Hey Home, Open Your Door, I'm Back! Authentication System using Ear Biometrics for Smart Home

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Abstract

Conventional authentication systems use secret knowledge like password either from alphanumeric PIN to graphical click-based or pattern password that impose memory burden to users. Biometrics appears to answer the problem related to conventional system. We propose an ear biometrics as an alternative to popular facial biometrics. One of the ways to implement biometrics authentication system is by authenticating them via image or video captured using a dedicated terminal as biometrics enrolment module. This biometrics module is pricey thus adding cost to overall cost of having smart properties for people. In addition, it can be destroyed by thieves to bypass biometrics authentication after alarm system being turned off. We perceive that smartphone camera can be used as replacement of dedicated enrolment module instead. The replacement will result a biometrics enrolment terminal that is firstly mobile and automatically practical unlocking home while user is within home proximity. With location-based service (LBS) support, it can enable convenient and implicit owner authentication system when accessing the protected smart premise and property (like smart home). In a situation that user calls to home then LBS could detect user's location within close range of proximity thus authenticating a user via its front camera that faces to ear while being used on calling home. Furthermore, it is cost-efficient because eliminating the necessity to install dedicated enrolment terminal in a property like smart home. In this paper, we present a novel approach to ear biometrics which considers both shape and texture information to represent ear image during ear recognition computation for authentication. We use local invariant patterns as ear image descriptor during recognition to have lightweight but accurate ear biometrics system on securing smart homes. We improve the original local invariant against noise that may reduce accuracy in potential deterrent conditions like over noise and illumination changes.

Keywords: *ear, biometrics, smartphone, camera, local invariant feature, smart home authentication system*

1. Introduction

Smart living is envisioned to be the standard of living for many people in near future. Smart living enables easy and understanding style of living where all computing is silently, seamlessly embodied in many human's life aspects. One smart living dream that attracts many research interests is smart home. Researches aspire to have intelligent smart home that is capable to cater daily human needs in automatic fashion. Many researches are geared towards realizing the function. However, there are still few researches focus on security aspect of entry access related to smart home. Smart home authentication system is an urgent system to be installed within smart homes' compounds. Conventional authentication systems use secret knowledge like password either from alphanumeric PIN to graphical click-based or pattern password [5, 6]. They are deemed inconvenience and difficult for users on remembering passwords and easy-to-crack passwords or secret words. Biometrics appears to answer the problem related to conventional system.

One of the ways to implement biometrics authentication system is by authenticating them via image or video captured using a dedicated terminal as biometrics enrollment module. This biometrics module is pricey and adding cost to overall cost of having smart home for people. In addition, it can be destroyed by thieves to bypass biometrics authentication after alarm system being turned off. We perceive that smartphone camera can be used as replacement of dedicated enrollment module instead. With location-based service (LBS) support, it can enable convenient and implicit owner authentication system when accessing entry point to the protected smart home. The replacement will result a biometrics enrollment terminal that is mobile and spatially intelligent. Furthermore, it is cost-efficient because eliminating the necessity to install dedicated enrollment terminal.

In this paper, we present our study on an approach to authenticate smart home users through their smartphone conveniently. Our proposed approach is very easy and simple thereby its simplicity allows very fast feature extraction. We foresee that this experiment is applicable individually on smartphone. However, we use authentication machine here because we need a machine as decision making machine to open the electronics machine once user is successfully authenticated.

The remaining parts of this paper are organized as follows. Section 2 describes related work on smart home authentication system that many of researches focusing on securing smart environment in smart home networks rather than physical entry access that usually considered saturated with conventional biometric system. Section 3 will discuss our intelligent authentication system for smart home using smartphone integrating two services of LBS and ear recognition for automatic fashion system complimentary to usual facial biometrics making use of smartphone camera. Section 4 presents our experimental result recognizing user with our method. Eventually, Section 5 summarizes our research's result and discussing potential future improvement as well as future direction.

2. Related Work on Smart Home Authentication

To the best of our knowledge, there are only narrow scopes of researches focusing on security in smart home researches. Majority of the current security research scope focuses on security pertaining to inner smart homes' network. Researches in [1, 2, and 3] paid attention to digital home networks authentication among home appliances or various mobile devices as a sensor network within a smart home. Meanwhile, our aim is towards smart homes' owner authentication to gain physical entry access to a smart home generally similar to researchers in [4]. We both focus on using biometrics to authenticate user enabling only real smart home owner entry access. In their research, they propose variant-based remote authentication scheme using rotor machine concept where the finger biometric template could be protected from template steal and forgery. However, in terms of method, we are different to them as we choose ear biometrics as the basis of authentication system instead of fingerprint. Also, we integrate location-based service (LBS) to provide automatic fashion of necessity to authentication process.

Researches on using ear as a biometrics have been interesting at least 100 years. Already at 1906, Imhofer discovered that in the set of 500 ears only 4 characteristics was need to state the ears unique [15]. Alfred Iannarelli's work is considered the most essential work among ear identification and he gathered up over 10.000 ears and found that they all were different [16] at 1989. In [17] and [18], they have used Principal Component Analysis (PCA) and Facial Recognition Technology (FERET) evaluation protocol for their research about the ears. In [19] researchers presented multiple identification method, which combines the results from several neural classifiers using feature outer ear points, information obtained from ear shape and wrinkles, and macro features extracted by compression network. Research in [20] describes a 3D ear reconstruction technique using multiple views. This method uses the fundamental matrix and motion estimation techniques to drive the 3D shape of the ear. In [21], the paper presents a 3D ear recognition method using local surface shape descriptor. Twenty range images from 100 individuals (2 images each) are used in the experiments and a 100% recognition rate is reported. In [22], the paper uses a two-step Iterative Closest Point (ICP) algorithm on a dataset of 30 subjects with 3D ear images. According to their report, this method shows two incorrect matches out of 30 persons. In [23], they presented an investigation of ear biometrics on a database containing 300 subjects. They experimented with several different approaches "Eigen-Ear" with 2D intensity images, PCA on 3D range images, Hausdorff matching of edge images from range images, and ICP matching of the 3D data. Experimental results for the different approaches included 63.8% rank-one recognition for the Eigen Ear, 55.3% for the 3D range image PCA, 67.5% for the Hausdorff matching, and 98.7% for the ICP matching. In brief, most of the cases better recognition performance could be achieved under limited conditions such as disregarding rotational variance, various illumination condition, and irrelevant noise that may affect actual recognition process.

3. Intelligent Authentication System for Smart Home using Smartphone

In our research, conventionally we perceive a typical biometrics authentication system is normally equipped with dedicated biometrics extraction terminal attached to a smart home for enrollment and submission of biometrics factor. We portray this idea as in Figure 1. We choose to have home server connected to smartphone as pictured in

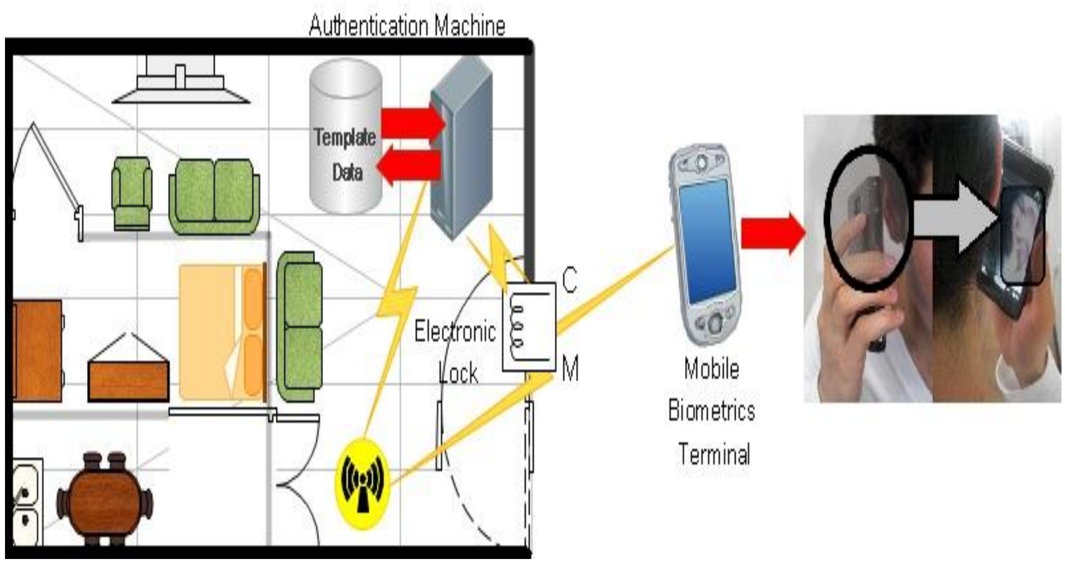


Figure 1. Smartphone-based Authentication System for Smart Home with LBS

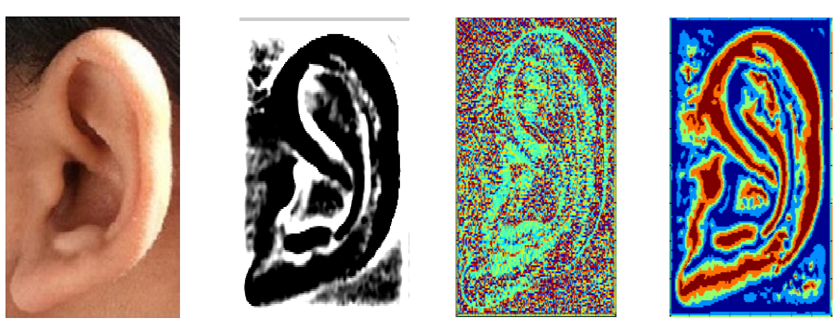
Figure 1 to authenticate users once users are within smart home proximity. LBS will play role on automatic detection of users thus enabling automatic unlocked door when owner is closer to home eliminating any owner's explicit effort to open door. This system reduces cost by eliminating the necessity of dedicated biometrics extraction terminal. Besides, it enables mobility and automatic authentication contextually according to user location.

We propose an ear biometrics as an alternative to popular facial biometrics. Ear biometrics is one of the passive biometrics. There are several reasons why we choose ear by comparing with other biometrics such as face, iris, and retina. First of all, ear does not change during human life as ascertained by The Prague doctor Imhofer [15], whereas face changes more significantly with age than any other part of human body. Cosmetics, facial hair and hair styling, emotions express different states of mind like sadness, happiness, fear or surprise. As well as this, color distribution is more uniform in ear than in human face, iris, retina, that is, while working with grayscale we do not lose much information. Besides, ear is smaller than face, which means that it is possible to work faster and more efficiently with the images with the lower resolution. In addition, it is important to note that ear images cannot be disturbed by glasses, beard or make-up. However, occlusion by either hair or earrings is possible. Nevertheless, we can get rid of these negative points for typical applications.

When dealing with ear as biometrics, we use 2D texture analysis and classification. In the beginning of 2D texture analysis most researches deal with statistical texture analysis over images. The results were pretty good but they have common weakness that is not persistent to rotational noise as the image must be similar in term of orientation. From this weakness, researchers have begun their researches to discover 2D texture analysis that is persistent from rotational noise (rotation invariant).

The original Local Binary Pattern (LBP) operator was introduced in [9]. This operator works with the eight neighbors of a pixel, using the value of this center pixel as threshold. If a neighbor pixel has a higher gray value than the center pixel (or the same gray value) than a one is assigned to that pixel, else it gets zero. The LBP code for the center pixel is then produced by concatenating the eight ones or zeros to binary code as shown in Figure 2. Later the LBP operator was extended to use neighborhoods of different sizes.

In our research, we perceive that rotational persistent is very important for convenient nature of use to user, hence we extract 2D texture of ear feature namely Local Binary Pattern (LBP) that is rotation invariant. Later on, an improved LBP called monogenic local binary



(a) (b) (c) (d)

Figure 2. An Ear Image (a) and its Monogenic Representation LBP (M-LBP) in Terms of (b) Magnitude Component, (c) Orientation Component, and (d) Phase Component

pattern (M-LBP) is derived by using monogenic signal analysis [7]. Monogenic signal is a two-dimensional (2D) generalization of the one-dimensional analytic signal measuring multi-resolution magnitude, orientation and phase of a 2D signal. The monogenic signal analysis [7] translates images so that through which the qualitative measure of local structure like in terms of the local phase, the local orientation and the local magnitude are obtained. The representations of one ear image can be seen as in Figure 2. The 2D signals representation is done via the Riesz transform [8]. From the 2D representation, we propose to use the histogram of M-LBP (HMLBP) to authenticate smart home owners accordingly.

In the monogenic representation of a face image, the magnitude A is a measurement of local structure energy, and we can use the conventional LBP operator [9] to encode the variation of local energy. The LBP operator can encode a local 3×3 patch into an 8-bits binary code. The uniform LBP operator was later proposed [10], which contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. The uniform LBP uses 6- bits to describe the local structure information without degrading much the performance of LBP. In our method, we use the uniform LBP to extract the local texture information in the monogenic magnitude component, and hence each pixel Z in the magnitude code map, denoted by B_m, at each scale will be 6-bits.

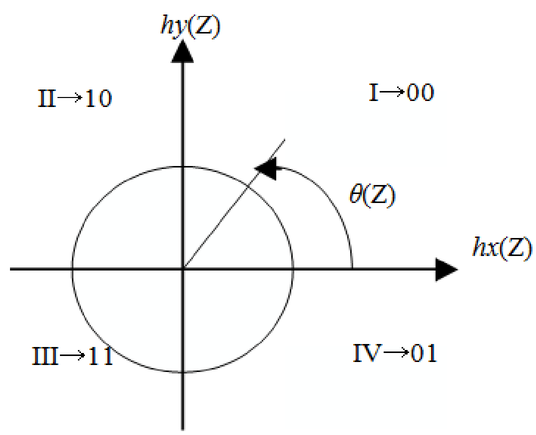


Figure 3. LBS Quadrant Bit Coding of Monogenic Orientation

Apart from the magnitude, the monogenic orientation θ indicates the dominant direction of local image variation, which is an important feature of image recognition. Here, we code the monogenic orientation information into a quadrant bit, which is illustrated in Figure 3. A pixel Z in the orientation map at each scale is encoded into two bits $B_\theta^x(\mathrm{Z})$ and $B_\theta^y(\mathrm{Z})$ by rules of

$$B_\theta^d(\mathrm{Z}) = \begin{cases} 0, if\ h_d\ (Z) > 0 \\ 1, if\ h_d\ (Z) \le 0 \end{cases}, \qquad d \in \{\mathrm{x}, \mathrm{y}\} \tag{1}$$

h_x and h_y are respectively the horizontal and vertical Riesz transform parts of monogenic signal representation. Finally the proposed M-LBP is combination of binary codes of orientation and uniform LBP of magnitudes is M-LBP $\{B_\theta^x(\mathrm{Z}), B_\theta^y(\mathrm{Z}), B_m(\mathrm{Z})\}$.

4. Simulation and Experimental Result

4.1. Experimental Framework Setup (Histogram of M-LBP)

The experiment is conducted on 20 subjects upon obtaining respondents' ethical agreement and concern approval of the ear images being captured and anonymously annotated with total 80 images from 20 subjects. These images are taken slightly different illumination conditions and viewing conditions with reference to mobile user. The original images, with a resolution of 1600x1200, are cropped to gray scale images with a resolution of 100x165. In this experiment, three images of a subject are taken as the training set while the remaining one serves as the testing set. The statistical local feature invariant can be represented by using histogram of M-LBP.

The representation is robust towards illumination changes and noises. Illustration of this is shown in Figure 4. First, image is divided into small regions from which LBPs are extracted initially representing the ear image. Second, we get Monogenic LBP by applying monogenic analysis function. After getting Monogenic LBP, we normalized all histogram to then we combine all HMLBP from each region in concatenation fashion so that we get one input feature HMLBP that will be our model for ear image ready to be fed into our classifier formally as

$$HMLBP = \Sigma H_{MBLP}(r),\ r = 1, .., L \qquad (2)$$

Where L is the number of regions at its scale, S is the total scale of monogenic signal representation and is $H_{MBLP}(r)$ the histogram of r^{th} region.

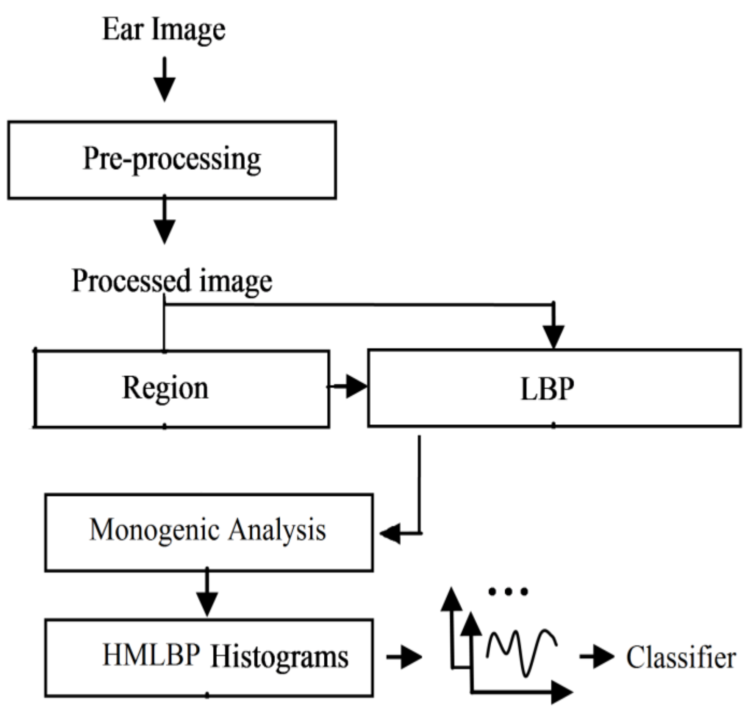


Figure 4. Framework of Ear Biometrics Authentication System using HMLBP

4.2. Experimental Result

Upon completing all experiments, the recognition rates (in %) are listed Table 1. In these experiments, in every methods' trial, the template set consists of three random images from each subject and the remaining images serve as the testing set. The original images, as shown

Figure 5. Sample of Ear Images from Respondent in our Experiment

some samples of them in Figure 5, with a resolution of 1600x1200, are cropped to gray scale images with a resolution of 100x165. In this experiment, three images of a subject are taken as the training set while the remaining one serves as the testing set. We compared one individual testing set with one template set from 20 persons with 3 template images each. Then, one test image is compared against all 60 template images using a classifier. The result per trial is the closest matching image in template. Using nearest-neighbour classifier, we obtain 92.5% accuracy.

Table 1. Our Experiments' Result Compared to Other Researches

Methods	Accuracy (%)
Principal Component Analysis (PCA) [11]	78.6
Independent Component Analysis (ICA) [12]	83.6
Fischer Discriminant Analysis (FDA) [11]	85.7
Geometric approach [13]	87
Rotation invariant descriptor [14]	88
Our approach	92.5

5. Conclusion and Future Works

We present our study about a novel intelligent system for smart home envisioning seamless integration of ubiquitous device like smartphone. In ear biometrics details, we take the ear recognition idea, which is ear images can be seen as a composition of micro-patterns that can be well described by MLBP, into account.

We present an approach to improve ear recognition towards noise and illumination variant for ear recognition with respect to smartphone as mobile biometric terminal devices. We believe this idea will result on efficient and convenient authentication system when deployed in smart home. With location-based system, this idea will be interesting in such a case that when smartphone detecting that an owner is closing nearby to her home, smartphone can automatically offer authentication service so that the smart home is unlocked automatically once owner is authenticated and close to home.

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