analysis. The combined texture information and data of colours from the luminance and the chrominance channels by taking out complementary low-level feature descriptions from different colour spaces are used. The colour local binary patterns (LBP) descriptors, finds the facial colour texture content using other descriptors such as the co-occurrence of adjacent local binary patterns (CoALBP), local phase quantization (LPQ). Here by using these features and characteristics the colour texture is analyzed and extracted by face descriptors from different colour band. To gain insight into which colour spaces are most suitable for discriminating genuine faces from fake ones, considered three colour spaces, namely RGB, HSV and YCbCr. A new and appealing approach using colour texture analysis and demonstrate that the chroma component can be very useful in discriminating fake faces from genuine ones. First, the face is detected, cropped and normalized into an M×N pixel image. 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. The ultimate characteristic vectors are given to a binary classifier and the output score value describes whether it is a real or a photo image.*

Keywords- Color texture analysis, feature descriptors, color spaces.

I. INTRODUCTION

On Comparison with established verification mechanisms including password, verification code and secret question, biometrics authentication is more user-friendly. As the human face has a ton of information for identifying different people, face becomes the most popular biometric way along with the excellent performance of identity recognition. Nowadays, recognition of an individual can easily use the face images captured from a distance without physical contact with the camera on the mobile devices, e.g. mobile phone. As the application of face recognition system becomes more and more popular with the widespread of the Mobile phone, their weaknesses of security become increasingly conspicuous. For example, owing to the popularity of social network, it is quite easy to access a person's face image on the Internet to attack a face recognition system. Hence, a deep attention for face spoofing detection has been drawn and it has motivated great quantity of studies in the past few years.In general, there are mainly four types of face spoofing attacks: photo attack, masking attack, video replay attack and 3D attack. Due to the high cost of the masking attack and 3D attack, therefore, the photo attack and video reply attack are the two most common attacks. Photo and video replay attacks can be launched with still face images and videos of the user in front of the camera, which are actually recaptured from the real ones. Obviously, the recaptured image is of lower quality compared with the real one in the same capture conditions. The lower quality of attacks can result from: lack of high frequency information image banding or more effects, video noise signatures, etc. Obviously, the image quality deterioration factors can work as the useful things to distinguish the real faces and the photo faces. Face spoofing detection has been designed to counter different types of spoofing attacks. The real and photo faces can be very distinctive in the chrominance channels. For instance, Burkinabe analyzed the impact of different colour spaces on face anti-spoofing and presented a shallow model based on colour features, achieving fairly good performance. To exploit and combine the effectiveness of colour and deep learning, we utilize a deep learning framework combined with LBP features extracted from different colour spaces (such as RGB, HSV, YCbCr. Among the significant contributions of our present work, (i) While most previous methods based on deep learning suffer from the lack of face training samples, we introduce a new deep learning model by fine tuning the VGG-face model. (ii) We combine deep learning with handcrafted features by extracting the LBP descriptions from the convolutional feature maps. (iii) We explore how well different colour spaces can be used for describing the intrinsic disparities in deep learning between genuine faces and fake ones. We also perform a fusion study to analyze the complementarity of different colour space.

II. BINARY PATTERNS AND FACE QUANTIZATION ALGORITHM

Here Texture descriptors originally designed for gray-scale images can be applied on colour images by combining the features extracted from different colour channels. Colour texture of the face images is analysed using three descriptors: Local Binary Patterns (LBP), Co-occurrence of Adjacent Local Binary Patterns (CoALBP), Local Phase Quantization (LPQ) have shown to be effective in gray-scale texture-based face anti-spoofing.

A) LBP (LOCAL BINARY PATTERN)

Local Binary Pattern is considered to be an elementary texture operating mechanism which labels the pixels of an image by selecting a threshold of the neighborhood of each pixel and it also takes the result as a binary number.

Implementation of the LBP operation: The first computational step of the LBP is to create an intermediate image that describes the original image given as the input.

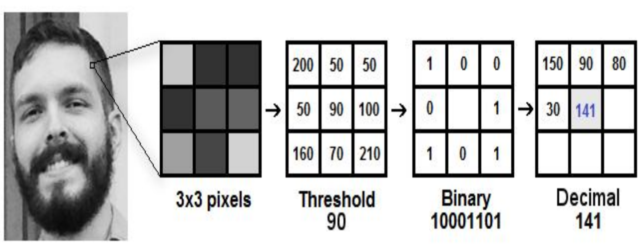

Figure 1 LBP image

For every neighbour of the middle value (threshold), we are setting a new binary value. 1 is set for values equal or greater than the threshold and 0 is set for values lower than the threshold value.Here, the matrix contains only binary values (not considering the threshold value) from figure 1. The binary values are concatenated from each position from the matrix line by line into a new binary value (e.g. 10001101). Although there are many other approaches to concatenate the binary values (e.g. clockwise direction), but the final result will be the same. Next we convert this binary value to a decimal value and set it to the threshold value of the matrix, which is actually a pixel from the original image. Atlast in this procedure (i .e, LBP procedure), we have a new image which represents better the characteristics of the original image. This procedure was elongated to use a varied number of radius and neighbors, it is called Circular LBP. This can be done by using bilinear interpolation. If the data points are between the pixels, it uses the values from the 4 nearest pixels (2x2) to estimate the value of the new data point.

B) LPQ (LOCAL PHASE QUANTIZATION)

During the past few years, high and more elongation materials are widely used. Hence, we have to investigate about the tensile characteristics and properties of high and more elongation elements for engineering applications. An equipment called Video extensometer is used for measuring the materials' tensile properties. The image processing technology to match data points and measures the actual deformation are used. When taking the measurements of high elongation materials, motion blur will appear on the gained images, which can affect the accuracy of image matching. Here, we have proposed that an image matching method which is based on Local Phase Quantization (LPQ) features to reduce the interference of the motion blur and improve the accuracy of the image matching algorithms as well. The simulations show that the proposed initialization method is sufficiently accurate and precise to enable the correct convergence of the subsequent optimization in the presence of motion blur. This result of uniaxial tensile also verifies the accuracy and robustness.

Greater elongation materials are so instrumental class of materials for structural applications such as transportation, civil infrastructures, and biomedical applications. Therefore, an original service conditions, these materials are often subject to both mechanical and environmental loads. The material properties will be changed and thus have a great influence on the service life and safety performance of these materials. The study of these factors, says that the tensile mechanical test should be carried out on these materials.

Nowadays, mechanical extensometer and video extensometer are the most commonly used equipment for the tensile mechanical test. The video extensometer and the mechanical extensometer which is kept directly onto the material via blade causes many problems such as the mutual friction will reduce the measurement accuracy; the total deformation cannot be easily measured in the uniaxial tensile test; the measuring range is limited.

On Comparison with mechanical extensometer, the video extensometer has many merits. Even though if the greater accuracy is pursued, some influence factors cannot be ignored, such as out-of-plane displacement, self-heating of the camera, lens distortion, and image blur induced by motion. This can explain us the measurement errors caused by out-of-plane displacement and self-heating of the camera; it further establishes a high-accuracy two-dimensional digital image correlation (2D-DIC) system using a bilateral telecentric lens to minimize the errors. The systematic errors due to lens distortion using the radial lens distortion model and in-plane translation tests; it finds out that the displacement and strain errors at an interrog interrogated image point not only are linear proportion to the distortion coefficient of the camera lens used but also depend on the distance relative to distortion center and its magnitude of the displacement; the paper also proposes a linear least-squares algorithm to estimate the distortion coefficients and then to eliminate the errors. An off-axis digital image correlation technique for real-time, noncontact, and target less measurement of vertical deflection of bridges to achieve sub pixel accuracy. Although, it has these many advantages few works about eliminating extensometer's measurement errors caused by motion-induced image blur to improve the accuracy have been reported. Therefore, we are proposing an image matching method for video extensometer to measure the parameters by utilizing Local Phase Quantization (LPQ) feature. It performs well on images with serious motion blur and deformation. Recording of the phase information in the Fourier coefficients is done by examining the signs of the real and imaginary parts of each component. By using a simple scalar quantization, where is the component of the vector. The output which is obtained is eight binary coefficients are represented as integer values within 0–255 using binary coding.

Finally, a histogram is formed by all the positions in the rectangular region and used as a 256-dimensional feature vector in the match.

C) CoALBP (CO-OCCURRENCE ADJACENT LOCAL BINARY PATTERN)

The new image feature based on spatial co-occurrence among micropatterns, where each micropattern is represented by a Local Binary Pattern (LBP). In conventional LBP-based features such as LBP histograms, all the LBPs of micropatterns in the image are packed into a single histogram which is clearly shown in figure 2. Doing so discards important information concerning spatial relations among the LBPs, even though they may contain information about the image's global structure. To consider such spatial relations, we measure their co-occurrence among multiple LBPs. The proposed feature is robust against variations in illumination, a feature inherited from the original LBP, and simultaneously retains more detail of image. The significant advantage of the proposed method versus conventional LBP-based features is demonstrated through experimental results of face and texture recognition using public databases.Spatial co-occurrence matrix could boost the discriminative power of the features, but it always suffers from the geometric and photometric variations. In this work, we investigate rotation invariant property of co-occurrence feature, and introduce a novel pairwise rotation invariant co-occurrence local binary pattern (PRI-CoLBP) feature which incorporates two types of context, spatial co-occurrence and orientation co-occurrence. Different from traditional rotation invariant local features, pairwise rotation invariant co-occurrence features preserve the relative angles between the orientations of individual features. The relative angle depicts the local curvature information, which is discriminative.

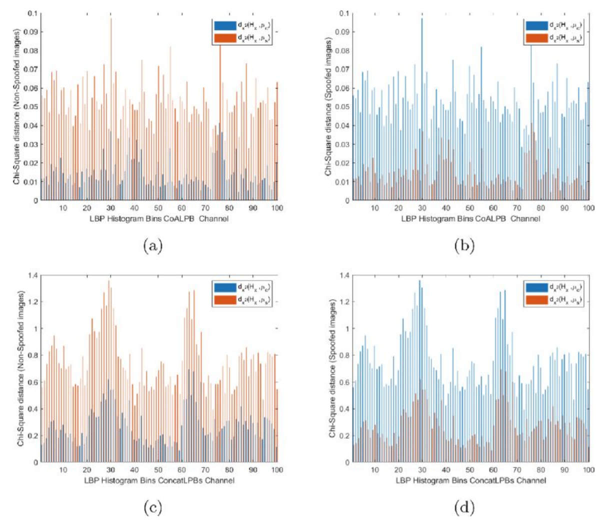

Figure 2 CoALBP image

The proposed PRI-CoLABP is computationally efficient and has been applied to six types of applications, including texture classification, material classification, flower recognition, leaf recognition and food recognition.

III. METHODOLOGY

A) INPUT IMAGE

Read and Display an input Image. Read an image into the workspace, using the misread command. In image processing, it is defined as the action of retrieving an image from some source, usually a hardware-based source for processing. It is the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed.

B)RGB COLOUR IMAGE

The RGB colour model is an additive colour model in which red, green, and blue light are added together in various ways to reproduce a broad array of colours. The name of the model comes from the initials of the three-additive primary colours, red, green, and blue.

The main purpose of the RGB colour model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB colour model already had a solid theory behind it, based in human perception of colours' is a device-dependent colour model: different devices detect or reproduce a given RGB value differently, since the colour elements (such as phosphors or dyes) and their response to the individual R, G, and B levels vary from manufacturer to manufacturer, or even in the same device over time in figure 3. Thus, an RGB value does not define the same colour across devices without some kind of colour management. Typical RGB input devices are colour TV and video cameras, image scanners, and digital cameras. Typical RGB output devices are TV sets of various technologies (CRT, LCD, plasma, etc.), computer and mobile phone displays, video projectors, multicolour LED displays, and large screens such as Jumbotron. Colour printers, on the other hand, are not RGB devices, but subtractive colour devices (typically CMYK colour model).

Figure 3 RGB image

C) GRAYSCALE

In photography and computing, a grayscale or greyscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colours, black, and white (also called bilevel or binary images). Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the presence of only one (mono) colour (chrome). Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also, they can be synthesized from a full colour image; see the section about converting to grayscale in figure 4.

Example of gray scale image is given below

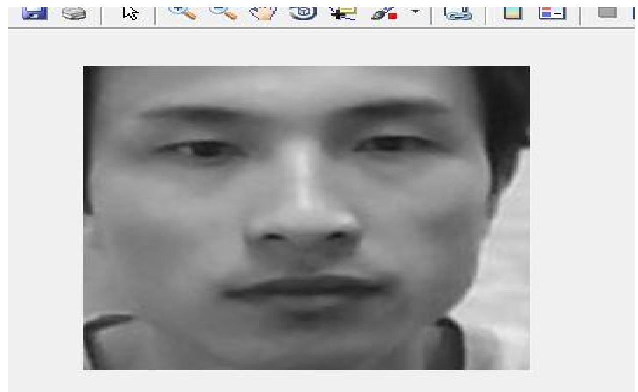

Figure 4 gray scale image

D) COLOUR CONVERSION

A colour space is a specific organization of colours. In combination with physical device profiling, it allows for reproducible representations of colour, in both analog and digital representations. A colour space may be arbitrary, with particular colours assigned to a set of physical colour swatches and corresponding assigned colour names or numbers such as with the Pantone collection, or structured mathematically as with the NCS System, Adobe RGB and sRGB. A "colour model" is an abstract mathematical model describing the way colours can be represented as tuples of numbers (e.g. triples in RGB or quadruples in CMYK); however, a colour model with no associated mapping function to an absolute colour space is a more or less arbitrary colour system with no connection to any globally understood system of colour interpretation. Adding a specific mapping function between a colour model and a reference colour space establishes within the reference colour space a definite "footprint", known as a gamut, and for a given colour model this defines a colour space. For example, Adobe RGB and sRGB are two different absolute colour spaces, both based on the RGB colour model. When defining a colour space, the usual reference standard is the CIELAB or CIEXYZ colour spaces, which were specifically designed to encompass all colours the average human can see. Since "colour space" identifies a particular combination of the colour model and the mapping function, the word is often used informally to identify a colour model. However, even though identifying a colour space automatically identifies the associated colour model, such a usage is incorrect in a strict sense. For example, although several specific colour spaces are based on the RGB colour model, there is no such thing as the singular RGB colour space.

E) PRE-PROCESSING

Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images.

The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Image pre-processing methods use the considerable redundancy in images. Neighbouring pixels corresponding to one object in real images have essentially the same or similar brightness value. Thus, distorted pixel can often be restored as an average value of neighbouring pixels.

F) FEATURE EXTRACTION

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

a) Shape features
b) colour features

G) CLASSIFICATION

Image classification refers to the task of extracting information classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. The recommended way to perform classification and multivariate analysis is through the Image Classification toolbar. There are many classification algorithms are available and some classification algorithm that are given below,

KNN (K-NEAREST NEIGHBOUR)

In pattern recognition, the k-nearest neighbours' algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression

In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbouring k-NN regression, the output is the property value for the objecting figure 5. This value is the average of the values of k nearest neighbours. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. Both for classification and regression, auseful technique can be to assign weights to the contributions of theneighbours, so that the nearer neighbours contribute more to the average than the more distant ones. For example, a commonweighting scheme consists in giving each neighbour a weight of 1/d, where d is the distance to the neighbour.

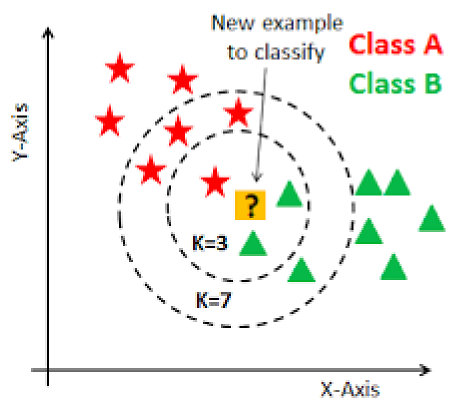

Figure 5 KNN

IV. CONCLUSION

In order to view the problem of face anti-spoofing from the colour texture analysis point of view. Here the observation on 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 are performed. The different facial colour texture representations were studied by extracting different local descriptors from the individual image channels in the different colour spaces. The facial colour texture representation seems be more stable in unknown conditions than texture descriptions extracted from gray-scale images. Thus, the use of colour texture information provides a way to improve the unsatisfying generalization capabilities of texture-based approaches. In order to benefit from the potential complementarity of the CoALBP and the LPQ face descriptions, to fuse them by concatenating their resulting histograms. The facial representations extracted from different colour spaces using different texture descriptors can also be concatenated in order to benefit from their complementarity. The different texture descriptors more closely in detecting various kinds of face spoofs by extracting holistic face representations from luminance and chrominance images in different colour spaces. In future, the T test is use for feature selection to reduce high time consumption due to high feature size, second the Classifier need high training sample so by applying sparse classifier it will be reduced.

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