Recent Advances in Biometric Recognition

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Abstract This paper presents recent advances in biometric recognition, where we focus on face, fingerprint and iris recognition, which are major research topics on biometric recognition. We summarize the research trend of face, fingerprint and iris recognition over the past decade. This paper also presents our activities of biometric recognition. Our approach employs the phase information obtained by Discrete Fourier Transform (DFT) of images. The phase information preserves the inherent features of the image, and its correlation function, called phase correlation or Phase-Only Correlation (POC), gives us both the good similarity measure for biometric recognition and the translational displacement for image registration. Our approach of using phase information has been successfully applied to fingerprint, face, iris, palmprint, finger knuckle and dental recognition. Among them, we present some interesting results of palmprint recognition, finger knuckle recognition and dental recognition.

Key words: biometrics, face recognition, fingerprint recognition, iris recognition, palmprint recognition, finger knuckle recognition, disaster victim identification, phase-only correlation

1. Introduction

Biometric authentication (or simply biometrics) is to identify a person based on the physiological or behavioral characteristics\(^{1,2}\) such as fingerprint, face, iris, voice, signature, etc. Biometrics has attracted extensive attention as a new authentication approach against traditional ones such as key, password, etc. Biometric traits are not stolen and forgotten compared with key, card and password. Therefore, biometrics techniques provide us better security and greater convenience than traditional person authentication techniques. Practical person authentication systems using fingerprint, face, iris, etc. have been commercially available and used in access control, ATM, etc.

Jain et al.\(^{3}\) summarized what biological measurements qualify to be a biometric trait. They introduced the following requirements to use physiological or behavioral characteristic as a biometric trait:

- **Universality**: each person should have the characteristic.
- **Distinctiveness**: any two persons should be sufficiently different in terms of the characteristic.
- **Permanence**: the characteristic should be sufficiently invariant over a period of time.
- **Collectability**: the characteristic can be measured quantitatively.

They also presented some issues to be considered in a practical biometric system:

- **Performance**, which refers to the achievable recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as the operational and environmental factors that affect the accuracy and speed.
- **Acceptability**, which indicates the extent to which people are willing to accept the use of a particular biometric trait in their daily lives.
- **Circumvention**, which reflects how easily the system can be fooled using fraudulent methods.

Biometric techniques to be used in the practical system depend heavily on application requirements. The above seven factors can be used to compare biometric techniques as shown in Table 1, which was derived on the perception of Jain et al.\(^{3}\). This table provides us good suggestions when we consider which biometric techniques are selected in practice. Let us focus on performance and collectability of biometric traits. A face has low performance due to weakness against environmental variations, while it is easy to capture a face by a camera. An iris has high performance due to its distinctive texture pattern, while an iris image is captured by a special imaging device. A face is suitable for low-security level application such as PC login because of its high collectability. On the other hand, an iris is suitable for high-security level application such as immigration control because of its high performance, al-
Table 1  Comparison of various biometric techniques on the perception of Jain et al.\textsuperscript{3)}, where H, M and L indicate High, Middle and Low, respectively.

<table>
<thead>
<tr>
<th>Biometric Trait</th>
<th>Universality</th>
<th>Distinctiveness</th>
<th>Permanence</th>
<th>Collectability</th>
<th>Performance</th>
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though a special imaging device is required to capture iris images. Performance can be complemented with combining multiple biometric traits such as face and iris to keep both high performance and high collectability. This approach is known as multimodal biometrics\textsuperscript{4)}, which is one of active research topics in biometrics.

Table 2 summarizes the number of papers for each biometric trait presented in the international conferences related to biometrics, where the number of papers was counted by the authors. This summary provides us the research trends in the field of biometrics over the past 13 years. Researches on face, fingerprint and iris are always hot, since the number of their papers is constantly large and is always more than other biometric traits. A face is a major research topic in many fields such as computer vision, pattern recognition, image processing and biometrics. A variety of face image processing methods has been proposed, since the performance of face image processing is significantly influenced by environmental changes such as head pose, expression and illumination changes. A new research topic on fingerprint recognition has been explored, since minutiae-based matching exhibits sufficient performance on fingerprint recognition and practical fingerprint recognition systems have been developed. Latent fingerprint recognition is one of the new topics, which requires new preprocessing methods such as fingerprint segmentation, ridge enhancement and minutiae extraction specially designed for latent fingerprint images. A new research topic on iris recognition has been explored as well as fingerprint recognition, since iriscode is the first choice of iris recognition because of its high recognition performance. The purpose of iris recognition is changed from a person to pedestrians from the viewpoint of surveillance applications. Therefore, ocular recognition, which uses the surrounding region of the eye for biometric recognition, is considered as a new topic instead of iris recognition, since iris recognition at a distance is a difficult problem.

Figure 1 shows a flow diagram of a standard biometrics system. Note that we assume an image-based system for a brief description in the following. This system consists of 5 components: (i) sensing, (ii) preprocessing, (iii) feature extraction, (iv) database and (v) matching. In the sensing step, an image of a biometric trait is captured using a sensor. For example, a camera is used in face, palmprint, finger knuckle and gait recognition and a special sensor is used in iris, signature and vein recognition. Preprocessing consists of a set of image processing methods such as contrast enhancement, noise removal, geometric transformation, Region Of Interest (ROI) extraction, etc. The performance of preprocessing is important for the subsequent step of feature extraction, since the captured image usually includes unnecessary background components for biometric recognition. In the feature extraction step, features to be matched are extracted from an ROI image, which is the most active topic in biometric recognition. Local features are designed depending on the type of biometric traits in the most cases. Database stores registered features for the matching step. In the matching step, a similarity or a dissimilarity between registered and input features is calculated to make a final decision. Each component is a major research topic on biometrics. In addition, there are other research topics considered in the biometric system such as anti-spoofing, template protection, cancelable biometrics and multimodal biometrics from the viewpoint of system security. As mentioned above, biometrics is a kind of multidisciplinary research fields and a variety of methods of com-
puter vision, pattern recognition and image processing techniques are required to develop a reliable and high-performance biometrics system, although biometrics is essentially a pattern recognition problem.

This paper presents recent advances in biometric recognition, where we focus on face, fingerprint and iris recognition, which are major research topics on biometric recognition. We summarize the research trend of face, fingerprint and iris recognition over the past decade. This paper also presents our activities of biometric recognition. Our approach employs the phase information obtained by Discrete Fourier Transform (DFT) of images. The phase information preserves the inherent features of the image, and its correlation function, called phase correlation or Phase-Only Correlation (POC), gives us both the good similarity measure for biometric recognition and the translational displacement for image registration. Our approach of using phase information has been successfully applied to fingerprint, face, iris, palmprint, finger knuckle and dental recognition. We provide a brief introduction of our research results of palmprint recognition, finger knuckle recognition and dental recognition, which are interesting, practical and useful in the field of biometrics.

2. Face Recognition

This section describes the research trend in face recognition. Figure 2 shows a standard flow diagram of face recognition systems, which consists of 4 steps: (i) face detection, (ii) normalization, (iii) feature extraction and (iv) matching. We summarize the technical advances in each step and present recent research topics on face recognition.

2.1 Face Detection

Face detection, which is the first process of face recognition, extracts a face region from an input image. The accuracy of face detection is important especially for face recognition at a distance such as surveillance application, since there are multiple faces with different size in an image captured by a surveillance camera. The most famous method was proposed by Viola et al.\(^5\), which is also called the Viola-Jones method. This method first extracts Haar-like features from an image, where the integral image is used for fast Haar-like feature extraction. Next, a variant of AdaBoost is used to select the best features and to train classifiers. A strong classifier is obtained by constructing a cascade of weak classifiers to boost the classification performance of simple classifiers. In the training, a huge number of face and non-face images are required to make a good face detector. The Viola-Jones method with trained classifiers is available in OpenCV\(*\), which is a famous computer vision library. The OpenCV implementation of the Viola-Jones method is a de-facto standard, since users do not need a time-consuming training to make a face detector.

The use of the Viola-Jones method makes it possible to detect near frontal faces from an image. Face detection in real-world applications has to take into account the unconstrained conditions such as large pose and expression changes, large occlusions, illumination changes, etc. and is still one of the most studied topics in computer vision\(**\). We introduce one of the state-of-the-art studies of face detection. Yang et al. created a face detection benchmark dataset, which is called the WIDER FACE dataset\(**\***\). The WIDER FACE dataset consists of 393,703 labeled face bounding boxes in 32,203 images. Images in the dataset have a high degree of variability in scale, pose, occlusion, expression, appearance (makeup) and illumination. Yang et al. proposed the baseline face detection method using Convolutional Neural Network (CNN)\(^7\), where this method employs the multi-scale cascade CNN to deal with large

\(\ast\) OpenCV: http://opencv.org/  
\(\ast\ast\) Please refer to the literature\(^6\) for the detailed survey of the recent face detection methods.  
\(\ast\ast\ast\) WIDER FACE: http://mlab.ie.cuhk.edu.hk/projects/WIDERFace/
scale variations of faces. They also compared the face detection accuracy of the proposed method with four representative methods. Using such a large-scale face image dataset, a lot of face detection methods using a deep learning approach has been proposed in recent years.

### 2.2 Normalization

Face images have to be normalized in terms of head pose and expression in order to exhibit good recognition performance. This process is important to deal with face images under the unconstrained conditions. In general, landmarks are detected on a face and are used to normalize head pose and expression. One of the famous landmark detection methods is Active Appearance Model (AAM) proposed by Cootes et al.\(^8\). AAM is a parametric face model of both landmarks and texture, which is derived by using Principal Component Analysis (PCA). The demo software is available on the web\(^9\). AAM cannot handle a large head pose change, since head pose changes are essentially 3D transformation. On the other hand, a 3D face model, which is called 3D Morphable Model (3DMM), has been proposed by Blanz et al.\(^9\). 3DMM can handle a large head pose change, while this method requires a lot of 3D face models in the training. Nowadays, it is easy to capture 3D face data and process them because of advances in computer technology. Large Scale Facial Model (LSFM) has been created from a large scale dataset by Booth et al.\(^10\), where the dataset includes face images and 3D data captured from 9,663 subjects. LSFM is a parametric 3D facial model of head pose, facial expression, age and ethnicity. The source code of LSFM is available on the web\(^*\). The use of such parametric 3D face models makes it possible to deal with faces under the unconstrained conditions.

### 2.3 Feature Extraction and Matching

Feature extraction and matching are core processes of face recognition. The traditional methods employ PCA, Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA)\(^11\), where such a feature is represented as a point on the subspace in PCA, ICA, and LDA. PCA-based method is known as Eigenface\(^12\) and LDA-based method is known as Fisherface\(^13\). Other methods employ subspace methods such as CLAss-Featuring Information Compression (CLAFIC) method\(^14\), subspace method\(^14\), mutual subspace method and its extensions such as constrained mutual subspace method\(^15\), and multiple constrained mutual subspace method\(^16\), etc., where such a feature is represented as a set of bases of the subspace. The approaches mentioned above transform the high-dimensional image space into the low-dimensional subspaces and provide good representation and good dis-

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\(^*\) aam_tools: http://personalpages.manchester.ac.uk/staff/timothy.f.cootes/software/am_tools_doc/index.html

\(^*\) LSFM: https://github.com/menpo/lsfm

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Fig. 1 Flow diagram of a standard biometrics system and research topics.

Fig. 2 Flow diagram of a general face recognition system.
crimination for face recognition by selecting effective subspaces. The drawback of such approaches is that position and intensity of all the face images have to be aligned. Therefore, these approaches may exhibit good recognition performance only for face images captured under the desired condition.

Recently, Local Binary Patterns (LBPs) have been proposed and applied to face recognition\(^{17}\). LBP is obtained by thresholding neighborhoods of each pixel with the center pixel value, and then the histogram of LBPs is used as a texture descriptor. So far, the improved versions of the LBP-based method have been proposed and been applied to various biometric recognition problems. LBP has the versatility for image matching and is applied to solve computer vision problems\(^{18}\), since LBP does not need any optimization process. On the other hand, LBP cannot handle large deformation of images and also may not exhibit the comparable performance with the other methods specified to each biometric trait due to its versatility. The original implementation of LBPs is available on the web\(^*\).

The deep learning-based approach has a significant impact on face recognition researchers. The face image dataset called Labeled Faces in the Wild (LFW)\(^{19}\) is known as one of difficult face image datasets, since this dataset is designed for studying the problem of unconstrained face recognition. Taigman et al.\(^{19}\) employ CNN to extract features to be matched. Their CNN model, which is called DeepFace, is trained using a large-scale face dataset collected from Facebook, where the number of face images is 4.4 million captured from 4,030 persons. The recognition accuracy of DeepFace is 97.35%, while that of human is 97.53%. The deep learning approach achieved a breakthrough in face recognition, since the state-of-the-art methods exhibited the recognition accuracy of about 90% at that time. Various CNN models have been proposed for face recognition since DeepFace was proposed and their recognition accuracy is comparable to a human quality.

### 2.4 Face Attributes

Face recognition can be used for practical situations because of the advent of deep learning as mentioned above. The state-of-the-art methods of face recognition exhibit comparable recognition performance of human even for face images captured under the unconstrained conditions such as large pose and expression changes, large occlusions, illumination changes, etc.

Further performance improvement of face recognition is to use face attributes. Various characteristics, i.e., face attributes, include in a face such as gender, hair, skin color, eyeglass, shape, etc. The use of such information makes it possible to classify face images according to categories of face attributes in advance, resulting in improving recognition performance and reducing the computation time. This approach is known as soft biometrics. Jain et al. defined that soft biometric traits as characteristics that provide some information about the individual, but lack the distinctiveness and permanence to sufficiently differentiate any two individuals\(^{20}\).

The initial approach of predicting face attributes employs the statistical approach such as Bayesian\(^{21}\). It is difficult to design feature descriptors for predicting attributes, since there is a lot of types of attributes included in a face, resulting in low accuracy of prediction. Recently, the deep learning approach is applied to predict face attributes\(^{22}\). The use of deep learning makes it possible to predict precise attributes from a face.

### 3. Fingerprint Recognition

This section describes the research trend in fingerprint recognition. Fingerprints are the most widely developed biometric traits and are used for person authentication more than 100 years ago\(^{23}\). The fingerprint technology has already been put to practical use in various applications from forensics to high-security access. New issues on fingerprint recognition have been explored until now, although the de-facto standard fingerprint recognition algorithm is available.

Figure 3 shows a standard flow diagram of fingerprint recognition systems, which consists of 4 steps: (i) segmentation, (ii) enhancement, (iii) minutiae extraction and (iv) matching. First, the area of a fingerprint is extracted from an input image. This segmentation can be done by simple image processing. Next, a fingerprint image is enhanced so as to extract minutiae accurately. Ridges of a fingerprint can be enhanced using a set of Gabor filters\(^{24}\). The MATLAB code is available on the web\(^{***}\). Binarization and thinning are applied to the enhanced fingerprint. Minutiae are extracted using a simple coordinate model. A pixel corresponding to minutiae is characterized by a crossing number, which is defined by the sum of differences between pairs of adjacent pixels in 8-neighborhood. The most common

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\(^*\) LBP software: http://www.cse.oulu.fi/wsgi/MVG/Downloads/LBPSoftware

\(^{**}\) LFW: http://vis-www.cs.umass.edu/lfw/

\(^{***}\) MATLAB code: http://www.peterkovesi.com/matlabfns/index.html#fingerprints
feature descriptor derived from minutiae information is a triplet consisting of minutia location coordinates and the minutia angle. In general, feature descriptor defined by the geometric relationship among neighboring minutiae is used to enhance robustness against fingerprint deformation\(^2\). The matching score is calculated by the distance between feature descriptors of minutiae.

We present recent research topics on fingerprint recognition in the following.

### 3.1 Fingerprint Matching

A huge number of fingerprint matching algorithms has been developed because of the existence of public fingerprint image datasets and evaluation protocols. One of the most famous fingerprint datasets is provided by Fingerprint Verification Competition (FVC)*\(^1\), where FVC was held in 2000, 2002, 2004 and 2006. The book\(^2\) includes fingerprint image datasets used in FVC2000, FVC2002 and FVC2004. FVC has been renewed as a web-based automated evaluation system for fingerprint recognition algorithms, which is called FVC-onGoing**. Fingerprint recognition algorithms made rapid growing, since academic and industrial researchers competed on recognition performance of fingerprint recognition algorithms through FVC. Fierrez et al.\(^2\) summarized fingerprint recognition algorithms submitted to FVC 2004 and consider the combination of algorithms to improve the performance of fingerprint recognition. Recently, a new minutia matching algorithms, called Minutiae Cylinder Code (MCC), was proposed by Cappelli et al.\(^2\), which is used as a baseline algorithm in FVC-onGoing. MCC describes a local structure of each minutia. This descriptor encodes spatial and directional relationships between the minutia and its neighborhood, which is represented as a cylinder whose base and height are related to the spatial and directional information, respectively. The SDK of MCC is available on the web***.

### 3.2 Latent Fingerprint Recognition

Latent fingerprints obtained from crime scenes have been used in forensic identification more than a century. The manual intervention of experts is still required for latent fingerprint verification, while the performance of Automated Fingerprint Identification Systems (AFISs) has been significantly improved with the recent development of technology. The difficulty in latent fingerprint recognition is mainly due to (i) poor quality of ridge information, (ii) small finger area and (iii) large nonlinear deformation\(^2\). Although minutiae matching is also used in latent fingerprint matching, it is significantly difficult to extract minutiae from latent fingerprint images. Therefore, preprocessing methods for latent fingerprint images such as segmentation, enhancement, minutiae extraction have been mainly proposed\(^2\). Latent fingerprint matching has been still an open problem in the field of fingerprint recognition because of its difficulty. There is a good survey paper for latent fingerprint matching\(^2\). For more details, please refer to this paper.

### 3.3 Hand-based Biometrics

A hand has a lot of biometrics traits other than a fingerprint. There are some relatively new biometric traits in a hand such as palmprint, finger knuckle and vein.

A palm is a large inner surface of a hand with many features such as principal lines, ridges, minutiae, texture, etc., and is expected to be one of the distinctive biometric traits\(^3\)\(^4\). Unlike a fingerprint, a palm image can be captured using a camera under unconstrained environments, resulting in realizing a user-friendly contactless biometric recognition system. One of the pioneer researches on palmprint recognition was reported by Zhang et al.\(^3\). They proposed a baseline palmprint recognition method and created a palmprint image database\(^4\). In addition, some practical systems using palmprint recognition have been proposed such as a palmprint recognition system for mobile phones\(^4\) and a touchless palmprint recognition system\(^4\). There is a good survey paper for palmprint recognition\(^3\)\(^5\). For more details, please refer to these papers.

An outer surface of a finger has three knuckles: a distal interphalangeal (DIP) joint, a proximal interphalangeal (PIP) joint and a metacarpophalangeal (MCP) joint as shown in Fig. 4. Kumar et al.\(^6\) categorized three finger joints into major and minor finger knuckles, where a DIP joint is a first minor finger knuckle, a PIP joint is a major finger knuckle and an MCP joint is a second minor finger knuckle. It is easy to capture such patterns on a finger knuckle by a camera. This advantage allows us to develop a flexible and compact biometric authentication system. A finger knuckle is also

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* FVC2000: http://bias.csr.unibo.it/fvc2000/
FVC2002: http://bias.csr.unibo.it/fvc2002/
FVC2004: http://bias.csr.unibo.it/fvc2004/
FVC2006: http://bias.csr.unibo.it/fvc2006/
** FVC-onGoing: https://biolab.csr.unibo.it/FVCOnGoing/UI/Form/Home.aspx
*** MCC SDK: http://biolab.csr.unibo.it/

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\(^4\) PolyU Palmprint Database: http://ww4.comp.polyu.edu.hk/~biometrics/
expected to be distinctive as well as a fingerprint and a palmprint, although statistical analysis using a huge dataset has to be required to demonstrate the uniqueness of finger knuckle patterns. A finger knuckle is a relatively new biometric trait in contrast with famous biometric traits such as face, fingerprint and iris, where one of pioneer researches has been reported in 2005 by Woodard et al. Some finger knuckle recognition methods have been reported, where most of literature use public dataset such as the PolyU FKP database.

A vein is a blood pattern under the hand skin. The advantage of vein patterns used in biometrics is high distinguishability and robustness against spoofing. Therefore, biometric recognition systems using vein patterns have been used in high-security applications such as ATM and access control. There are two types of vein patterns such as hand vein and finger vein. Recently, the international competition of finger vein recognition has been held in conjunction with International Conference on Biometrics.

4. Iris Recognition

This section describes the research trend in iris recognition. An iris is the annular part between the pupil and the white sclera and has a complex pattern determined by the chaotic morphogenetic processes during embryonic development. The iris pattern is unique to each person and to each eye and is essentially stable over a lifetime. Furthermore, an iris image is typically captured using a contactless imaging device, which is of great importance in practical applications. Figure 5 shows a standard flow diagram of iris recognition systems, which consists of 4 steps: (i) iris segmentation, (ii) iris normalization, (iii) feature extraction and (iv) matching.

Most of the commercial iris recognition systems implement the iriscode algorithm proposed by Daugman, which is a famous iris recognition algorithm. The standard procedure of the iriscode algorithm is briefly described in the following. First, an image including an eye is captured by a camera. In most cases, infrared illumination is used in image acquisition, since it is difficult to separate a dark iris of Asians from their black pupil. Next, the iris region is extracted from the captured image, where this step is called iris segmentation. Then, the iris region is normalized to compensate for the elastic deformations in iris texture by mapping pixel values from the Cartesian coordinate system to the polar coordinate system. Feature vectors are extracted by applying Gabor filters to the normalized image. The outputs are binarized to generate a 2Kbit iriscode. Finally, the Hamming distance between two iriscodes is used for matching.

The iris recognition system has been put into prac-

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Iris recognition is heavily influenced by the accuracy of iris segmentation. It is, however, difficult to perform accurate iris segmentation under unconstrained conditions. The iris is often partially occluded by eyelids, eyelashes, and shadows and is occluded by specular reflections when the user wears glasses. The pupillary and limbic boundaries are noncircular. Other challenges of iris segmentation include defocusing, motion blur, poor contrast, oversaturation, etc. Iris segmentation needs to find the pupillary and limbic boundaries of the iris, localize its upper and lower eyelids if they occlude, and detect and exclude any superimposed occlusions of eyelashes, shadows, or reflections. The traditional approach of iris segmentation employs circle fitting, while this approach cannot be used under unconstrained conditions. To accurately segment the iris region depending on the iris shape, Shar et al. used geodesic active contours (GACs) and He et al. used an elastic model with spline-based edge fitting.

4.2 Ocular Recognition

Iris recognition at a distance is considered to realize high-level security in surveillance applications due to its high discriminant capability compared with other biometric traits. The competition for iris recognition at a distance was held in 2008 by National Institute of Standards and Technology (NIST), the United States, which is called Multiple Biometric Grand Challenge (MBGC)\. The video sequence of a walking person captured with near-infrared illumination was used for iris recognition in MBGC. There is no expected algorithm submitted due to high difficulty in iris recognition such as heavy motion blur, low resolution, poor texture, etc. Addressing the above problem, an ocular image, which is the surrounding region of the eye including the iris, is used as a new biometric trait for the purpose of person authentication at a distance with high-level security\. Person authentication using eye regions is called ocular recognition or periocular recognition. In the case of using ocular images, iris segmentation is not required. Therefore, it is expected that ocular recognition can be used for recognizing pedestrians. NIST held the competition of ocular recognition, which is called Face and Ocular Challenge Series (FOCS)\**, to explore new biometric recognition algorithms using ocular images. Although there has been some literature for ocular recognition, further improvement of algorithms is required, since the recognition performance of these algorithms is about 90% in the FOCS dataset.

5. Biometric Recognition Using Phase-Only Correlation

This section presents our activities of biometric recognition. We consider employing the phase information obtained by DFT of images. The phase information preserves the inherent features of the image, and its correlation function, called phase correlation or POC, gives us both the good similarity measure for biometric recognition and the translational displacement for image registration. The image matching method using phase information called Band-Limited Phase-Only Correlation (BLPOC) has been proposed to dedicate POC to similarity measure. POC and BLPOC cannot handle the nonlinear deformation of images, since the

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phase information includes only translational displacement. The approach combined with phase-based correspondence matching\(^{58}\) and BLPOC has been proposed to deal with nonlinear deformation\(^ {59}\). So far, we have applied POC techniques to various biometric recognition problems\(^ {59} \)\(^ {63}\) as shown in Fig. 6. We summarize (i) the importance of phase information in images, (ii) fundamentals of POC, BLPOC, correspondence matching and local phase features and (iii) applications to some biometric recognition problems in palmprint, finger knuckle and dental in the following.

5.1 The Importance of Phase Information in Images

The importance of the phase information in images has been reported in some literature\(^ {64} \)\(^ {65}\). Oppenheim\(^ {65}\) said that many of the important features of a signal are preserved if only the phase is retained. We demonstrate the importance of phase information in images by replacing phase components between images as shown in Fig. 7 (Similar discussion has been given in Refs.\(^ {65} \)\(^ {66}\)). First, we calculate DFT of Image A and Image B, and obtain amplitude and phase components of each image. Next, we synthesize new frequency components of the image by replacing the phase components of Image A with those of Image B. Then, we calculate Inverse DFT (IDFT) of the synthesized frequency components and obtain the new images whose phase components are replaced. As observed in Fig. 7, the synthesized images are similar to the image having the corresponding phase components. This result indicates that the phase components contain the most important information to construct the image.

5.2 Phase-Only Correlation (POC)

As mentioned above, the phase components include the important information of the image. Accurate image matching can be realized when using only the phase components. The following describes the fundamental of POC\(^ {64} \)\(^ {67}\).

Consider two \(N_1 \times N_2\) images, \(f(n_1, n_2)\) and \(g(n_1, n_2)\), where we assume that the index ranges are \(n_1 = -M_1, \cdots, M_1\) \((M_1 > 0)\) and \(n_2 = -M_2, \cdots, M_2\) \((M_2 > 0)\) for mathematical simplicity, and hence \(N_1 = 2M_1 + 1\) and \(N_2 = 2M_2 + 1\). The discussion could be easily generalized to non-negative index ranges with power-of-two image size. Let \(F(k_1, k_2)\) and \(G(k_1, k_2)\) denote the 2D DFTs of \(f(n_1, n_2)\) and \(g(n_1, n_2)\), respectively. According to the definition of DFT\(^ {60} \), \(F(k_1, k_2)\) and \(G(k_1, k_2)\) are given by

\[
F(k_1, k_2) = \sum_{n_1, n_2} f(n_1, n_2)W_{N_1}^{n_1}W_{N_2}^{n_2} = A_F(k_1, k_2)e^{j\theta_F(k_1, k_2)},
\]

\[
G(k_1, k_2) = \sum_{n_1, n_2} g(n_1, n_2)W_{N_1}^{n_1}W_{N_2}^{n_2} = A_G(k_1, k_2)e^{j\theta_G(k_1, k_2)},
\]

respectively, where \(k_1 = -M_1, \cdots, M_1\), \(k_2 = -M_2, \cdots, M_2\), \(W_{N_1} = e^{-j\frac{\pi}{N_1}}\), \(W_{N_2} = e^{-j\frac{\pi}{N_2}}\), and \(\sum_{n_1, n_2}\) denotes \(\sum_{n_1=-M_1}^{M_1} \sum_{n_2=-M_2}^{M_2}\). \(A_F(k_1, k_2)\) and \(A_G(k_1, k_2)\) are amplitude, and \(\theta_F(k_1, k_2)\) and \(\theta_G(k_1, k_2)\)
are phase. The normalized cross power spectrum \( R_{FG}(k_1, k_2) \) is given by

\[
R_{FG}(k_1, k_2) = \frac{F(k_1, k_2)G(k_1, k_2)}{|F(k_1, k_2)G(k_1, k_2)|} = e^{i\theta(k_1, k_2)},
\]

where \( G(k_1, k_2) \) is the complex conjugate of \( G(k_1, k_2) \) and \( \theta(k_1, k_2) \) denotes the phase difference \( \theta_F(k_1, k_2) - \theta_G(k_1, k_2) \). The POC function \( r_{fg}(n_1, n_2) \) is the 2D IDFT of \( R_{FG}(k_1, k_2) \) and is given by

\[
r_{fg}(n_1, n_2) = \frac{1}{N_1N_2} \sum_{k_1,k_2} R_{FG}(k_1, k_2) \\
\times W_{N_1}^{-1}\delta_{k_1n_1}W_{N_2}^{-1}\delta_{k_2n_2},
\]

where \( \sum_{k_1,k_2} \) denotes \( \sum_{k_1=-M_1}^{M_1} \sum_{k_2=-M_2}^{M_2} \). When two images are similar, their POC function gives a distinct sharp peak. When two images are not similar, the peak drops significantly. The height of the peak gives a good similarity measure for image matching, and the location of the peak shows the translational displacement between the images.

We have proposed a high-accuracy translational displacement estimation method, which employs (i) an analytical function fitting technique to estimate the sub-pixel position of the correlation peak, (ii) a windowing technique to eliminate the effect of periodicity in 2D DFT, and (iii) a spectrum weighting technique to reduce the effect of aliasing and noise.

### 5.3 Band-Limited POC (BLPOC)

We have proposed a BLPOC function dedicated to the similarity measurement task. The idea to improve the matching performance is to eliminate meaningless high-frequency components in the calculation of normalized cross power spectrum \( R_{FG} \) depending on the inherent frequency components of images. Assume that the ranges of the inherent frequency band are given by \( k_1 = -K_1, \cdots, K_1 \) and \( k_2 = -K_2, \cdots, K_2 \), where \( 0 \leq K_1 \leq M_1 \) and \( 0 \leq K_2 \leq M_2 \). Thus, the effective size of frequency spectrum is given by \( L_1 = 2K_1 + 1 \) and \( L_2 = 2K_2 + 1 \). The BLPOC function is given by

\[
r_{fg}(n_1, n_2) = \frac{1}{L_1L_2} \sum_{k_1,k_2} R_{FG}(k_1, k_2) \\
\times W_{L_1}^{-1}\delta_{k_1n_1}W_{L_2}^{-1}\delta_{k_2n_2},
\]

where \( n_1 = -K_1, \cdots, K_1 \), \( n_2 = -K_2, \cdots, K_2 \), and \( \sum_{k_1,k_2} \) denotes \( \sum_{k_1=-K_1}^{K_1} \sum_{k_2=-K_2}^{K_2} \). Note that the maximum value of the correlation peak of the BLPOC function is always normalized to 1 and does not depend on \( L_1 \) and \( L_2 \).

### 5.4 Phase-based correspondence matching

In order to handle the nonlinear deformation of images, we employ the approach of correspondence matching using POC, which employs (i) a coarse-to-fine strategy using image pyramids for robust correspondence search and (ii) a translational displacement estimation method using POC for local block matching. Let \( p \) be a coordinate vector of a reference pixel in the reference image \( I(n_1, n_2) \). The problem of correspondence search is to find a real-number coordinate vector \( q \) in the input image \( J(n_1, n_2) \) that corresponds to the reference pixel \( p \) in \( I(n_1, n_2) \). Figure 8 shows a flow of BLPOC-based correspondence matching for biometric recognition. We briefly explain the procedure as follows.

**Step 1:** For \( l = 1, 2, \cdots, l_{\text{max}} \), create the \( l \)-th layer images \( I_l(n_1, n_2) \) and \( J_l(n_1, n_2) \), i.e., coarser versions of \( I_0(n_1, n_2) (= I(n_1, n_2)) \) and \( J_0(n_1, n_2) (= J(n_1, n_2)) \), recursively as follows:

\[
I_l(n_1, n_2) = \frac{1}{4} \sum_{i_1=0}^{1} \sum_{i_2=0}^{1} I_{l-1}(2n_1 + i_1, 2n_2 + i_2),
\]

\[
J_l(n_1, n_2) = \frac{1}{4} \sum_{i_1=0}^{1} \sum_{i_2=0}^{1} J_{l-1}(2n_1 + i_1, 2n_2 + i_2).
\]

**Step 2:** Estimate the displacement between \( I_{l_{\text{max}}}(n_1, n_2) \) and \( J_{l_{\text{max}}}(n_1, n_2) \) using BLPOC-based image matching. Let the estimated displacement vector be \( \delta_{l_{\text{max}}} \).

**Step 3:** For every layer \( l = 1, 2, \cdots, l_{\text{max}} \), calculate the coordinate \( p_l = (p_{l,1}, p_{l,2}) \) corresponding to the original reference point \( p_0 = (p) \) recursively as follows:

\[
p_l = \frac{1}{2} p_{l-1} = \left( \left\lfloor \frac{1}{2} p_{l-1,1} \right\rfloor, \left\lfloor \frac{1}{2} p_{l-1,2} \right\rfloor \right),
\]
where \([z]\) denotes the operation to round the element of \(z\) to the nearest integer towards minus infinity.

**Step 4:** We assume that \(q_{l_{\text{max}}} = p_{l_{\text{max}}} + \delta_{l_{\text{max}}}\) in the coarsest layer. Let \(l = l_{\text{max}} - 1\).

**Step 5:** From the \(l\)-th layer images \(I_l(n_1,n_2)\) and \(J_l(n_1,n_2)\), extract two local image blocks \(f_l(n_1,n_2)\) and \(g_l(n_1,n_2)\) with their centers on \(p_l\) and \(2q_{l+1}\), respectively. The size of image blocks is \(W_e \times W_e\) pixels.

**Step 6:** Estimate the displacement between \(f_l(n_1,n_2)\) and \(g_l(n_1,n_2)\) using BLPOC-based image matching. Let the estimated displacement vector be \(\delta_l\). The \(l\)-th layer correspondence \(q_l\) is determined as follows:

\[
q_l = 2q_{l+1} + \delta_l. \tag{9}
\]

**Step 7:** Decrement the counter by 1 as \(l \leftarrow l - 1\) and repeat from Step 5 to Step 7 while \(l \geq 0\).

**Step 8:** From the original images \(I_0(n_1,n_2)\) and \(J_0(n_1,n_2)\), extract two image blocks with their centers on \(p_0\) and \(q_0\), respectively. Calculate BLPOC functions for all the pairs of two image blocks. The matching score \(S\) is evaluated by

\[
S = \frac{N_{l_{\text{th}}}}{N_{\text{block}}}. \tag{10}
\]

where \(N_{l_{\text{th}}}\) is the number of image block pairs whose peak value of the BLPOC function is over the threshold and \(N_{\text{block}}\) is the number of image blocks.

### 5.5 Local Phase Features

We have proposed local phase features extracted from each layer of multi-scale image pyramids, which are designed for biometric recognition\(^{69}\). Figure 9 shows an example of extracting local phase features from a finger knuckle image and Fig. 10 shows an example of matching local phase features and an input finger knuckle image. Using the proposed local phase features, we can align the global translation between images in the top (or coarsest) layer, align the minute translation between local block images in the middle layer, and finally evaluate the similarity between local block images in the bottom (or original image) layer. The size of local phase features can also be reduced by phase quantization without sacrificing the performance of biometric recognition.

#### 5.6 Applications

We describe some our research results in the following: (i) palmprint, (ii) finger knuckle and (iii) dental.

1. **Palmprint**

Palmprint recognition is one of the good applications of POC, since a palm includes rich texture information to be matched. We have considered a practical contactless palmprint recognition system\(^{70}\) based on the result of the excellent performance of POC in palmprint recognition\(^{69}\).

A palm image can be easily taken by a built-in camera of smartphones. We have developed a user authentication app using palm images\(^{71}\) as shown in Fig. 11. The palmprint recognition algorithm combining a set of
simple image processing, which consists of preprocessing and matching steps, is used to effectively utilize the limited computational resources of smartphones. The preprocessing step extracts a hand from the input image using skin-color thresholding and region growing, detects keypoints and extracts an ROI. The matching step normalizes affine transformation between ROIs according to the correspondence between ROIs obtained by phase-based correspondence matching and then calculates the matching score. Experimental evaluation using palmprint image databases demonstrates the efficient performance of the proposed algorithm compared with conventional algorithms.

We have addressed one of challenging issues in palmprint recognition\cite{72}. Accurate ROI extraction is indispensable in contactless authentication, since the performance of contactless palmprint recognition significantly depends on the accuracy of ROI extraction. Therefore, a variety of hand pose changes must be considered to realize reliable and accurate palmprint recognition. The conventional approaches of ROI extraction\cite{35,73,74} assume that all fingers spread and a palm is not rolled, since these approaches are based on binarized images to extract a palm region from a hand image. In practical situations, this assumption is not always satisfied from our experience. It is trivial for some persons that fingers are closed together when acquiring a hand image. In such cases, it is difficult to detect valley points between fingers and to use a finger shape, since fingers in the binarized hand image are not separated as shown in Fig. 12. The public palmprint databases such as PolyU palmprint database and CASIA palmprint database are also constructed based on the above assumption. Addressing the above problem and realizing practical contactless palmprint recognition, we proposed an accurate and robust palm region extraction method\cite{72}. The proposed method employs the combination of image binarization and edge detection to detect keypoints as shown in Fig. 13. The use of the combined approach makes it possible to detect valley points between fingers accurately, even if fingers are closed and a hand is rolled. Figure 14 shows some examples of ROI extraction from palm images under unconstrained conditions compared with conventional methods proposed by Zhang et al.\cite{33}, Han et al.\cite{75} and Leng et al.\cite{74}. Conventional methods do not extract palm regions on the correct location or extract palm regions with different size and location. The proposed method extracts palm regions whose accuracy is comparable with the ground truth, since the keypoints are accurately detected by the proposed method.

\section*{(2) Finger Knuckle}

An outer surface of a finger has three knuckles: a distal interphalangeal (DIP) joint, a proximal interphalangeal (PIP) joint and a metacarpophalangeal (MCP) joint as mentioned in Sect. 3.3. We have developed a practical person authentication system using PIP joints\cite{63,76} and MCP joints\cite{77} for door security. Finger knuckle patterns can be captured by a camera when a user takes hold of a door handle. This image acquisition procedure is not intrusive for the user, since this procedure is a trivial action for everyone to open the door. Hence, the users do not pay attention to the authentication process. Our systems also used the combined information of the four knuckles to improve the performance of finger knuckle recognition. In the case of PIP joints, a camera is embedded into a door so as to face the camera toward PIP joints as shown in Fig. 15 (a). In the case of MCP joints, a camera is attached on a door handle as shown in Fig. 15 (b). PIP joints have rich texture, resulting in better recognition accuracy than MCP joints, while all the PIP joints are not always faced toward a camera due to the structure of a hand\cite{63,76}. All the MCP joints can be extracted from the captured image, resulting in more stable than PIP joints, while nonlinear deformation of MCP joints has to be addressed to obtain good performance\cite{77}. The accuracy of PIP joint recognition is good, although all the PIP joints are not always extracted from only one still images\cite{76}.
(3) Dental

Person identification using dental information is one of the most important works in our research activities. We summarize techniques of victim identification actually used in the Great East Japan Earthquake and Tsunami on March 11, 2011. We also present future prospects of advanced radiograph-based human identification techniques, which may have a significant impact on reducing the time and improving the reliability of large-scale disaster victim identification (DVI).

The Great East Japan Earthquake was a magnitude 9.0 undersea megathrust earthquake off the coast of Japan that occurred on March 11, 2011. The epicenter of the earthquake is approximately 70 km (43 mi) east of the Oshika Peninsula in Miyagi Prefecture. The earthquake triggered huge tsunami waves that reached heights of up to 40.5 m (133 ft) in Miyako, Iwate Prefecture, and which traveled up to 10 km (6 mi) inland in the Sendai area. As of April 10, 2013, the National Police Agency of Japan has confirmed 15,883 deaths and 2,681 people missing across twelve prefectures. The largest number of victims were confirmed in Miyagi Prefecture, where 9,537 deaths (60% of the total deaths) and 1,315 people missing. Forensic dentistry played a key role of human identification in the Great East Japan Earthquake and Tsunami. The authors have contributed to (A) preparation of standard instruments package for dental identification, (B) development of dental record matching software Dental...
Finder, and (C) design and implementation of overall workflow of dental identification as shown in Fig. 16. For more details, please refer to the literature\(^{11}\) and the project web page\(^*\).

We briefly describe the procedure of dental record matching. Dental record matching is done by comparing each tooth status of antemortem (AM) and postmortem (PM) dental records. Dentists have given a detailed description of each tooth status in AM and PM dental records. Hence, dentists may make different observations of tooth status each other due to a variety of treatment statuses, even if their observations are essentially the same. Addressing this problem, we classify the precise tooth statuses into major classes. Dental Finder employs 5-class expressions of individual tooth status as shown in Table 3. The 5-class AM or PM dental records are input into a database of Dental Finder using the data input interface. Then, Dental Finder evaluates the similarity between AM and PM pairs using the following four similarities: (i) the number of completely matched teeth, (ii) the number of matched teeth in class 2 or 3, (iii) the number of teeth with a consistent state transition and (iv) the matching score. The matching score is calculated using the weight table for all the tooth pairs between AM and PM, where the weights are optimized using the known genuine pairs in advance. In addition to the above similarities, we introduce the matching priority to Dental Finder. The matching priority indicates the possibility that the top-1 pair is a genuine pair, which is defined by the difference of similarities between top-1 and top-2 pairs. Therefore, the dentists only have to check from top-1 pairs having high matching priority. The matching results are provided for all the possible combinations denoted by “full-combination search” or for the selected tooth denoted by “individual search.” In practice, we find matching candidates having high matching priority using full-combination search and then confirm their detailed matching results using individual search.

To address future crisis and DVI, we have developed a novel and automated dental radiograph matching system that can assist the task of forensic experts. The system uses a highly accurate image matching technique, i.e., POC, in order to find corresponding points between the two X-ray images, correct image distortion and measure their similarity, as illustrated in Fig.

17. We apply the system to a large-scale identification problem, where the system is used to find a specific individual in a whole radiograph database actually used in a dental clinic during 2005–2008\(^{9,10}\). The database consists of 4,810 intraoral radiographs from 1,714 subjects. We randomly select 100 subjects (as imaginary “disaster victims”) who have at least three different pairs of radiographs, with each pair taken from the same oral region before and after dental treatment. The 100 × 3 radiographs taken after treatment are assumed as “postmortem” (PM) images, and are removed from the original database. Hence, our “antemortem” (AM) database contains 4,510 images from 1,714 subjects. Our problem is to search the 100 victims within AM database using three PM images as the identity key for every victim. We demonstrated that the proposed system can reduce the number of pairs to be matched by forensic experts to only 0.7% (= 33/4,510) when three PM radiographs are available.

6. Conclusion

This paper has presented a brief introduction of recent advances in biometric recognition, especially in face, fingerprint and iris recognition. Researchers seek more difficult problems such as person authentication under unconstrained conditions and also new biometric traits to enhance the accuracy and convenience of biometric recognition. We have also presented our activities of biometric recognition. Our approach employs the phase information obtained by Discrete Fourier Transform (DFT) of images. The correlation function of phase information, called Phase-Only Correlation (POC), gives us both the good similarity measure for biometric recognition and the translational displacement.
### Table 3: Correspondence table between dental charts obtained from recovered bodies and 5-class expression of individual tooth status for Dental Finder.

<table>
<thead>
<tr>
<th>Class</th>
<th>Brief treatment status</th>
<th>Detailed treatment status</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sound tooth, caries, resin filling, etc.</td>
<td>Sealant, wedge-shaped detect, temporary splint, C1, C2, C3, resin filling, cement filling, glass ionomer filling, root canal filling, incisal edge fracture, remaining tooth, etc.</td>
</tr>
<tr>
<td>2</td>
<td>Partial restoration (metal)</td>
<td>Inlay, onlay, amalgam filling, 4/5 cast crown, 4/5 temporary crown, etc.</td>
</tr>
<tr>
<td>3</td>
<td>Full restoration</td>
<td>Resin facing cast crown, metal bond crown, facing cast crown, hard resin jacket crown, post crown, temporary crown, core, etc.</td>
</tr>
<tr>
<td>4</td>
<td>C4 and missing</td>
<td>Coping, denture, pontic, missing tooth, unerupted tooth, implant, etc.</td>
</tr>
<tr>
<td>5</td>
<td>N/A</td>
<td>N/A, lost postmortem, partial loss of body, impacted tooth, etc.</td>
</tr>
</tbody>
</table>

**Fig. 17** Dental radiograph matching using POC.

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