

Biometric Analysis of Ear Recognition using Shallow and Deep Techniques

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**Biometric Analysis of Ear Recognition using Shallow and Deep
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Abstract

Biometric ear authentication has received enormous popularity in re-cent years due to its uniqueness for each and every individual, even for identical twins. In this paper, two scale and rotation invariant feature detectors, SIFT and SURF, are adopted for recognition and authentication of ear images. An extensive analysis has been made on how these two descriptors work under certain real-life conditions; and a performance measure has been given. The proposed technique is evaluated and compared with other approaches on two data sets. Extensive experimental study demonstrates the effectiveness of the proposed strategy. Deep Learning has become a new way to detect features in objects and is also used extensively for recognition purposes. Sophisticated deep learning techniques like Convolution Neural Networks(CNNs) have also been implemented and analysis has been done.

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Chapter 1

Introduction

Biometric authentication of people based on various anatomical characteristics, like eye, ear, face, iris, and fingerprint have attracted lots of attention during the past few decades, and some of these techniques have already been successfully applied for recognition and authentication. However, many systems are not very robust and may fail to work under certain conditions. Biometric ear recognition is a relatively new technique that may surpass the existing systems due to several significant reasons. For example, the acquisition of ear images is relatively easy and, unlike iris, can be captured without the co-operation of individuals [1]

Human ear contains rich and stable features which are more reliable than face features, as the structure of the ear is not subject to change with age. It has also been found out that no two ears are exactly the same even for identical twins [2]. The detailed structure of ear is not only very unique but also permanent, since the shape of a human ear never shows drastic changes over the course of life. The research on ear identification was first conducted by Bertillon, a French criminologist, in 1890. The process was refined by American police officer, Iannarelli [20], who divided the ear based on various distinctive features of seven parts: i.e. he-

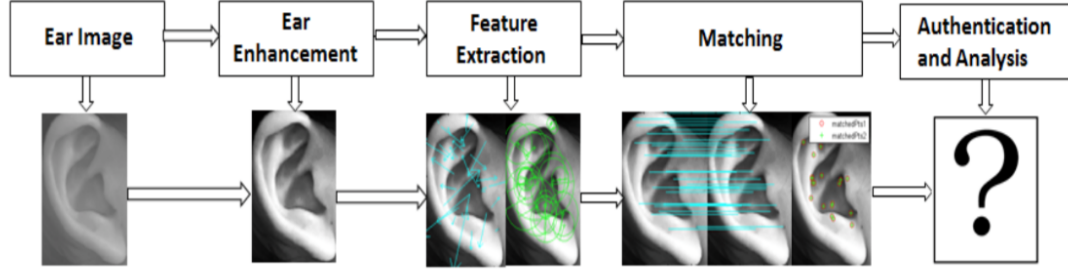


Figure 1.1. The pipeline of the proposed Ear Recognition System

lix, concha, antihelix, crux of helix, inter- tragic notch, tragus, and antitragus [3].

Here, we propose to use two scale and rotation invariant feature detectors, i.e. SIFT (scale invariant feature transform) and SURF (speed up robust features), for ear recognition. Both SIFT and SURF extract specific interest points from an image and generate descriptors for the feature points to form a reliable matching results.

Extensive experiments have been carried out on two different sets of databases to evaluate their performance with respect to various rotations and scales. One of the most important feature of ear images is its easiness in acquisition, however, the acquired images may be in different scales, rotations, and illumination. The scale and rotation invariant property of the SIFT and SURF algorithms makes them perfect for ear authentication under various circumstances.

A new concept in the field of machine learning and computer vision has come up which has surpassed the traditional object recognition methods. This new approach is called deep learning. Deep Learning is a branch of Machine Learning which has multiple levels of representations and abstractions. It is basically a rebranding of the term Artificial Neural Networks. Deep Learning algorithms have already been applied in Apple’s Siri, Google’s Streetview etc.

The rest is organized as follows. Some background and related research are discussed in Section 2; the proposed method is presented in details in Section 3; some experimental results and analysis are given in Section 4; and the paper is concluded in Section 5.

Chapter 2

Statement of the Problem

2.1 Types of Biometrics

Biometrics has been an active field of research over the last decade. The reason behind their success is that biometric characteristics are universal, unique and permanent. Unlike other forms of authentication such as passwords or identification cards which can be stolen or faked easily.

There are many kinds of biometrics which can be used for authentication purposes. Among them the prominent being, Face, Ear, Palm, Fingerprint, Iris and others which are frequently being used these days in day to day life to authenticate an individual. Another reason biometrics have been used these days are due to terrorist activities and other fraudulent ways in which people impersonate themselves which are harder to catch. These days biometrics are used everywhere from Airports to ATMs to secured entry to corporate offices where checking the identity of an individual is mandatory before access is given. It helps to strengthen the security of an organization or country potential threat. As men-

tioned above, the different types of biometrics, different biometrics have different purposes and importance. The most popular being face recognition which is being used everywhere to authenticate people, the only disadvantage being the change in facial expression and with age the face changes upto a certain extent which makes it difficult to recognize and authenticate. Fingerprint is also being used in almost any high priority zone nowadays to authenticate and is very successful but it requires complete co-operation of an individual in order to authenticate them. The same problem happens with iris authentication where it becomes very difficult to extract the iris image to match and authenticate.

Ear authentication comes to the rescue in such a situation due to many reasons. The primary being the stability in the human ear structure and ear images can easily be captured without the co-operation of an individual. Each ear is unique, so any side image of an individual is enough in order to authenticate a person.

2.2 Purpose of Biometric Ear Recognition

Ear authentication and recognition is being considered as one of the most innovative processes as of today. The human ear can be divided into six main parts: Outer helix, the antihelix, the lobe, the tragus, the antitragus and the concha. The shape of the outer ear evolves during the embryonic state from six growth nodules. The structure is completely random, the randomness can be observed by comparing the left and right ear of the same person - thus they are not symmetric. French criminologist Alphonse Bertillon was the first to be aware of ear to be used for human identification purposes. His work was carried on by Alfred Ianarelli whoc collected 10,000 ear images and determined 12 characteristics needed to identify a person. He also conducted studies on twins and triplets

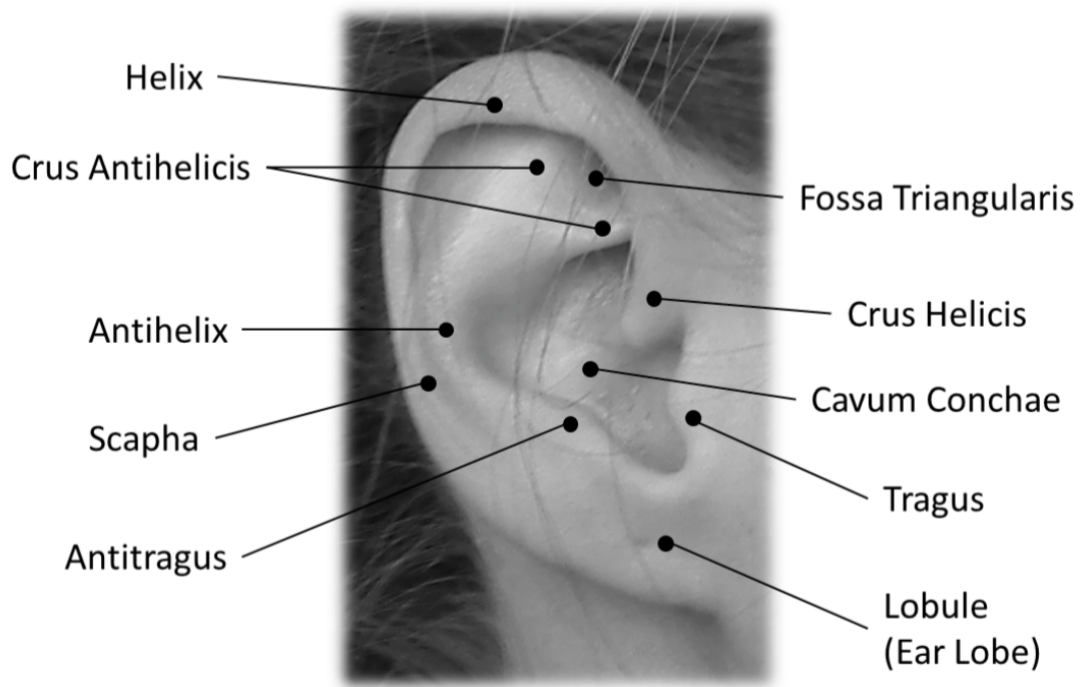


Figure 2.1. Characteristics of Human Ear [1]

thereby discovering that ears are unique even among genetically identical persons [1]. The different parts of the ear are shown in Figure 2.1

The typical ear biometric system can be viewed as a system where an input image can be reduced to a set of features that is used to compare with the features of other images to determine its identity. The salient features of a classical ear recognition system are [2]

1. Ear Detection/ Segmentation - The first stage which is used to localize the position of the ear in the image.
2. Ear Normalization and Enhancement - The size of the ear image is normalized for standardization and enhanced using standard image processing techniques in order for more features to be extracted.

3. Feature Extraction - Feature extraction refers to a process in which the ear image is being reduced to a mathematical model called a feature vector to get information.
4. Matching Features - The features extracted are then compared to the features that are extracted earlier and stored in the database to find a match.
5. Decision - Matching scores are generated by the model used to train the features to give a decision of whether the image is matched or not.

2.3 Contributions of this Project

The main goal of this work is to develop shallow and deep techniques to extract efficient features from a set of ear images in order to authenticate a human being. A thorough comparison of two traditional techniques called SIFT(Scale-Invariant Feature Transform)[] and SURF(Speed-up of Robust Features have been provided)[], then another comparison has been done with modern deep learning models constructed with the help of convolution neural networks[].

Chapter 3

Background

Human ears start to develop between fifth and seventh weeks of pregnancy. At this stage, the embryo face takes on more definition as mouth perforation, nostrils and ear indentations become visible. Forensic science literature reports that ear growth after the first four months of birth is highly linear [20]. The rate of stretching is five times greater than normal during the period from 4 months to the age of 8, after which, it is constant until the age of seventy when it again increases. Thus it can be said that ear remains almost unchanged during a substantial period of 62 years and, thus, it is one of the strong points of considering ear for biometric authentication.

Haar-based methods have given fairly better results for face detection as it is robust and fast. The different types of ear recognition systems include those of intensity-based, force-field based, 2D curves geometry, wavelet transformation, Gabor filters, SIFT, and 3D features. The force-field transforms gained popularity due to its uniqueness and efficiency [22]. Similar methods have also been implemented on other kinds of ear recognition systems [8][10].

Deep Methods have already come up and showing good performances on other

face recognition systems which shows that it can also be applied to ear recognition systems. Hand-crafted feature detectors have not been able to work properly and are not robust, so deep features have been extracted to improve upon the performance. But one of the few drawbacks about deep learning is that it needs a large amount of data to train the model. There are not many ear databases that are too big but an attempt has been made to apply deep learning on a small scale database and analyze the results.

Chapter 4

Related Works

A lot of work has been happening in the ear biometrics over the past decade. The approaches are varied with some working on Intensity-based features while others on 2-D and 3-D curves etc. Chang et al.[2003] whole worked on the UND database and got an accuracy of 72.7p.c. using the PCA approach.

Chapter 5

Design of Proposed Approach

5.1 Traditional Approach

The initial scheduler in the HybridThreads system used a simple FIFO scheduling mechanism that was internal to the Thread Manager (TM) [?]. The `add_thread` system call would be routed to the Thread Manager and the TM would then insert the thread into a singly-linked FIFO ready-to-run queue. The main problem with this scheduling structure is that the ready-to-run queue was built in to the Thread Manager's attribute structures used for data storage for thread management status. This means that thread management (allocation, creation, and control) and thread scheduling (ready-to-run queue management, and scheduling decisions) activities could not occur in parallel. Additionally, any changes in scheduling mechanisms and scheduling data arrangement would also affect the management mechanisms, and vice-versa, so maintenance of the management and scheduling services would be difficult, cumbersome, and error-prone.

Both the thread management and thread scheduling mechanisms would have to be modified if either were to be extended in their functionality or data storage

requirements. The scheduling mechanism was going to be upgraded to allow for priority scheduling and eventually would have to handle the scheduling of both SW and HW threads, so it was decided to make the scheduler a separate IP module that would have its own interface to the HybridThreads system bus. Many thread management operations result in the invocation of scheduling operations, so essentially the TM uses the scheduler module as a coprocessor for any and all scheduling operations. Many of these coprocessor operations can only occur as a result of a management operation so the TM will always be the "caller" in these cases. This, in conjunction with the scheduler becoming a separate module, means that all outgoing operations from the TM to the scheduler will result in a bus operation; however if the TM is using the scheduler to complete a management operation, then the bus will already be locked by the caller of the TM operation. This meant that a special interface must be created between the TM and the new scheduler module to allow access to scheduling operations while the system bus was locked. Additionally, since other scheduler specific operations are not ever called as the result of a thread management operation, then these scheduling operations can be called via the new interface used to attach the independent scheduler module to the HybridThreads system bus.

The TMcom interface is a dedicated hardware interface between the scheduler module and the TM that consists of a total of seven control and data signals as well as access to a read-only interface (B-port) of the TM's Block RAM (BRAM). The data signals include `Next_Thread_ID`, `Current_Thread_ID`, and `Thread_ID_2_Sched`. The `Next_Thread_ID` signal represents the identifier of the thread chosen to run next on the CPU. This signal is writable by the scheduler module and readable by the TM. The `Current_Thread_ID` signal repre-

sents the identifier of the thread that is currently running on the CPU (PowerPC 405). This signal is readable by the scheduler module and writable by the TM. The **Thread_ID_2_Sched** signal contains the identifier of the thread that is being added to the ready-to-run queue by the TM. This signal is readable by the scheduler and writable by the TM. The control signals include **Next_Thread_Valid**, **Dequeue_Request**, **Enqueue_Request**, and **Enqueue_Busy**. The **Next_Thread_Valid** signal represents whether or not that the scheduling decision available from the scheduler module on the **Next_Thread_ID** signal is valid or not (Valid = 1, Invalid = 0). This signal is writable by the scheduler module and readable by the TM. The **Dequeue_Request** signal is used by the TM to request the scheduler module to perform a dequeue operation of the thread whose identifier is on the **Next_Thread_ID** signal. This signal is readable by the scheduler module and writable by the TM. The **Enqueue_Request** signal is used by the TM to request the scheduler module to perform an enqueue operation of the thread whose identifier is on the **Thread_ID_2_Sched** signal. This signal is readable by the scheduler module and writable by the TM. The **Enqueue_Busy** signal represents whether or not the scheduler is currently busy performing an enqueue operation (Busy = 1, Not Busy = 0). This signal is writable by the scheduler module and readable by the TM. The B-Port interface to the TM's BRAM allows the scheduler module to query thread management information in order to perform error-checking that concerns the parent-child relationships of threads that the TM's data structures hold. The purpose of the TMcom interface is to allow the TM to request scheduling operations as a result of thread management operations whose side-effects alter the scheduling status of the system (i.e. the status of the ready-to-run queue). The operations available through the TMcom interface can be seen in table 5.1.

Table 5.1. Command Set of Scheduler Module, Build 1

Type	Name	Actions
TMcom	Enqueue	Schedules a thread
TMcom	Dequeue	Removes a thread from the ready-to-run queue
BUScom	Get_Entry	Returns a thread's table attribute entry
BUScom	Toggle_Preemption	Toggle preemption interrupt on/off
BUScom	Get_Entry	Returns a thread's table attribute entry (for debug use)
BUScom	Get_Priority	Returns the priority-level of a thread
BUScom	Set_Priority	Sets the priority-level of a thread
BUScom	Set_Default_Priority	Sets the priority-level of a thread (no error-checking)

5.2 SIFT and SURF Descriptor

The main goal of the second redesign of the scheduler module is to further reduce the amount of overhead and jitter involved in thread scheduling

5.3 Training Model

One of the main goals of The new hardware components used to schedule both SW and HW threads were fully integrated into the existing scheduler module. Results from simulation and synthesis tests to verify scheduler correct scheduler functionality of the new hybrid features along with $O(1)$ ready-to-run queue structure can be found in chapter 6.

5.4 Deep Learning Approach

5.5 Convolution Neural Network

5.6 Our Deep Network and Model

Chapter 6

Implementation Results

The modules from each of the scheduler redesigns have undergone a series of tests in both simulated and synthesized forms. These tests help show the performance differences between the different ready-to-run queue structures in terms of scheduling overhead and jitter as well as the effects of the hybridization of the scheduler on the entire HybridThreads operating system.

6.1 Results of the Traditional Approach

making a scheduling decision is hidden because it occurs during a context switch. However, if a scheduling event occurs very soon after a thread is initially context switched to, the system may have to wait for the scheduler to finish calculating the next scheduling decision resulting from the context switch. This is more likely to happen with more threads in the ready-to-run queue, due to increased execution-times of scheduling operations due to the $O(n)$ nature of the queue itself. Although the amount of jitter is in the microsecond range, it can still be further reduced by restructuring the ready-to-run queue so that its functions

are able to operate in constant amounts of time.

6.2 Results of the Deep Approach

Synthesis of the second redesign of the scheduler module targeting a Xilinx [?] Virtex-II Pro 30 yields the following FPGA resource statistics: 1,034 out of 13,696 slices, 522 out of 27,392 slice flip-flops, 1,900 out of 27,392 4-input LUTs, and 2 out of 136 BRAMs. The module has a maximum operating frequency of 143.8 MHz, which easily meets our goal of a 100 MHz clock frequency.

6.3 Comparison of the Approaches

Synthesis of the third redesign of the scheduler module targeting a Xilinx [?] Virtex-II Pro 30 yields the following FPGA resource statistics: 1,455 out of 13,696 slices, 973 out of 27,392 slice flip-flops, 2,425 out of 27,392 4-input LUTs, and 3 out of 136 BRAMs. The module has a maximum operating frequency of 119.6 MHz, which easily meets our goal of a 100 MHz clock frequency.

Chapter 7

Conclusion

In this paper we have presented the scheduling operations that execute in under 50 clock cycles (500 ns) or less at the base hardware level. From the system level, the hardware scheduler module provides very fast scheduling operations with an end-to-end scheduling delay of 1.9 μ s with 1.4 μ s of jitter with 250 active threads running on a Xilinx [?] Virtex-II Pro FPGA. The integrated system level tests have shown that the migration of scheduling services into the fabric of the FPGA have drastically reduced the amount of system overhead and jitter related

HybridThreads project [?], which furthers the future impacts of the project even more. More detailed descriptions of the hybrid threads project can be found in [?].

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Bibliography

- [1] A. Pflug and C. Busch, “Ear biometrics: a survey of detection, feature extraction and recognition methods,” *Biometrics, IET*, vol. 1, no. 2, pp. 114–129, 2012.
- [2] A. Abaza, A. Ross, C. Hebert, M. A. F. Harrison, and M. S. Nixon, “A survey on ear biometrics,” *ACM computing surveys (CSUR)*, vol. 45, no. 2, p. 22, 2013.
- [3] A. Tariq and M. U. Akram, “Personal identification using ear recognition,” *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 10, no. 2, pp. 321–326, 2012.