Chapter 1

Introduction

1.1 Biometric Systems and Biometric Features

Recently, identity verification has become an increasingly important and challenging task for security access systems. Traditional personal verification systems have been based on something that one possesses (Identification cards, for example) or one knows (passwords, for example). However, things like ID cards or passwords cannot ensure positive identification of a person. ID cards are routinely counterfeited, stolen or lost and passwords are often forgotten or stolen. To achieve more reliable verification or identification we should use information that really characterizes the person under examination. Biometrics offer automated methods of identity verification or identification on the principle of measurable physiological or behavioral characteristics [1, 2]. Unlike conventional identifiers (such as ID cards and passwords), biometrics are inextricably linked to a specific person and cannot be forgotten, counterfeited, or stolen. Biometrics can be thought of as a very secure key. Unless a biometric gate is unlocked by the presence of a specific person, no one else can gain the access.

With the recent advances in optical and digital technologies, novel sensors, and matching algorithms, a variety of biometric systems have attracted increasing research attention. The key issue for a biometric identification system is the selection of features. A functional biometric system requires that the specific human characteristics in use to be [1]:

(1) Universal: each person should have his/her own characteristic;

(2) Distinctive: any two persons should have separable characteristics;

(3) Permanent: the characteristic should be sufficiently invariant, under a certain matching criterion, over a period of time;

(4) Collectable: the characteristic must be a measurable quantity.

Several biometric systems have been developed to distinguish individuals utilizing a variety of biometric features.

Fingerprint :

Fingerprinting is a well established authentication method, matching high accuracy with easy enrollment and deployment. By measuring the distance between predefined points and structures in the print, a reliable, unique, one-way hash is easily generated [3]. Close proximity to the device is required, but fingerprint scanning is both compact and easily deployable. Handheld devices are now cheaply available, making finger scanning appropriate for mobile environments. Reliability has also been long established [4, 5], applying this technology to be a suitable identification device for many applications.

Voiceprint :

Recognition through unique aspects of a speaker’s voice is an established identification mechanism [6, 7]. Reliable identification of speakers is possible through the same microphones used for human detection, using several enhancement techniques [8]. While training is necessary, identification can be performed without requiring specific text to be spoken [7]. Identification through voice recognition requires little on the part of the humans being identified and may be carried out without their intervention.

Iris Imaging :

This well-known mechanism involves the unique properties of the human eye. Iris imaging has gained prominence in recent year as an ideal biometric identification systems, especially in high-throughput security applications. Imaging is performed at a range of 18-36 inches, using the phase information in the imaged iris to generate a pattern unique to every human. Iris scanning devices have lately become widely available. However, most devices have short working ranges, and users must look into the device in a specific manner. Results are highly accurate [9] and therefore ideal for high security environments.

Facial Imaging :

Face recognition is performed by standard imaging devices through a three-step process. The locations of possible faces are first determined through color analysis [10, 11]. A variety of computational methods [10, 12, 13] are used to extract the relative positions of facial features, such as eyes, nose, and mouth. After matching feature distribution using pre-defined templates, high accuracy recognition is accomplished [14]. Face recognition algorithms are complicated by their need for the user to be directly facing the device; in the study of smart spaces this difficulty is overcome by using the multiple detection devices distributed throughout the space. Typical authentication through facial recognition involves intensive computation process but provides a portable extension to existing video detection networks.

Palm Vein:

The pattern of blood veins is unique to every individual, even between identical twins. Palms have a broad and complicated vascular pattern and thus contain a wealth of differentiating features for personal identification [15-22]. It is a highly secure method of authentication because this blood vein pattern lies under the skin. This makes it almost impossible for others to read or copy. An individual's vein pattern image is captured by scanning his/her hand with near-infrared rays. The reflection method illuminates the palm using an infrared ray and captures the light given off by the region after diffusion through the palm. This vein pattern is then verified against a preregistered pattern to authenticate the individual.

Other biometric techniques, mostly still in exploratory stages including DNA biometrics [23], ear shape [24-27], fingernails [28] or odor [29-32]. However, most of the cited methods are subject to one of the three following conditions: the person must be positioned close to the detection device, high resolution capture device is required or significant computation is required to determine the person's identity.

1.2 Human Infrared Sensing

Our primary research interest in this study is to detect information about humans using their infrared properties. Human bodies are very good infrared sources and radiate heat to their environment. There is a constant heat exchange between the body and the environment due to the difference in their temperatures. The human body as a thermal source has been actively studied for military applications, evaluating thermal images or for biomedical applications [33-35]. The radiation characteristics of any object can be analyzed using the black-body radiation curve governed by Planck's Law [36]. For a typical human body with an internal temperature of 37 ^{o}C, this curve is shown in Fig. 1.1. It can be seen that essentially all of the radiation is in the infrared region with the peak radiation occurring at 9.55 μm. The amount of power that the human body radiates within the wavelength range of interest is determined by integrating the blackbody radiation curve (Fig. 1.1) over this range. About 52% of the power lies in the 5~ 14 μm wavelength band.

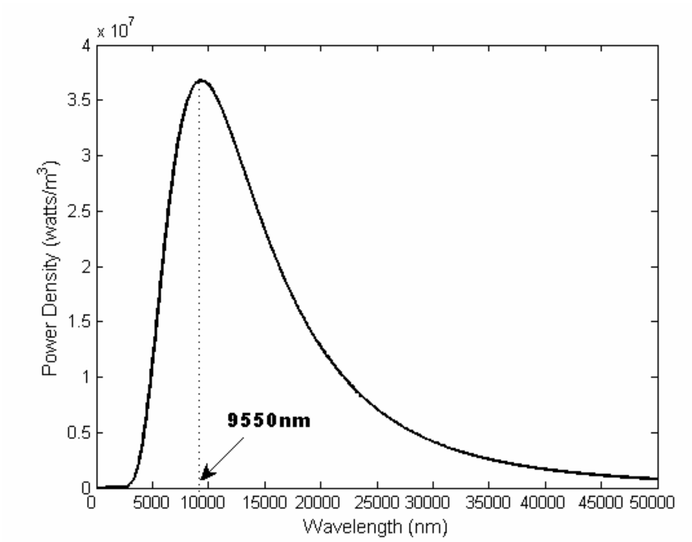

Fig.1.1 Black-body radiation curve of human body at 37^{o} C.

1.3 Human Thermal Model

To estimate human body radiation of heat to their environment, the Stefan-Boltzman's Law can be used. The amount of power per unit area leaving an object is obtained by

$$\psi(T) = \sigma(T_h^4 - T_c^4), \tag{1-1}$$

where T_h is the temperature (in deg Kelvin) of the human body which is typically about 37 ^{o}C, T_c is the ambient temperature in Kelvin and σ is the Stefan- Boltzmann's constant valued at $5.67\times10^{-8}\dfrac{W}{m^2K^4}$ and $\psi(T)$ is the power per unit area emitted from the hot body.

In order to account for the non-ideal nature of the human body as a radiator, an emissivity factor ε is included in the above equation. This factor has a typical value of 0.98 for a human body to account for the absorption that occurs in the skin [33-35]. If 'A' is the area of the radiating surface of the body, the total power radiated from the human body now becomes

$$\psi(T) = A\varepsilon\sigma(T_h^4 - T_c^4), \tag{1-2}$$

Assigning typical values to each of the variables as: T_h = 310K, T_c = 293K, A=2 m^2, we get $\psi(T)$ = 200 W. In order to account for the absorption by clothes, the power is scaled down by a factor of 2. Thus, the power radiated by the body effectively becomes about 100 W.

1.4 Computational Imaging System

Most optical imaging systems implement an isomorphic one-to-one mapping between the source space and the measurement space. These systems rely on a lens to form an image of the object's field on to a focal plane array or a photographic film. The focus of an optical system design has primarily been on implementations of better isomorphisms in order to improve resolution, depth of field and field of view. With the recent advances in digital processing, focal planes and availability of ample ubiquitous computing power, a new class of imaging systems that integrate optical and electronic processing to achieve new functionalities has emerged. These systems are referred to as "Integrated Computational imaging systems". A typical computational imaging system is illustrated in Fig. 1.2. Some of these systems use non-conventional optical elements to preprocess the field for digital analysis. These non-conventional optical elements can perform a wide range of transformations that can be used to implement complicated multidimensional/multi-spectral mapping of a source space into a measurement space. Several existing computational imaging systems include wave-front coding [37, 38], computed-tomography imager [39, 40], coded apertures [41, 42], multidimensional/multi-spectral imaging [43, 44]. Other potential advantages include increased depth of field [45, 46], improved computational efficiency and improved target recognition or tracking capabilities [47, 48].

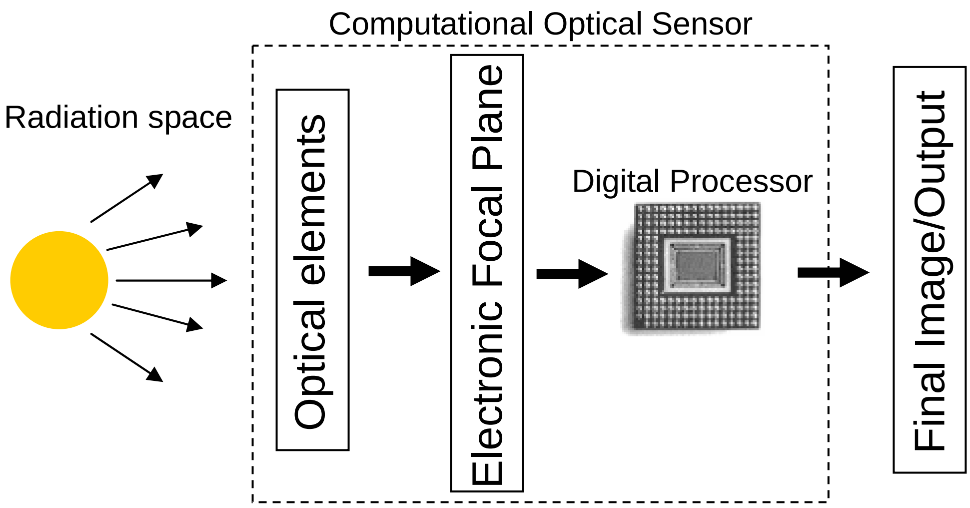

Fig.1.2 A typical computational system.

This methodology of computational systems gives the designer control over the optics, detection, signal processing, optical and mechanical tolerance, fabrication and signal processing implementation. Systems can be optimized based on application-specific operation, such as feature recognition algorithms for surveillance, machine vision analysis, biomedical diagnosis or bar code reading, for example. The desired result in many of these systems is not always a high quality image, but often a number or set of numbers that accurately describe a scene. Therefore, in some cases, systems are not based on creating visually appealing images, but instead are based on maximizing the information transfer between the object space and the image processing, recognition, or identification algorithms.

1.5 Motivation

When a human walks, the motion of various parts of the body, including the torso, arms, and legs, produces a characteristic signature. Human walking motion is a complex process and it is difficult to decouple the individual biomechanical contributions in a motion cycle for an analysis. Much work on motion analysis as a behavioral biometric has used video cameras to stream large amounts of data from which the identity of the person of interest can be extracted in a computationally expensive way [1, 49]. Also, if networks of cameras are used, the system requires large amounts of bandwidth in order to stream in real-time data to the processing computer. Recently, continuous wave (CW) radar has been developed to record signatures corresponding to the walking human gait [50]. These CW radar based systems utilize the Doppler effect to produce characteristic signals of a person walking.

From the thermal perspective, each person acts as a distributed infrared source whose thermal distribution is determined by his/her geometric shape and the IR emission from the body. Combined with the various idiosyncrasies in how an individual carries himself, the human thermal signature will impact a surrounding sensor field in a unique way. In this thesis, we will propose novel designs for computational sensor systems that use non-conventional imaging approaches to capture thermal motion features of humans to achieve real-time path-dependent and path-independent human identifications with low cost, low bandwidth utilization, low power consumption, easy deployment, and efficient measurement of the human information.

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