Fog Computing Based Face Identification and Resolution Scheme in Internet of Things

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***Abstract*—The identification and resolution technology are the prerequisite for realizing identity consistency of physical–cyber space mapping in the Internet of Things (IoT). Face, as a distinctive noncoded and unstructured identifier, has especial advantages in identification applications. With the increase of face identification based applications, the requirements for computation, communication, and storage capability are becoming higher and higher. To solve this problem, we propose a fog computing based face identification and resolution scheme. Face identifier is first generated by the identification system model to identify an individual. Then, a fog computing based resolution framework is proposed to efficiently resolve the individual's identity. Some computing overhead is offloaded from a cloud to network edge devices in order to improve processing efficiency and reduce network transmission. Finally, a prototype system based on local binary patterns (LBP) identifier is implemented to evaluate the scheme. Experimental results show that this scheme can effectively save bandwidth and improve efficiency of face identification and resolution.**

***Index Terms*—Face identification, face resolution, fog computing, Internet of Things (IoT), local binary patterns (LBP).**

I. Introduction

THE Internet of Things (IoT) paradigm enables universal interactions among the ubiquitous things anywhere at any time [1], [2]. With the development of the mobile internet, IoT, and cyber-physical system, more and more physical objects (e.g., persons, sensors, mobile devices, actuators, etc.) in physical space are accessed on the Internet [3]. Correspondingly, a large number of cyber objects are generated in cyberspace [4]. They can directly or indirectly communicate and cooperate with each other to provide services for various IoT applications [5], [6]. In order to ensure the consistency in physical–cyber space mapping, the identity of every physical object needs to be uniquely identified with appropriate identifier and can be resolved by the corresponding resolution mechanism [7]. Therefore, identification and resolution technology is the prerequisite for the development, deployment, and operation of large-scale IoT applications and services.

Physical object's identification is a process by which an object is uniquely recognized with an appropriate identifier in a certain application range. The identifier is the object's property collected from ubiquitous sensors (e.g., RFID, camera, fingerprint scanner, voice collector, radar, etc.). There are two main purposes for object's identification: (1) retrieving and capturing relevant information of objects; (2) controlling and managing objects. A physical object's resolution process refers to obtaining the detailed information or personalized service based on the object's identifier. By this way, physical objects can be matched with their corresponding identity and attribute information in the cyber world [8].

By now, research on identification and resolution of physical objects with an identification (ID) code is relatively mature, such as electronic product code [9], ubiquitous ID [10], [11], European article number, etc. We called them ID physical objects. This type of an identification scheme has a specific ID code, which is mainly composed of numbers or alphabets. So it is an accurate identifier and has strong readability. Currently, various IoT applications, including logistics, supply chain management, and retail, mainly adopt the ID-based schemes [12], [13].

With increase in the number and type of objects accessed on IoT, there are many objects without any available ID in some IoT scenarios. Ning *et al.* named them non-ID physical objects that are unattached ID or attached unreadable and untrusted ID [14]. In these cases, ID-based identification and resolution schemes are not applicable. However, for non-ID physical objects, some of their properties, for example, biometric, space-time information, and other characteristics, can be used as non-ID identifier, which is complementary with the ID code [15]. ID and non-ID are jointly composed of IoT identification and resolution system. Biometric-based non-ID technology is inherently more reliable and distinctive compared with other properties [16]–[19]. It is noteworthy for the realization of every human connected.

Face is a typical non-ID identifier, as one of the biometrics, which widely applied to automatically identify an individual [20]. Face identification is a nonintrusive method and easy to be collected. It has high distinctiveness, universality, and acceptability, so it is very suitable for identifying individual [21]. A highly accurate and automatic face identification and resolution system is very crucial for obtaining personalized intelligent service and protecting personal information in IoT. In general,

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facial feature needs to be extracted by some algorithms in face identification applications. It is essentially face representation by analyzing face images [22]. The common face representation methods include principal components analysis (PCA) [23], linear discriminant analysis [24], independent component analysis [25], Laplacianfaces [26], two-dimensional PCA [27], Gabor feature [28], local binary patterns (LBP) [29], scale-invariant feature transform feature [30]. These methods represent face from different perspectives. All of them can be used to generate face identifiers. By face identifier, an individual in physical-space can ensure the consistency with his/her identity in cyberspace during the physical–cyber space mapping.

The process of face resolution refers to obtaining the detailed information about an individual based on the face image of tested individual. This process consists of multiple tasks, including face detection, preprocessing raw facial image, feature extraction, feature matching, and identity information acquisition. The collected face images need to be singly compared with all the face templates which are stored in the database. The raw facial image data are unstructured form whose file's size is relatively larger and data structure is more complex than ID code. Therefore, the requirement for computation, communication, and storage capability is greater. In the current era of big data, with the increase of the face resolution application in IoT and the expansion of face image database, these requirements will become more and more obvious. In some scenarios of face recognition, researchers adopt the cloud computing technology to improve computation and storage capability of system [31]. However, cloud computing is a service computing with high polymerization degree. This centralized processing architecture requires that all applications request services from the cloud. The whole process of resolution is completed on the cloud and the raw facial images need to be transmitted to the cloud. So it will consume a large amount of network bandwidth. With the increasing demand of applications and users, the network traffic will hugely increase. It will result in the interruption of service, network delay, and other issues, though there are many methods for optimizing network transmission [32]. However, it is unnecessary to send the raw facial images to the cloud, because the process of face identification and resolution only requires a small part of facial feature information. This situation facilitates the requirement which designs an identification and resolution scheme, which can extract the useful facial feature information sent to the cloud and reduce the amount of network transmission.

Fog computing is a new computational model. It extends cloud computing and services to the edge of network. The aim is that data storage, processing, and applications are dispersed on devices located at the network edge rather than implemented almost entirely in the cloud [33]. It can make full use of the computing power and storage capacity of the network edge devices [34]. Compared with cloud computing, the computing power and data storage are closer to the end devices. The amount of network transmission and delay are notably reduced [35]. So fog computing is adopted to perform face resolution in this paper. Part of the resolution tasks, including face detection, facial image preprocessing, and feature extraction, are migrated to fog nodes (FNs). Compared with the traditional cloud computing model in which the whole resolution tasks are executed on the cloud and the raw facial image data are transmitted to the cloud, fog computing model only transmits the feature value to the cloud to match with the face identifiers database. This mechanism results in massive reduction of network transmission load. Especially in the case of poor bandwidth, this scheme is still able to provide high-quality service.

This paper proposes a novel face identification and resolution scheme. The main contributions can be summarized as follows:

1) A face identification system model is presented to realize the conversion from the face of an individual in physical-space to the face identifier in cyberspace during the physical–cyber space mapping. The face feature representation algorithms can be chosen flexibly according to application scenarios in this model.
2) A fog computing based face resolution framework is proposed to resolve and obtain the identity information services with facial image. This framework can notably reduce the amount of network transmission and the total response time of resolution, and effectively solve the bottleneck of bandwidth resulted from large-scale access of cloud resolution services.
3) A prototype system using an LBP-based face identifier generation model is implemented to demonstrate that the proposed scheme is technically feasible and can provide effective resolution service.

The remainder of this paper is organized as follows: Section II discusses the related works about face identification and resolution. Section III proposes the fog computing based face identification system model. Section IV presents fog computing based face resolution framework. The prototype system and results of experiment are presented, the performance of proposed scheme is evaluated, and discussed in Section V. Section VI concludes this paper.

II. Related Work

The characteristic of face identifier and the method of face matching decide that the face resolution scheme needs more computation, communication, and storage resource than ID-based resolution schemes. In some research works, the cloud computing architecture is adopted to meet these demands.

Peer *et al.* [36] proposed cloud-based biometric services, which could provide powerful storage and unprecedented processing power. But only the processes of moving existing biometric technology to a cloud platform are introduced, technical details are not involved. In another paper, Peer *et al.* [37] proposed the fusion strategies for combining multiple unimodal biometric, namely face and fingerprint, into the multibiometric cloud service. This method can meet the requirements of scalability, processing power, and storage.

Kohlwey *et al.* [38] presented a Hadoop-based prototype system that applies cloud computing in biometric identification to improve matching efficiency. Similarly, Raghava [39] used Hadoop-based cloud computing in iris recognition to speed up the matching process. In their research work, cloud computing technology is applied to improve computation power, but bandwidth problem is not solved.

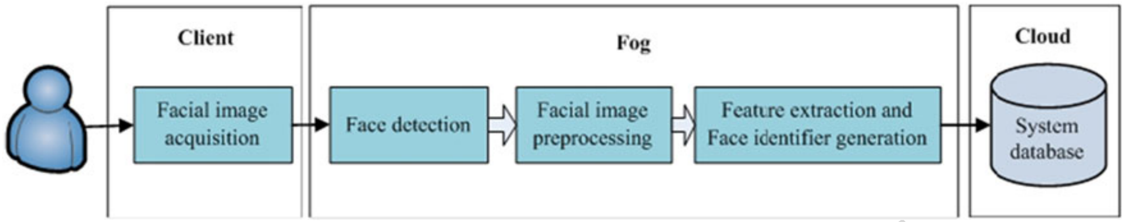

Fig. 1. Block diagram of a face identification system.

Ayad *et al.* [40] introduced the mobile cloud computing technology that was used in face recognition. The computing and storage tasks were moved from mobile devices to the cloud. It can solve the problem of low computing power, limited bandwidth, and storage about mobile devices.

In above-mentioned research works, cloud computing has helped to improve computation and storage capability of the face recognition system. Service capabilities and efficiency has been remarkably improved. However, cloud computing is a centralized processing architecture that requires all applications to request services on the cloud. The whole resolution process is completed on the cloud. With the increase of applications and users, the network traffic will clearly increase and the bottleneck of bandwidth will become increasingly serious, especially in the case of poor network bandwidth or extreme environments (e.g., underwater [41]). In order to solve this problem, some researchers present the improvement for the cloud computing architecture.

Stojmenovic [42] introduced that the limiting factors on cloud biometric applications are the battery power of devices and the throughput of the communication channel after offloading part task from a computationally weak mobile device to the cloud. The authors analyzed that the reduced packet size transmitted in the network is very important.

Chun and Maniatis [43] proposed the dynamically partitioning of applications between weak devices and clouds. The partitioning problem was regarded as an optimization. It can minimize execution time in the case of given resource constraints. Soyata *et al.* [44] designed and implemented a face recognition system using the mobile–cloudlet–cloud architecture. The computation load was distributed among cloudlets to minimize the response time. Bommagani *et al.* [45] presented a framework that face recognition could be performed in a cloud environment. A mobile device only performed a small portion of operations by offloading the actual recognition tasks to the cloud. These researches improved the face resolution efficiency to some extent by dividing recognition operations and felicitously allocating them to cloud and mobile devices. They are helpful to solve the bottleneck of bandwidth for designing a face identification and resolution scheme.

The fog computing moves the computation and data storage to network edge, and partitions partial tasks to FNs to improve process efficiency. Pang and Tan [46] allocated computation tasks at the edge of network to improve the availability and scalability of the system architecture. It can reduce the transmission load and processing burden of the cloud. Stojmenovic and Wen [47] researched the interference problem of big data brought by IoT, and presented the layered and distributed fog computing architecture and analyzed its resource advantages in large-scale distributed computing. Considering the advantages in improving computational efficiency and reducing bandwidth consumption, fog computing technology is adopted to perform face resolution in this paper.

III. Fog Computing Based Face identification System Model

In this section, we describe the face identifier generation model and fog computing based face identification system. The face identification system plays a significant role in efficient representing and identifying an individual's identity, and it is closely related to face resolution. A good identification model is not only helpful to the face classification and resolution, but also can reduce the amount of data stored in the database.

A. Face Identifier Generation Model

In IoT, the face of an individual in physical-space is sensed by camera. Then the face identifier generation model converts a face image into a face identifier, which is used to identify the individual's identity in cyberspace. By this way, during the physical–cyber space mapping, individual in physical-space can ensure the consistency with his/her identity in cyberspace.

The face identifier generation model is responsible for extracting the feature value from a facial image by image processing and computer vision technology to generate a face identifier. The model consists of face detection, facial image preprocessing, feature extraction, and face identifier generation. As is shown in Fig. 1, this model is deployed in FN. For a facial image, face detection and preprocessing algorithms are executed firstly to extract the facial region and enhance image feature. Then some features (e.g., algebraic feature, geometric feature, the position of feature point such as eye, nose, and mouth) are extracted by corresponding extraction algorithms. In order to reduce the sparseness of feature, dimensionality reduction methods are usually considered to reduce the size of an extracted feature vector. The final feature vector is used as the face identifier.

The accuracy and performance of face identification mainly depends on these factors, e.g., the representation ability of features, the discrimination of features, the number, and type of features. In this paper, our scheme is not limited to utilize any facial feature extraction methods. These algorithms can be chosen flexibly according to application scenarios. The scheme just focuses on the extracted facial feature vectors, which are used to generate face identifiers. In Section V, we will take the LBP

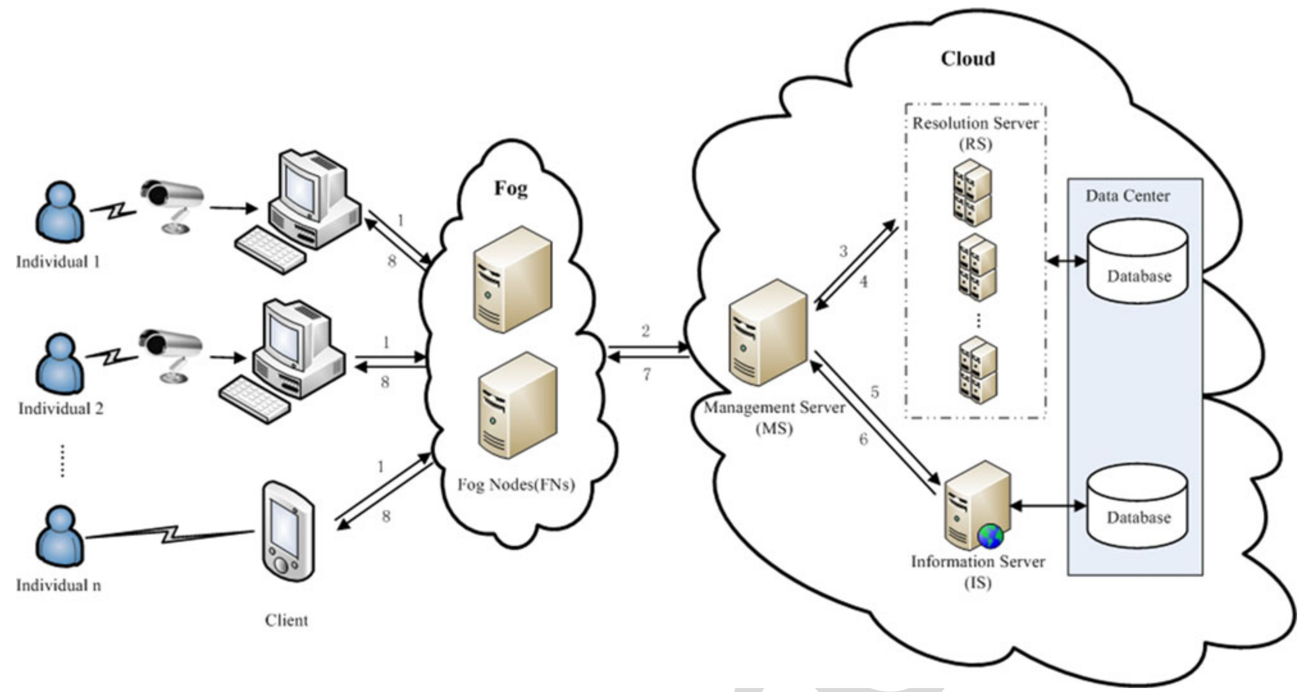

Fig. 2. Fog computing based face resolution framework.

feature as an example to present the face identifier generation model in detail. In future, with the development of computer vision technology, more and more facial feature extraction methods that have better representation ability and discrimination may emerge. They may also be used for face identification to improve the performance.

B. Fog Computing Based Face Identification System

The face identification system consists of the following five main components:

1) facial image acquisition;
2) face detection;
3) facial image preprocessing;
4) feature extraction and face identifier generation;
5) system database.

They are distributed in the client, fog, and cloud. Fig. 1 shows the block diagram of a face identification system.

The executed operations on each module are as follows:

1) *Facial image acquisition module:* This module is located in the client and responsible for capturing facial image data of an individual by vision sensors, mainly cameras. The quality of the facial image should be high to ensure the accuracy of identification.
2) *Face detection module:* For a facial image, we only need the face region to generate the face identifier. Other regions are valueless for face identification and resolution. In this module, the face detection algorithms are executed to extract the facial region and remove the unrelated regions.
3) *Facial image preprocessing module:* The quality of a raw facial image is easily influenced by the factors of environment and sensors, e.g., lighting, articulation, etc. Preprocessing a facial image can significantly reduce the impact of these factors and improve the accuracy rate of resolution. In this module, some image preprocessing algorithms (e.g., histogram equalization, graying colorized image, linear filtering, median filtering, etc.) are executed to improve contrast and enhance the image.
4) *Feature extraction and face identifier generation module:* This module is the core of the identification system. A set of salient and discriminative facial features are extracted by specific features extraction algorithms, computer vision, or pattern recognition technologies. The extracted feature vector is used as a face identifier.
5) *System database module:* System database is located in the cloud and responsible for storing the face identifiers and identity information of registered users.

In practical applications, the appropriate algorithms are selected for each operation according to the actual demands. For this system, the modules of face detection, preprocessing, feature extraction, and face identifier generation are performed on FNs, which can make full use of the computing power of network edge devices. System database is located in the cloud, which can make full use of the advantage of powerful storage capabilities. These modules cooperate with each other to implement the face identification.

IV. Fog Computing Based Face Resolution Framework

The process of face resolution refers to obtaining the detailed information about an individual by applying the results of the face identification model. Along with the increasing of applications and access users, the bandwidth will be a big bottleneck for resolution service. This situation determines that it is not suitable to use a centralized processing architecture. Moreover, reducing as much as possible the size of data packet to be transferred to cloud is very important for decreasing the throughput of the communication channel and improving communication capability. Considering these factors comprehensively, fog computing is used to design the face resolution scheme.

In the resolution process, the face identifier of tested individual needs to be generated first by the face identifier generation model. Then the identifier is singly compared with all the face identifiers stored in the database to find out the address of user's identity information. According to the address, detailed identity information can be obtained. The whole resolution process is composed of five components, namely face detection, image preprocessing, feature extraction and face identifier generation, face matching, and identity information acquisition.

In the fog computing based face resolution scheme, we offload partial computation tasks from the cloud to FNs. The operations, including face detection, image preprocessing, feature extraction, and face identifier generation, are deployed on FNs. Another two operations, face matching and identity information acquisition, are processed on the cloud. After completing the operations on fog, only identifier is transmitted to the cloud, rather than the raw image. Fig. 2 shows the fog computing based face resolution framework.

This face resolution scheme consists of three main parts: client, fog, and cloud. A client comprises massive computers, mobile phones, or other terminal devices. Fog is composed of many FNs. A cloud comprises management server (MS), resolution server (RS), information server (IS), and data center. The function of each module is as follows:

1) *Client:* A client is responsible for managing various visual sensing devices, collecting facial image data, and requesting the face resolution service to FNs. After successful resolution, it will present detailed identity information or specific services to users. Client is composed of a computer and a mobile phone with a camera.
2) *FNs:* FNs are located at the network edge. They can be some network edge devices (e.g., switch and router) with computation capability, or dedicated fog server. In exceptional circumstances, the client devices (such as computer or mobile phone), which directly access the Internet, can also be used as FNs. In this paper, we consider the general situation in which the dedicated fog servers are applied as FNs. FNs are mainly responsible for face detection, facial image preprocessing, and feature extraction and face identifier generation. These operations are performed in the same way as presented in Section III. After these operations, the data size will be profoundly reduced. The face identifier is generated by using the face identification model. Then FNs are responsible for requesting the resolution service to the cloud. Finally, the face identifier is transmitted to the cloud for identity resolution.
3) *MS:* MS connects with FNs, RS, and IS and is responsible for managing RSs and ISs in cloud, scheduling of resources, and allocating computing tasks. It provides the standard face resolution service interfaces, and FNs can access it conveniently in various IoT applications. After receiving facial identifiers, it guides them to the corresponding RS to request identity matching services, and then requests identity information to IS according to the uniform resource identifier (URI) resolved from RS. Finally, it returns the detailed identity information to FNs.
4) *RS:* RS is the core of the whole resolution scheme, and responsible for matching facial identifiers by performing the identifier matching algorithm. When given a face identifier, RS returns a \address where individual's identity information or personalized service is located. RS is deployed in the manner of a server cluster that has strong computing power and processing speed. The face identifier, which has registered identity information in identification phase, and the URI of IS in which individual's detailed identity information is located are stored together in the database in the form of two-tuples. When loaded identifier is successfully matched, the corresponding URI will be returned. For RS, the precision and performance of face matching algorithms is the key factor affecting the result of resolution.
5) *IS:* IS is responsible for managing individuals' identity information. It can provide identity information services for users or specific applications by definite way, for example, PML document, web service, data file, etc.
6) *Data center:* Data center is responsible for storing and managing face identifiers data, identity data of individuals, and URI addresses of identity information or service resource. It has powerful data storage capability.

The fog computing and cloud computing work together to complete the resolution process. The detailed resolution processes are as follows:

1) Visual sensing devices acquire facial images of individuals and send it to client. Then client requests the face resolution service to FNs. After network connection is established successfully, the client sends raw facial images to FNs in the fog.
2) FNs execute the operations of face detection, facial image preprocessing, feature extraction, and face identifier generation to get the face identifier. Then FNs request the face identifier resolution service to the cloud. When network connection is established successfully, FNs send the face identifier to MS in the cloud.
3) MS receives the face identifier and sends it to RS to execute face resolution.
4) RS receives the face identifier. Then two operations are implemented on RS. First, extracted facial identifier is seriatim matched with the face identifiers stored in data center. Second, RS gets the URI address of corresponding identity information, which is paired with the matched face identifier successfully. Finally, RS returns the URI address to MS.
5) MS connects with IS by the URI address to acquire the individual's detailed identity information.
6) IS returns the detailed identity information to MS in a specific way.
7) MS transmits the detailed identity information to FNs.
8) FNs transmit the individual's detailed identity information to client, and then present it to end users.

This resolution scheme realizes the conversion from face in physical-space to identity information in cyberspace. It makes full use of the power of network edge devices, which undertake partial computation tasks, rather than all the resolution processes are executed in the cloud. It only transmits the extracted face identifier in the network, rather than the raw facial image data. In this way, it not only improves computation and storage capability, but also reduces the amount of network transmission remarkably and saves the bandwidth. In addition, the identification and resolution processes for most of other biometrics are similar with face. They also need to extract feature value and generate identifier first, and then perform identifier matching by using the corresponding matching algorithm. So this framework can also be suitable for them.

V. Experiment and Performance Evaluation

In this section, we did the experiments to measure and evaluate the proposed fog computing based face identification and resolution scheme. In our experiment, we introduced the face identifier generation model based on facial LBP feature and face identifier matching algorithm based on the Euclidean distance in detail. By using the proposed resolution framework, a prototype system was implemented to demonstrate the practical feasibility of the scheme.

A. Experimental Setup

We deployed the face identification and resolution algorithms on the FNs and cloud server. The cloud server was equipped with octa-core Intel Xeon CPU 2.80 GHz, 8 GB memory, and Windows Server 2008 OS. We used a computer as the FN, which was equipped with quad-core Intel Core i5-3550 CPU 3.00 GHz, 4 GB memory, and Windows 7 OS. In this paper, we only realized the situation that computer was used as client. The laptop was equipped with dual-core Intel Core i5-4200U CPU 2.60 GHz, 4GB memory, and Windows 7 OS was applied as client. Client and FN were connected through the Asymmetric Digital Subscriber Line technology which the upload link speed was 512 Kb/s. FN and cloud server were connected through Internet. The software environment was Microsoft Visual Studio 2010 and OpenCV libraries. Microsoft SQL Server 2008 database was used as system database.

To simplify the experiment processes, MS, RS, and IS were deployed on one cloud server in the form of a functional module. They were executed by different CPU threads to emulate many servers. In order to realize the parallel processing of matching, we also used different CPU threads to emulate RSs.

In this experiment, three public face databases, including the Georgia Tech (GT) face database, the Caltech face database, and the BioID face database, were used as test database to precisely evaluate the performance of our scheme. The introductions of these face databases were as follows:

1) *GT face database:* It contains 750 color images of 50 people. For each individual, there are 15 color images with different facial expressions, lighting conditions, and scale. The average size of these images file is about 185 KB. We randomly choose 14 images for each individual as a training set and one image as a test set.
2) *Caltech face database:* It contains 450 color face images. It has about 27 or so unique people with different lighting or expressions or backgrounds. The average size of these images file is about 152 KB. We randomly choose one image as the test set for each individual and others as training set.
3) *BioID face database:* It contains 1521 gray level images of 23 persons. The average size of these images file is 108 KB. We randomly choose one images as test set for each individual and others as training set.

B. Prototype System Using an LBP-Based Face Identifier Generation Model and a Euclidean Distance Based Face Identifier Matching Algorithm

LBP is a kind of operator used to describe the local texture feature of the image [48]. The operator is defined as a rotation invariance and grayscale invariant texture descriptor. It has been proven to be highly discriminative [49]. For improving the identification effectiveness, we use the uniform LBP model to generate the face identifier [50]. The face identifier generation model is introduced in detail in the following paragraph.

For a given facial image, it only retains the face region and is transformed into a grayscale image by face detection and preprocessing technology. In a 3×3 region of the grayscale facial image, the center pixel value is used as the threshold. Eight pixel values on this edge of the region are individually compared with it. If the pixel value is larger than the center pixel value, the edge pixel will be assigned 1, otherwise it will be assigned 0. In this way, eight bits binary string is generated. It can be converted to a decimal number between 0 and 255, which is called the LBP-code. The center pixel value is replaced by the LBP-code, which contains 256 kinds. Similarly, we can get the LBP-code of all the pixels in the grayscale facial image. The LBP-code is used to reflect the texture information of a region. This is the original form of LBP. It only covers a small area within a fixed radius when the LBP-code of every pixel is calculated.

In order to meet the needs of different scales and different frequencies of textures, a variable number of neighbor pixels at different radii are adopted. For a grayscale facial image *F*, the LBP-code can be denoted by $\mathrm{LBP}_{P,R}$, where *P* is the total of neighbor pixels on the edge of the circle at radius *R*. Because the distribution of the original pattern is too sparse, the uniform LBP is adopted. A LBP-code is classified as a uniform pattern if the binary pattern has at most two bitwise transitions from 0 to 1 or 1 to 0. Others are classified as one category, called a nonuniform pattern. The uniform pattern can be denoted by $\mathrm{LBP}^{u2}_{P,R}$, where *u2* stands for using uniform LBP. Compared with 2^P kinds of original pattern LBP-codes, all the LBP-codes are divided into $P*(P-1)+3$ categories, which include $P*(P-1)+2$ uniform patterns and one nonuniform pattern.

We define g_c as the *c*th pixel value of *F*, define g_p as the *p*th neighbor pixel value of the center pixel g_c, $p = 0, 1,..., P-1$.

The LBP-code of the cth pixel is calculated by

$$\mathrm{LBP}_{P,R}(c) = \sum_{p=0}^{P-1} s(g_p - g_c) \times 2^p \tag{1}$$

where

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0. \end{cases}$$

An LBP is called a uniform pattern when it meets

$$U(\mathrm{LBP}_{P,R}(c)) \leq 2 \tag{2}$$

where

$$\begin{aligned} U(\mathrm{LBP}_{P,R}(c)) = \ & |s(g_{P-1} - g_c) - s(g_0 - g_c)| \\ & + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|. \end{aligned}$$

For a uniform pattern,

$$\mathrm{LBP}_{P,R}^{u2}(c) = \mathrm{LBP}_{P,R}(c). \tag{3}$$

The LBP feature is closely related to location information. If we extract the LBP feature directly to analyze and match, a larger error will be produced due to the unaligned location. So, we divide the facial image into *m* small regions, $R_1, R_2, \ldots, R_m$, and extract the LBP feature of each region. We do not use the LBP-codes as the feature vector for identifying the face, but the histogram of LBP-codes of all pixels. The histogram is computed independently for each small region. For a small region, every uniform pattern LBP-codes have a separate bin and the entire nonuniform pattern LBP-codes are allocated to a single bin in the LBP histogram. Since the histograms of small regions have different sizes, they need to be normalized to get a coherent description. Finally, *m* histograms are concatenated to form a global histogram of the face. The feature vector ***V*** is comprised of the normalized global histogram.

We define h_k as the histogram of a small region R_k, $k = 1, 2, \ldots, m$, and $h_k(i)$ as the histogram value of the *i*th bin of h_k, $i = 1, 2, \ldots, P*(P-1)+3$. For given values *R* and *P*, there are 2^P binary strings of *P* bits. It is known that the binary strings belong to the uniform pattern or nonuniform pattern. So the entire uniform pattern LBP-codes of region R_k are $P*(P-1)+2$ definite values, which are defined as $b_k(i)$, and define $b_k(P*(P-1)+3)$ as the bin of nonuniform pattern LBP-codes. The LBP histogram of uniform pattern LBP-codes for region R_k can be calculated by

$$h_k(i) = \sum_{c \in R_k} \theta_i(\mathrm{LBP}_{P,R}^{u2}(c)) \tag{4}$$

for $i = 1, 2, \ldots, P*(P-1)+2$, where

$$\theta_i(y) = \begin{cases} 1, & y = b_k(i) \\ 0, & \text{otherwise.} \end{cases}$$

The LBP histogram of nonuniform pattern LBP-codes for region R_k can be calculated by

$$h_k(i) = \sum_{c \in R_k} \varepsilon_i(\mathrm{LBP}_{P,R}(c)) \tag{5}$$

for $i = P*(P-1)+3$, where

$$\varepsilon_i(z) = \begin{cases} 1, & U(\mathrm{LBP}_{P,R}(c)) > 2 \cup c \in R_k \\ 0, & U(\mathrm{LBP}_{P,R}(c)) \leq 2 \cup c \in R_k. \end{cases}$$

The LBP histograms of uniform and nonuniform pattern LBP-codes are combined to compose the LBP histogram of region R_k. The normalized histogram can be calculated by

$$N_k(i) = \frac{h_k(i)}{\sum_{j=1}^{P\times(P+1)+3} h_k(j)} \tag{6}$$

for $i = 1, 2, \ldots, P*(P-1)+3$.

The normalized histograms of *m* regions are combined together to compose the feature vector ***V*** of facial image *F*. Its size is $m*(P*(P-1)+3)$. This feature vector is smaller than the original pattern for which the size of feature vector is $m*2^P$ dimensions. It achieves the goal of dimensionality reduction. Thus, the feature vector ***V*** is used as the face identifier.

In the matching phase, the face identifier of a tested individual needs to be independently compared with all the face identifiers $(\boldsymbol{V}_1, \boldsymbol{V}_2, \ldots, \boldsymbol{V}_t)$ stored in the database, where *t* is the total of face identifiers in the database. In this paper, we use the Euclidean distance as the standard to measure the similarity of two face identifiers. The face identifier matching algorithm based on the Euclidean distance is presented in detail as following.

For the feature vector $\boldsymbol{V}'$, we define $d_n(\boldsymbol{V}', \boldsymbol{V}_n)$ as the Euclidean metric of $\boldsymbol{V}'$ and $\boldsymbol{V}_n$, for *n* = 1, 2,. . ., *t*. The $d_n(\boldsymbol{V}', \boldsymbol{V}_n)$ can be calculated by

$$d_n(V', V_n) = \sqrt{\sum_{i=1}^{m\times(P\times(P+1)+3)} (V'(i) - V_n(i))^2} \tag{7}$$

where $V'(i)$ and $V_n(i)$ are, respectively, the *i*th elements of feature vector $\boldsymbol{V}'$ and $\boldsymbol{V}_n$.

The most similar facial image is the one that has minimum distance. Its index is

$$n = \mathrm{argmin}\{d_n(V', V_n)\}. \tag{8}$$

That is to say, the facial image *F(n)* whose corresponding feature vector is $\boldsymbol{V}_n$ is the most likely image. Generally, threshold *T* is set in a specific scenario. If $d_n(\boldsymbol{V}', \boldsymbol{V}_n)$ meets

$$d_n(V', V_n) \leq T \tag{9}$$

the facial image *F(n)* matches successfully with the tested individual. Otherwise, face matching fails.

We implement the prototype system using the above-mentioned face identifier generation model and matching algorithm. It consists of client, FNs, and cloud server. HTTP protocol is used for data transmission. The system is deployed in accordance with the framework presented in Fig. 2. The processing methods used for each operation in prototype system are as follows:

1) *Face detection:* We apply the Haar face detection method, which is a face detector contained in OpenCV, in these images to extract the facial region, and remove the unrelated regions [51].
2) *Facial image preprocessing:* In this processing, we transform the colorized facial image into gray level image

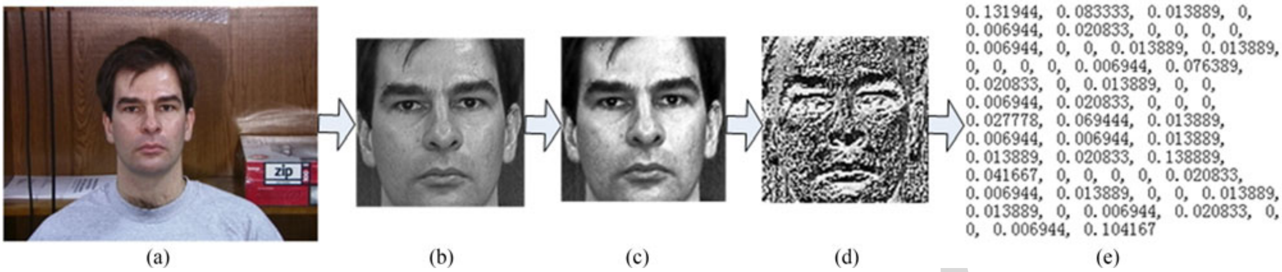

Fig. 3. Process of face identifier generation. (a) Raw facial image. (b) Face detection. (c) Image preprocessing. (d) LBP feature extraction. (e) Face identifier.

first. Then histogram equalization algorithm is executed to improve contrast and enhance the image.

3) *Feature extraction and face identifier generation:* We apply the above-mentioned LBP-based face identifier generation model to extract the LBP feature and generate the face identifier. In this model, we divide the facial image into $m = 8 \times 8$ small regions, and set the radius $R = 1$ and the number $P = 8$ of neighbor pixels on the edge of the circle.

4) *Face identifier matching:* We apply the above-mentioned face identifier matching algorithm based on the Euclidean distance to calculate the similarity of two face identifiers.

The face identification and resolution system consists of two phases: Face identification and face resolution. The process of face identification is first executed to generate face identifiers on training set, and identity information of respective individual is stored in database. Test set is used for practically testing the process of face resolution. The average value of results is calculated as the measurement criteria of performance.

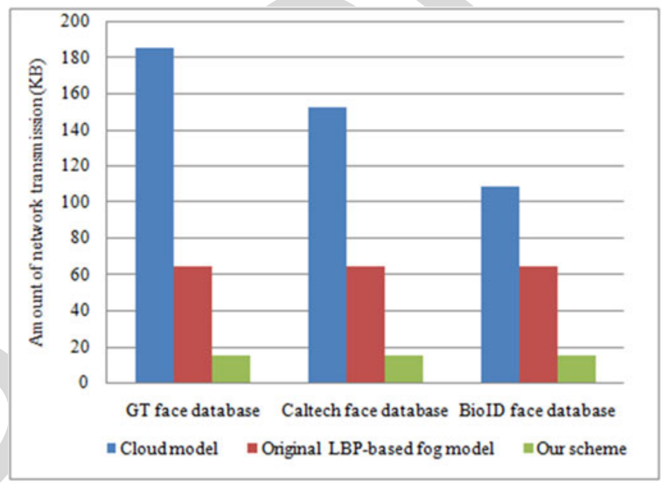

Fig. 4. Amount of network transmission using different resolution schemes.

C. Experimental Results and Performance

We take a facial image in the GT face database as an example to present the process of identifier generation. The algorithms of face detection, image preprocessing, feature extraction, and face identifier generation are executed to generate the face identifier. The result of each operation is show in Fig. 3. The generated identifier is used for implementing face resolution.

For evaluating the performance of the proposed scheme, namely the uniform LBP-based fog model, we compare it with another two resolution schemes—1) cloud model: the client transmits the raw facial image to the cloud directly and the whole resolution tasks are accomplished on the cloud, the uniform LBP-based face identifier generation model proposed in this article is applied; 2) original LBP-based fog model: fog computing based resolution framework is applied, but the face identifier generation model adopts the original LBP feature whose dimension's size (64×256) has not been reduced. We evaluate the performance of our scheme from the following aspects.

1) Amount of Network Transmission: Fig. 4 shows the average amount of network transmission for three resolution models in three face databases. In our scheme, since only the face identifier is transmitted, the average amount of network transmission is about 14.75 KB for three resolution models. In the cloud model for which the raw facial image is transmitted, the average amount of network transmission is equal to image size, which is far more than our scheme. The results indicate that our scheme notably reduces the amount of network transmission and saves the bandwidth. For the original LBP-based fog model, the average amount of network transmission is about 64 KB, which is the size of the face identifier. Comparing with the results of our scheme, it indicates that dimensionality reduction for the feature vector can also reduce the amount of network transmission.

2) Response Time for Different Face Databases: We count the time cost from requesting the resolution service to receiving the identity information in the client as the system response time. It contains the time of network transmission, identifier generation, and resolution. Fig. 5 shows the average response time for three resolution models in three face databases. The time consumption for cloud model is more than our scheme. This shows that, in the case when all the resolution operations of the two schemes are the same, the larger the amount of network transmission is, the longer the response time will be. The time consumption for the original LBP-based fog model is also more than our scheme. Because the feature vector has not been reduced, dimension and the size of feature vector is larger. The above-mentioned analysis shows that our scheme can effectively reduce the total response time.

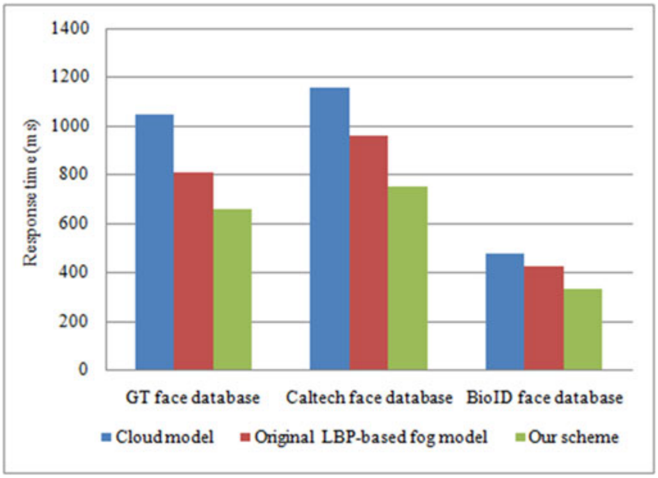

Fig. 5. Average response time using different resolution schemes.

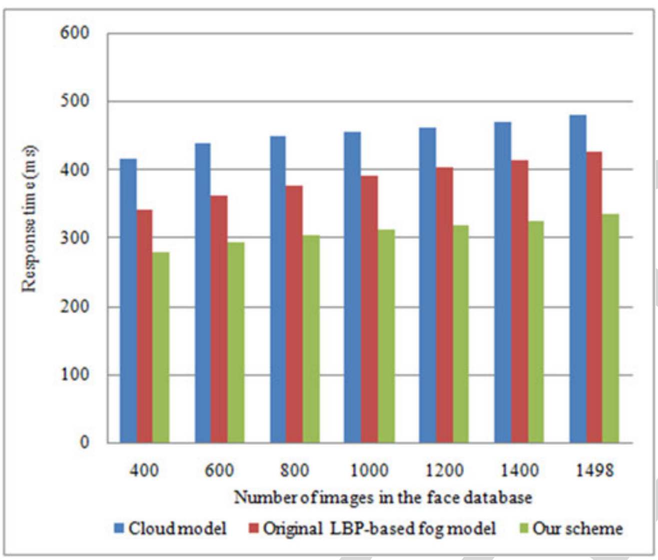

Fig. 6. Average response time for different sizes of the face database using different resolution schemes.

3) Response Time for Different Size of Face Database: Taking the BioID face database as an example, we store different numbers of images in face database to count the time cost of the whole resolution process. Fig. 6 shows the average response time for different sizes of the face database using different resolution schemes. Although the response time increases with the increasing size of face database, our scheme is minimum for different sizes of the face database. And the increment speed of our scheme is slower than each of other two schemes. The results indicate that our scheme is able to keep superiority in stability to provide an efficient face resolution service.

4) Resolution Rate: The statistical result shows that the resolution rates are the same for the three resolution schemes in the same face database. In detail, GT is 90%, BioID is 96.77%, and Caltech is 92.31%. The resolution rate is directly influenced by the face identifier generation model and matching algorithm. The cloud model and our scheme are the same in identification model and matching algorithm, and only different in resolution framework. So their resolution rates are the same. The original LBP-based fog model and our scheme have the same resolution rate in three face databases. The former can describe facial details more comprehensively, but the feature histogram is too sparse and the dimension of face identifier is too high. Our scheme effectively reduces the dimension without decreasing the accuracy rate. In future, with the emergence of face identification and resolution methods, which have better representation ability and discrimination, the resolution rate will be further improved.

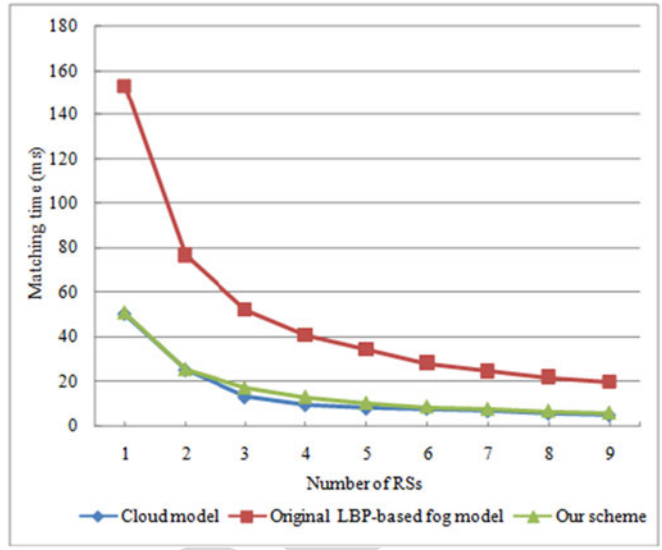

Fig. 7. Average matching time using multi-RSs.

5) Matching Time Using Parallel Process Mechanism: For the whole resolution process, identifier matching is an operation that consumes large computation resources, especially when the face database is quite high. In order to further improve the performance, we applied multithreading parallel processing technology for identifier matching. Multiple resolution servers synchronously execute identifier matching operations. Fig. 7 shows the average matching time for three resolution models using different numbers of RS threads in the GT face database. The results indicate that the matching time consumption of three models have been markedly decreased by parallel computation. Since the process of identifier matching for cloud model is almost same as our scheme, their matching time consumptions are very close. The dimension of the identifier is slightly large for the original LBP-based fog model, which results in the computational complexity of identifier matching being comparatively higher than our scheme. So its matching time consumption is more. Since not all the processes are parallel, the time consumption is not reduced exponentially. Cloud and fog computing has high parallelism and computation capacity, which can further improve the performance of the resolution system.

From these experimental results, it is obvious that the combination of fog computing, face identification and resolution has indeed promoted the performance. It significantly reduces the communication bandwidth requirements and response time; therefore it can still provide a good service, even in the case when the Internet is unavailable or bandwidth is low. Based on this framework, various applications based on face identification can conveniently access the face resolution services in some places with poor network bandwidth, for example, airport, coffee house, and so on.

VI. Conclusion

In this paper, we propose a fog computing based face identification and resolution scheme to solve the problem of computation, communication, and storage faced in large-scale access to the cloud resolution services. This framework can also be suitable for most of other biometrics. For face identification, we apply appropriate the face representation method to establish the face identifier generation model. Based on it, the face identification system has been presented to generate the face identifier. For face resolution, a fog computing based framework has been proposed to realize face resolution according to the face identifier. It makes full use of the computing power of devices located at the edge of network and offloads some computing overhead from the cloud to FNs by applying the task partitioning. Under the premise of ensuring the computing and storage capacity, it enormously reduces the amount of network transmission and saves the bandwidth. The experimental prototype system has been implemented. In our experiment, the face identifier generation model based on facial LBP feature and the matching algorithm based on the Euclidean distance have been presented in detail. The experimental results show that our proposed scheme can effectively reduce the bandwidth consumption and total response time, and dominantly improve the resolution efficiency. It can meet the requirements of face identification and resolution for computation, communication, and storage capability in current big data environment. In our future work, the parallel processing mechanism will be further explored to improve resolution efficiency. Furthermore, privacy protection, security mechanism, and mobile fog computing technology will be considered.

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