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HandShot ID

A Fast 3-D Imaging System for Capturing Fingerprints, Palm Prints and Hand Geometry

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1. Abstract

Taking advantage of plummeting digital camera costs and increasing computer-controlled macro photography capabilities of commercial off-the-shelf chip-cameras as well as the internationally-renown machine vision expertise of Carnegie Mellon University, we propose to create a direct high-contrast, high-resolution imaging system to simultaneously obtain 1000 ppi images of all 10 rolled-equivalent finger and both palm friction ridge patterns and minutiae within less than 5 seconds. We call this the "HandShot ID System." We obtain well-focused, high-resolution images through the use of multiple cameras. We obtain high-contrast, surface-topology-discriminant images in HandShot through the use of oblique blue light and special spot lights from various angles operating sequentially in millions of a second. We obviate the need for an operator to individually roll fingers through the use of cameras positioned at different angles. By obviating the rolling of fingers, we enable truly high-throughput processing. We also eliminate sequencing errors by having physically distinct right and left hand non-contact placement areas and by simultaneously capturing all 10 digits and both palms. We eliminate the need for routine cleaning of a glass platen by eliminating any glass platen and instead directly image hands in the air. For the same reason, we eliminate hygiene concerns.

In order for HandShot to accurately and instantly capture and record friction ridge skin detail on 10 rolled-equivalent fingerprints and both palm prints within 5 seconds, HandShot constructs a visual 3-dimensional model of both hands, including palms, fingerprints, fingertips, and sides of the fingers. Our associated HandShot algorithms: (1) stitch images from multiple cameras together forming a complete 3-D model of both hands using active models to normalize for pose; (2) extract ridge detail based on contrast assessment under varying illumination effects; and, (3) translate 3-D images to standardized formats. Having robust, detailed and extensive images supports traditional, as well as, new and improved applications in criminal, security and commercial identification, recognition and authentication tasks. For example, extraction of 10 rolled equivalent fingerprints from the 3-D model is possible for forensic comparison. Similarly, partial latent prints appearing on the palm, fingers (or sides) can be matched. Hand geometry and other new fast methods can be supported for security and commercial uses.

HandShot complies with significant standards in the field. Image specifications meet or exceed the FBI's CJIS EFTS as well as the NIST M1 committee standards for fingerprints and palm prints. Output complies with ANSI/NIST-ITL 1-2000 data format interchange standards.

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2. Purpose, Goals and Objectives

2.1. Escalating Need

Fingerprints are the cornerstone of modern biometric technology for identification, recognition and authentication of humans. Fingerprints are a distinctive feature and remain invariant over the lifetime of a subject, except for cuts and bruises. Friction ridges on the fingers, palms, and soles of the feet are the basis for these distinctive features. They have been studied ("dactylography", "ridgeology") and used for well over a century. Feature detail can be divided as Level I basic loop/whorl/arch classification, Level II ridge bifurcation, ending, and other such "minutiae", and Level III ridge width and pore placement, and other fine minutiae that is typically analyzed only in the identification of latent prints from crime scenes. The analytic methodology in the community which uses this impression information is described as "ACE-V" (analysis, comparison, evaluation, and verification). In short, society has come to rely on fingerprint identification.

The need for fingerprint background checks is rapidly proliferating. Fingerprint checks are increasingly sought for federally mandated and voluntary background screenings. Federal databases in which images of fingerprints are stored exist for a wide variety of contexts related to maintaining security and preventing, interdicting, and allowing attribution of crime and terrorism. Background checks are performed where persons apply for employment in positions of public or private trust, with access to dangerous or sensitive materials. Fingerprints of aliens seeking entry into the U.S. are now screened. Biometric authentication systems that recognize fingerprints offer several advantages over systems based on password, PIN or passport-based systems. Increasingly records supported by fingerprint verification are used to identity the person to whom the record pertains, not just within government, but within day-to-day modern commerce where identity theft looms large. Furthermore, fingerprints and/or palm prints of suspects are used to yield matches of latent prints at scenes of crimes or instruments or materials handled. The FBI fingerprint database is reported to be over 200 million and is growing at a rate of 30,000 to 50,000 per day. Given these demands, it is not surprising that computer technology has attempted to help in capturing, storing and comparing fingerprints.

Progress has been made in order to electronically capture finger prints directly. Computers have also been used to digitize cards containing manually rolled prints to expedite storage and comparison. But these have shortcomings (as further described in Section 3). What is needed is technology to rapidly capture fingerprints and palm prints, including the sides of the fingers, in such a way as to support accurate, infallible identification, recognition and authentication of humans in criminal, commercial and security applications. We propose the HandShot ID System as one solution, but before we further describe HandShot, we first state the problem.

2.2. Problem Statement

Today, fingerprint friction ridge information is typically acquired using ink and cards or "live-scan" inkless scanner technology. Current live-scan technology is generally reliable, but could be improved. Limitations include the need for trained operators, the need to roll individual fingers, sensitivity to contamination, moisture or excessive dryness. Impression capture generally requires between 5 and 10 minutes per person. Our HandShot ID System permits improvements in convenience, speed, reliability, accuracy, and cost. Such technology would enable proliferation and solidification of the nation's public and private infrastructure.

2.3. HandShot Performance Specifications

We will develop and deliver to NIJ a working prototype of the HandShot ID System for independent evaluation. The HandShot ID System will:

- Accurately capture and record the friction ridge skin detail on 10 rolled-equivalent fingerprints and both palm prints.
- Capture image data from ten rolled-equivalent fingers and palm prints within 5 seconds.
- Capture image data without operator manipulation of the hands of the person whose prints are taken and allowing for use as access control of unattended operation.
- Meet or exceed the image specification standards of the FBI s CJIS EFTS version 7 Appendix F as well as the NIST M1 committee for both fingerprints and palm prints.
- Acquire at 1000 pixels per inch (ppi).
- Generate immediate feedback to the device operator of the quality of the images to permit Go/No Go qualitative assessments.
- Eliminate sequencing errors.
- Identify specific finger position and handle non-recordable information, e.g. bandages, worn surfaces, and amputations.
- Require maintenance and calibration that minimally impacts operations.
- Formats output information in compliance with ANSI/NIST-ITL 1-2000 data format interchange standards.
- We will comply with the significant standards in the field, including:
    - The Scientific Working Group on Friction Ridge Analysis, Study and Technology (SWGFAST) friction ridge impression digital image quality guidelines [1] call for capture at 1000 ppi or higher resolution with a grayscale at a minimum of 8 bits or color imaging at a minimum of 24 bits. The guidelines also call for storage of images without compression or with lossless compression as well as with a method to permit authentication. These guidelines are primarily for latent print comparisons.
    - The Criminal Justice Information System (CJIS) Electronic Fingerprint Transmission Specifications define the IAFIS Image Quality Specifications [2]. They call for a high fidelity image without any banding, streaking or other visual defects. Finer detail such as pores and incipient ridges are needed. Additionally the grayscale dynamic range must be captured with sufficient depth to support image enhancement and restoration algorithms. Specific requirements are stated for geometric image accuracy, modulation transfer function, signal-to-noise ratio, gray-scale range of image data, gray-scale linearity, and output gray level uniformity.
    - The InterNational Committee for Information Technology Standards (INCITS) has established a technical committee on biometrics (M1). The committee has promulgated generic standards for data interchange, common file formats, application program interfaces, profiles, and performance testing and reporting [3].
    - The National Institute of Standards and Technology (NIST) has published Special Publication 500-245 which sets forth an American National Standard for Information Systems Data Format for the Interchange of Fingerprint, Facial, & Scar Mark & Tattoo (SMT) Information (ANSI/NIST-ITL 10-2000) [4].

3. Background

In this section, we review relevant technologies involved in fingerprint and palm print capture, identifying advantages and disadvantages. We then list the kinds of uses to which these technologies are deployed and how they compare in automated fingerprint identification tests. This section ends with a description of our proposed HandShot ID System in light of the shortcomings noted in current technologies.

3.1. Current Fingerprint Technology

As described earlier in Section 2.1, there is tremendous demand to capture and compare fingerprints. Current technologies include the manual ink card system (3.1.1.) and inkless live-scan scanners (3.1.2). The sensor is the most important component of a fingerprint scanner. Almost all sensing elements can be classified as belonging to one of the families: optical sensors (3.1.3), solid-state sensors (3.1.4), ultrasonic sensors (3.1.5), or thermal-electric sensors (3.1.6). Each of these technologies is described below.

3.1.1. Manual Ink Cards

Although, the first fingerprint scanners were introduced 30 years ago, the manual ink-based technique is still commonly used. Ink cards are inexpensive, intuitive to use, and particularly amenable to "rolled" impressions that produce more information from the sides of the fingers than "flat" ("dab", "slap") impressions, the latter being generated by merely pressing a finger against a flat imprint area (no rolling). However, ink cards are messy and subject to too much and too little ink resulting in poor quality impressions and inconsistencies.

Ink cards can be converted to digital images, particularly for storage, retrieval, and comparison in databases and automated fingerprint identification systems (AFIS) have resulted. Ink cards are generally imaged at 500 pixels per inch (ppi) with at least an 8 bit grayscale resolution. Typical file size is 10MB (megabytes) per fingerprint card.

3.1.2. Inkless Live-scan Scanners

Ink cards are being replaced by "live-scan" technology where the friction ridge pattern is captured without ink from the live human subject and stored automatically as a digitized image. Live-scan systems are perhaps most typically seen in police booking centers. Generally, an "operator" will assist the subject and operate the instrumentation. Images from the subject's fingers permit the operator to make an initial assessment of the suitability of the images acquired and redo scans as necessary. These live-scan scanners often feed directly into computer networks and AFIS software systems and thus enable real-time identification and authentication of subjects. Some capture only fingers and others will also permit the capture of palm prints.

3.1.3 Optical Sensors

In commercial use, optical technology is widespread, internationally. The finger is placed on a coated platen, usually built of hard plastic but proprietary to each company. In most devices, a charged coupled device (CCD) converts the image of the fingerprint, with dark ridges and light valleys, into a digital signal. The brightness is either adjusted automatically (preferable) or manually (difficult), leading to the final image. Pros: most proven over time, withstand slight temperature fluctuations, fairly cheap, and resolutions up to 500 dpi. Cons: size, latent prints, coating and CCD arrays wear with age. Optical is the most implemented technology by a significant margin, developed mainly by Identicator, Identix, and Motorola.

In law-enforcement and security, the most common sensor is a Frustrated Total Internal Reflection (FTIR) optical system. Fingers are placed on a plastic or glass prism and light from another side of the prism is randomly scattered where ridges touch the surface (appearing dark) while light at the valleys is reflected back (appearing bright). This light is sensed through the third surface of the prism by a CCD or CMOS image sensor. Distortion is created in several ways, but most notably "trapezoidal" distortion occurs because the fingerprint plane is not parallel to the detector plane. This distortion is corrected optically or by software. A significant feature of such instrumentation is its large size due to the necessarily long optical path and thus they have not been made portable. A fresnel lens ("sheet prism") can replace a single large prism, but the quality of the image suffers. A fiber-optic platen can be used to permit direct imaging. Essentially, a CCD or CMOS array is positioned on the opposite side of a clear pane to where a finger is pressed. Thus, the intermediate lens is eliminated. However, the CCD or CMOS detectors have to cover the area to be imaged, resulting in a higher cost instrument. Electro-optical devices are built which detect differences in potential voltages across a polymer coating. The polymer will emit light into a photodiode array based upon the sensed potential.

3.1.4. Solid-state Sensors

Solid-state silicon sensors became commercially available in the mid 1990's to overcome size and cost problems as then perceived. The sensing can be based upon capacitive, thermal, electric field or piezoelectric methods—the most common of which is capacitive. Although, such systems are not easily deceived by a photograph, sensitive and accurate capacitive measurement is difficult. Moreover, salts from perspiration effect create significant variability in these systems. Finally, the thin coating of these devices is subject to electrostatic damage, corrosion, and wear (particularly scratches).

The silicon sensor acts as one plate of a capacitor, and the finger is the other. The capacitance between platen and the finger is converted into an 8-bit grayscale digital image. Pros: better image quality with less surface area, than optical (the chip is made of discreet rows and columns, between 200-300 lines in each direction on a 1cm x 1.5cm wafer), can be integrated in small devices. Cons: durability has yet to be proven, with the reduction in sensor size it is very important to ensure enrollment and verification. Primary developed by Veridicom (Lucent), recently by Infineon (Siemens) and Sony.

3.1.5. Ultrasonic Sensors

Ultrasonography can visualize the echogenic chambers between the ridges formed when the finger touches the detector surface. However, to date the instrumentation has been large and expensive. Ultrasonic sensors transmit acoustic waves and measures the distance based on the impedance of the finger, the platen, and air. Pros: capable of penetrating dirt and residue on the platen and the finger. Cons: difficult to assess its long-term performance since seldom used. Technology developed by Ultra-Scan Corporation (USC).

3.1.6. Thermal-electric Sensors

Thermal-electric technology is recent. Sweeping the finger across a sensor array captures successive images (slices), then special software reconstructs the whole image and returns a large (500 dpi) image of the fingerprint with 256 gray-scales. The sensor measures the temperature differential between the skin ridges and the air caught in the fingerprint valleys. This method provides a high quality image even on poor quality fingerprints (dry or worn with little depth between the peaks and valleys of the fingerprint). Pros: small, sweeping self-cleans the sensor, penetrates dirt and oil, works in low-temperature and high humidity environments, provides very big images of good quality. Cons: image quality depends on the users skill in using the scanner, the heating of the sensor array increases the power-consumption. Currently developed by Atmel, their FingerChip is the only product on the market. Systems employing sweeping of the finger can be built less expensively due to the need for fewer sensors, however some distortion can be introduced as the time domain corrections are imperfect.

3.2. Nail-to-Nail Rolled Impression (Capturing Sides of Fingers)

A significant hurdle for any automated system is to capture the information in the friction ridges of the sides of the fingers. Ink cards involve rolling the fingers “nail-to-nail” to permit the printing from both sides as well as palmar aspect of the fingers. A print of approximately three quarters of the circumference of a finger is thereby captured. There is significant additional information in the side prints that assists in distinguishing fingerprints. This information may be crucial to a partial latent print at the scene of a crime. It may be that sufficient information is present in the ridge detail of the palmar aspect of the finger for identification purposes by greater attention to Level III features, but current systems are based on this expanded print. Merely, photographing a hand placed on a glass platen, even with force, will not suffice to capture this expanded print. Thus, current live-scan systems require rolling each finger individually. This is a major drawback to many current fingerprint capture technologies. Our proposed HandShot ID System provides fingerprint and palm print capture that includes the palms, fingers, sides of the fingers and hands, and fingertips. The 3-D image models constructed in our HandShot ID System can be used to generate an equivalent 10 finger rolled print, among other uses.

3.3. Current Palm print Technology

Current palm prints capturing technology is concurrent with that of fingerprints, and usually serves as a byproduct, with optical devices as a mainstream. The leading companies include Motorola, Cross Match Technologies and NEC. Recently, there has been another direction of palm-print technology explored by Fujitsu, which instead of producing a palm surface image, outputs the pattern of blood veins in the palm. The device developed by Fujitsu is based on infrared light and thus contactless. However, because normal contact would not leave traces for this type of pattern, this technology is not of broad law enforcement use.

Academic research on palm prints has been focused on the analysis side. Palm prints have many creases as compared to fingerprints, and the heart-line, head-line, and life-line are rotational invariant. Gabor filters, wavelets, Fouries transformation, local texture energy, directional line energy, prominent palm line feature points, local palm print features, local gray level directional map, and morphological and Sobel edges based methods have been discussed in research literature. Our proposed HandShot ID System provides a robust means to capture palm prints, while also capturing finger prints (including the sides of the fingers and hands).

3.4. Uses of Current Fingerprint and Palm Print Technologies

Fingerprint technology is used to access networks and PCs, enter restricted areas, and to authorize transactions. Most international commercial deployments are one-to-one, written 1:1, in which the person is verified as the person matching the single stored print. In Asia, for example, mobile phones may require a fingerprint scan to operate as part of a theft deterrent. There are a number of "one-to-few" deployments in which individuals are matched against modest databases, typically of 10-50 users. Large-scale 1:N applications, in which a user is identified from a large fingerprint database, are classified as AFIS (Automated Fingerprint Identification System), as noted earlier.

Law-enforcement uses have been underscored throughout the earlier sections. The main civil applications of AFIS technology are: (1) background searches to screen job applicants in industries such as financial services and air travel; and (2) public benefits programs such as welfare issuance, aid to families with dependent children, etc. The technology is implemented to locate duplicate sets of fingerprints, which would indicate that a user is committing fraud. AFIS technology is also in a similar fashion in national ID programs. Background searches use ten fingerprints, while benefits and ID programs normally use two to four fingerprints.

According to the International Biometric Group a "largely untapped segment of the AFIS market" is what they call *transactional* AFIS. The increase in computing power and matching algorithms made possible for private entities to set up small-scale AFIS systems, for example, health care providers. These systems can be used to identify patients and providers from databases of tens to hundreds of thousands of fingerprint, with response times of few-minutes.

Our proposed HandShot ID System supports traditional, as well as, new and improved applications in criminal, security and commercial identification, recognition and authentication tasks.

3.5. Problems with Current Fingerprint and Palm Print Technologies

Besides the limitation on the ability of capturing sides of fingers discussed earlier (Section 3.2), other shortcomings exist, as discussed below.

The “biometric paradigm” views the fingerprint scanner as biometric signal acquisition. This primary signal will vary from presentation to presentation and will not allow direct pixel-based matching. Instead it requires a signal processing stage to construct a more invariant representation of this basic input signal; in this case, fingerprint minutiae. It is this invariant biometric data (the “template”) that permits the identification of an individual in a large database. So, proper abstraction of image details is crucial despite possible distortion, bias, or artifacts appearing in the image as a result of the capturing technology used.

Fingerprint identification requires not simply the ability to resolve ridges (100-300 μm), but also the ability to see smaller breaks in the ridge pattern; however the ability to resolve sweat pores (60-250 μm) is not necessary for general authentication. Most live-scan scanners operate at 500 ppi, consistent with most standards in the field. For latent print work, images are generally captured at a higher resolution, 1000 ppi, in order to analyze Level III detail. Conversion form 1,000 ppi to 500 ppi is trivial, but the reverse is not possible.

The digital image of finger friction ridges includes features, such as ridge bifurcations and ridge endings, collectively referred to as “minutiae.” These features may be recognized using an automatic feature extraction algorithm. Each feature is commonly represented by its location coordinates and ridge direction. Due to sensor noise and distortion in the imaging process, the feature extraction may miss some minutiae or generate artifactual minutiae. Further, due to the elasticity of the skin, the relationship between minutiae may be distorted from one impression to the next. Finally, a matching algorithm scores the similarity between sets of fingerprint images after compensating for scale, rotation, and translation.

Because of the high quality capturing possible by our proposed HandShot ID System, resulting images, even when translated to standard formats may have far less distortion than possible with most other current technologies.

3.6. Evaluation of Current Technologies

Automated fingerprint identification systems (AFIS) are compared by system performance criteria such as "failure-to-enroll rates" FER, "false acceptance rates" FAR, and "false rejection rates" FRR. Failure to enroll occurs from rejection of poor quality images from non-cooperative subjects, dirty fingers, platen contamination, and from the approximate 3% of the population with very faint or nonexistent friction ridges. Current state-of-the-art FAR and FER are both approximately 2%. There is a trade-off in the decision threshold between acceptance sensitivity and rejection error (manifest in a receiver operating characteristic curve); current commercial systems typically operate at the recommended equal error rate (EER) in which FER = FRR. Higher security biometric systems will operate at a lower FAR. High-performance fingerprint recognition systems can support error rates in the range of 10^{-6} for false acceptance and 10^{-4} for false rejection, although these vendor claims are often not born out in practice. Improvements in error rates could be achieved by 1) eliminating human entry and sequencing errors, 2) improved platen cleaning and eliminating platen contamination, 3) higher quality image data, and 4) more image data (such as Level III detail described in Section 2.1).

In comparing performances of current technologies, we adopt the following definitions. A "matcher" implicitly performs a battery of statistical tests between the image X provided by the scanner and the images $Y(i)$ present in the database corresponding to the identities $i \in I$. The underlying hypotheses for each of these tests are: H0: $i(X) \neq i$, and H1: $i(X) = i$. Define False Acceptance Rate (FAR) and False Rejection Rate (FRR) as the probability to make the following mistakes:

- **FAR** = type I error = α. That is, (possibly) an impostor is granted access to a secure area, or an innocent individual in the FBI database is identified as the primary suspect for committing a crime.
- **FRR** = type II error = β. That is, a genuine employee is denied access to his lab, or a guilty individual is not identified as the primary suspect for committing a crime.

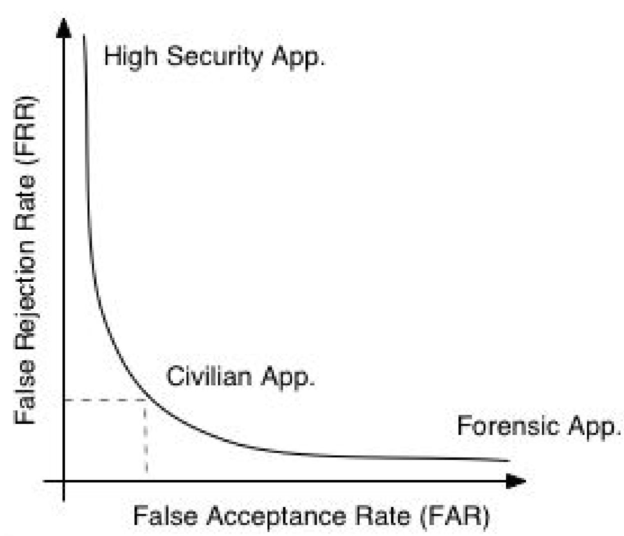


Figure 1. False Rejection Rates (FRR) versus False Acceptance Rates (FAR) in terms of applications.

Company	Type	FAR	FRR
Biometrix Int. (biometrix.at)	Capacitative	1 in 10ML	1 in 100000
Sony (sony.com)	Capacitative	1 in 100000	1 in 100
NEC (nectech.com)	Capacitative	1 in 2ML	1 in 50000
Startek (startek.com.tw)	Optical	1 in 100000	1 in 30
Biolink USA (biolinkusa.com)	Optical	1 in 1BL	1 in 10000
Bergdata Biometrics (bergdata.com)	NA	1 in 500000	1 in 1000
Ultra-Scan Corp. (ultra-scan.com)	Ultrasound	1 in 500000	1 in 2000

Figure 2. Error rates claimed by various vendors. Seem unrealistic in comparison to the results from the Fingerprint Verification Competition 2002 (see Figure 3).

The FBI requirement for an automatic fingerprint identification system are a FAR less than 1 in 100 people, and a FRR of 1 in 5 people. Below is a table that summarizes the results of the fingerprint verification competition 2002. The results of the fingerprint verification competition 2004 will be released on April 15.

Developer	Algorithm	FAR (FRR 1/100)	FAR (FRR 1/1000)	FAR (FRR 0)	Match time
Bioscrypt Inc.	PA15	1.5 in 1000	2.8 in 1000	3.8 in 1000	1.97 sec
NA	PA27	2.8 in 1000	5.6 in 1000	14.4 in 1000	1.98 sec
NA	PB27	3.4 in 1000	5.9 in 1000	12.9 in 1000	1.13 sec
Bioscrypt Inc.	PB15	7.7 in 1000	10.4 in 1000	12.9 in 1000	0.22 sec
Siemens AG	PB05	14.6 in 1000	18.7 in 1000	22.9 in 1000	0.52 sec

Figure 3. Results of best algorithms of the Fingerprint Verification Competition 2002.

FRR	FAR (twin-twin)	FAR (twin-nontwin)
1.1 in 100	8.5 in 100	2.2 in 100
2.2 in 100	4.8 in 100	1.0 in 100
3.0 in 100	2.1 in 100	0.5 in 100
3.5 in 100	1.1 in 100	0.3 in 100

Figure 4. Results of best algorithm in Salil (2001).

Current algorithms yield results decent for some civil and forensic applications, but not good enough for the escalating need described in Section 2.1. What is needed is improved image capturing technology for fingerprints and palm prints. We propose our HandShot ID System as a means to acquire more detailed images efficiently and economically.

3.7. HandShot Proposed Solution

We propose to improve and advance the current state of biometric technology by capturing friction ridge detail data comparable to 10 rolled-equivalent fingerprints and palm prints, where capturing is simultaneous and achieved without rolling. Thus, our proposal for the HandShot ID System will substantially enhance the nation's security, criminal attribution systems, as well as potentially preventing many fraudulent transactions by means of a less error-prone, high-throughput, information rich image acquisition system.

Our HandShot ID System obtains well-focused, high-resolution images through the use of multiple cameras. We obtain high-contrast, surface-topology-discriminant images in HandShot through the use of oblique blue light and special spot lights from various angles operating sequentially in millions of a second. We obviate the need for an operator to individually roll fingers through the use of cameras positioned at different angles. By obviating the rolling of fingers, we enable truly high-throughput processing. Here is a summary.

Highlights of our HandShot ID System

- Information-rich Data Acquisition: Our proposed HandShot ID System will capture images of all 10 rolled-equivalent finger and both palm friction ridge patterns and minutiae. Furthermore, overlapping images will permit correction and fills of coverage area that might otherwise be lost by single signal acquisition.
- High-Resolution: Our proposed HandShot ID System obtains well-focused, high-resolution images through the use of multiple cameras positioned appropriately for the position and topology of each area of the hand. We will achieve imaging at 1,000 ppi and resolution permitting Level III analysis.
- High-Contrast: Our proposed HandShot ID System obtains high-contrast, surface-topology-discriminant images through the use of oblique blue light from various angles flashed sequentially. Oblique light permits shadowing that will maximize the 3D surface structure. We will use monochromatic blue light to improve surface reflectivity.
- High-Throughput: Images will be taken of all surfaces simultaneously. We obviate the need for an operator to individually roll fingers and thus enable truly high-throughput processing. Thus, we will enable complete data capture within less than 5 seconds.
- Less Error-Prone: We eliminate sequencing errors, in which an operator inadvertently rolls the wrong finger, by physically distinct right and left hand cradles and simultaneous capture of all 10 digits and both palms.
- Operator-free Operations: By eliminating the need for individual finger rolling and through automated "go/no-go" decisions, we enable operator-free instrumental operation.
- Less Maintenance: We eliminate the need for routine cleaning of a glass platen by eliminating any glass platen and instead directly imaging the hand in the air.
- Hygienic Operation: By eliminating finger touching of a surface, we eliminate hygiene concerns.

The concept of direct optical imaging is not really new. However, the ability to generate well-focused, high-contrast, high-resolution images of all appropriate surfaces is a very difficult problem and potential solutions have previously been cost prohibitive. Our project, HandShot ID, is now enabled by the concurrence of three factors:

- The development of practical high-resolution commercial off-the-shelf (COTS) CMOS/CCD cameras.
- The development of blue LEDs and their use to create a series of shadow-enhanced images.
- The internationally-renown and extensive machine vision expertise of Carnegie Mellon University, particularly to appropriately warp and stitch together image tiles.

Our HandShot ID System will generate image data files compatible with current law enforcement community AFIS systems. We are not proposing a print matching system. A description of the specific performance details for the working prototype device (named HandShot ID) that we intend to develop and deliver to NIJ are listed in Section 2.3.

4. Research Design and Metrics

The benefits of our proposed HandShot ID System have been underscored in the previous sections. In this section, we describe our HandShot ID System as a technology for the unprecedented demand currently facing fingerprint and palm print identification, recognition, and authentication tasks. Our HandShot ID System captures more detailed and complete print information accurately, robustly, quickly, and efficiently. HandShot achieves this by controlling an integrated network of cameras and lights to produce a rapid sequence of high resolution pictures of a person's hands and then using sophisticated algorithms to combine the views into standard print formats. Not only are all parts of the palms, fingerprints, sides of the fingers and fingertips captured, but the images are captured in milliseconds. Each camera takes a sequence of 5 consecutive images, while special effect lights change the position of shadows appearing on the hands. A final composite image is composed incorporating the different views, which are images captured from a variety of angles and under changing illumination effects to produce detailed, "shadow less" images. The result is a high-contrast, high-resolution imaging system to simultaneously obtain 1000 ppi images of all 10 rolled-equivalent finger and both palm friction ridge patterns and minutiae. This is all achieved without operator manipulation of the hands. Performance specifications for the HandShot ID System are listed in Section 2.3. A comparison of the HandShot ID System to current technology appears in Section 3.7. The following sections describe how HandShot achieves these feats.

The overall approach taken in the HandShot ID System is inspired (in part) by a similar system designed, implemented and currently in use by Ralph Gross, a key person on this proposal. Ralph's prior work uses digital video cameras to capture face and expression images. His system uses multiple video cameras with controlled lighting to perform 360^0 face image captures in milliseconds. While there are important differences, Ralph's prior work provides an existence proof of a system similar to the HandShot ID System.

4.1. System Overview

The HandShot ID System is an image capture station that contains the camera network, lighting system, hand positioning system, and an internal computer to acquire the images of all 10 fingerprints and both palm prints simultaneously. Only power lines and data cables connect to the station. An external computer can communicate with, configure, and/or control the standalone HandShot capture station, but no external machine is required for capture.

Figure 5. HandShot ID Capture Station

Both hands are simultaneously inserted into vertical slots in the frontal face of the HandShot image capture station. The hands are spread and positioned against the inside of the outer walls, automatically triggering the images to be taken. Optionally, image capture can be triggered by an operator using an external computer, but no such operator is required. In the absence of an operator, capture is triggered by detection of the inserted hands appearing in proper positions and orientation.

Cameras and light sources are mounted internally. Each of the cameras are placed and directed by positioning supports. The light sources are located physically behind the plane of the cameras to prevent direct exposure. All internal surfaces have an absorbent black matte finish or black velvet lining.

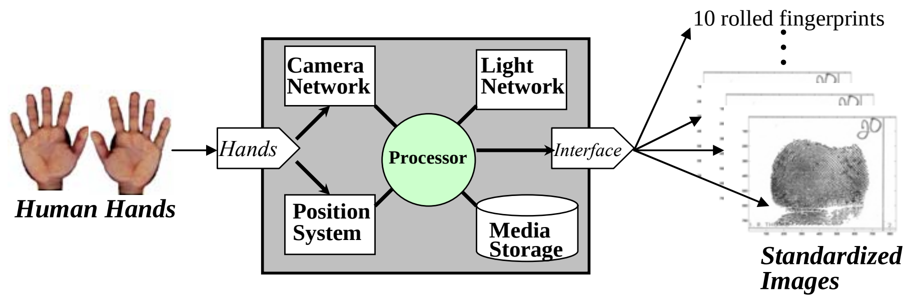


Figure 6. Architectural Block Diagram of the HandShot ID System

We envision that an eventual commercialization product could provide a ruggedized version for "real-world" abusive operation and possibly for outdoor or field use. The HandShot ID System could be made wireless and portable, but doing so is outside the scope of this proposal. The current cabinet size is 18in x 14in x14in, but may vary based on optical path lengths necessary and specific to the camera models, lenses and lights used.

An architectural overview of the HandShot ID System appears in Figure 6. Operation is controlled by a computer processor, which is directly connected to the network of cameras, network of lights, hand positioning switch, and hard drive (or equivalent media) storage. When both hands are inserted into the capture station, automated capture mode, which does not involve a human operator, proceeds as follows:

1	The hand Positioning System alerts the user by displaying a green (rather than previously red light) on the outside of the unit. The Positioning System also alerts the Processor.
2	The processor sends an "are you ready" signal to each camera in the network.
3	Each cameras responds to the Processor in the affirmative if its auto focus has been successful in identifying its targeted field. Sometimes because of the size of the hand, for example, a camera may not be able to send an affirmative response.
4	Upon sufficient response from the cameras, the Processors lights the backlights and starts the automated capture sequence timer.
5	At first, each camera takes a picture (storing the information local to the camera). Then, in the next time step (within milliseconds), a special effect light will shine and the cameras will then take the next picture. This process continues through 4 special effect lights, providing a total of 5 sequenced pictures from each camera. These images are then sent to the Processor which stores them on internal media (a hard drive or equivalent).

Figure 7. Basic Automated Capture Algorithm of the HandShot ID System

4.2. HandShot's Sub-Systems

4.2.1. Camera Sub-System

The number of cameras required for the HandShot ID System to achieve both coverage (spatial area and 3D topographic surface contours) and resolution (to permit analysis of third level minutiae) is from 7 to 18 cameras, depending on the camera and lens used. In drafting this proposal, 3 different cameras were evaluated. For any camera used, the size of the in-focus capture area at 1000 ppi must be computed. This is proportional to the pixel resolution of the camera [57]. In general, more expensive cameras have a greater pixel resolution and therefore a larger 1000ppi capture area. Figure 8 shows a comparison of 3 cameras. It would require seven

16 megapixel cameras (for a total of $8400 per hand), fourteen 6 megapixel cameras (for a total of $7000 per hand), or eighteen 5 megapixel cameras (for a total of $5400 per hand). All prices reflect current street retail prices.

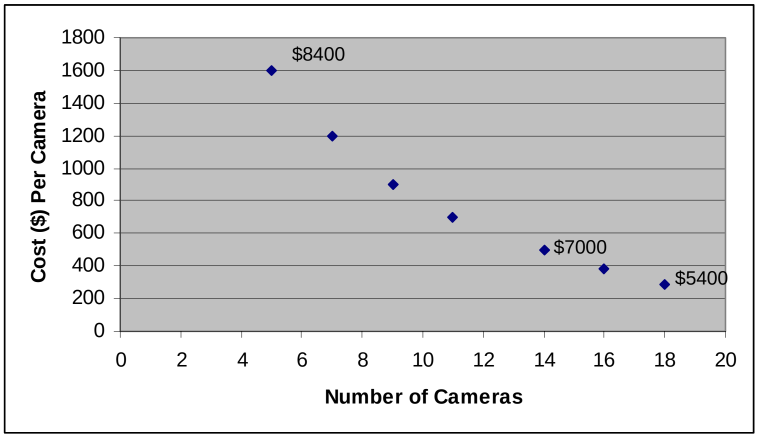


Figure 8. Comparison of Camera costs based on number of cameras needed.

Using 18 Kodak DX7590 cameras with 1:1 macro lens was the economical option ($5400 per hand). All further configuration information in this proposal therefore refers to this camera, unless otherwise noted or obvious from content. The version of the HandShot ID prototype delivered under this proposal will use the most economical camera option found on the market at the time.

Figure 9. These cameras are really a charge-coupled device (CCD) or "camera on a chip" and may be purchased in retail format, as shown on left, or in a more space efficient (unpackaged format), as exposed in the camera on the right.

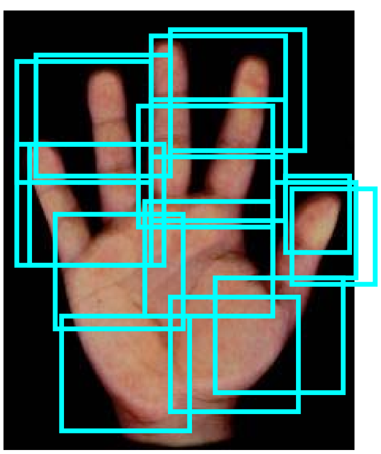


Figure 10. Demonstration of overlapping in-focus capture areas at 1000 ppi. Each box shows the viewing area of a camera in the network. Some of the cameras are at different angles (to capture between finger, finger tip and thumb content).

Below is a discussion of the arrangement of 18 Kodak cameras in the HandShot ID System given the camera's in-focus capture area of 2.5in x 2in.

Overall: One camera is used for a low-resolution overall image of the hand. This overall image assists tiling of the high-resolution images and permits filling of any gaps appearing between high-resolution images. This image is useful in recognizing and locating the hand, palm, and digit positions. We note that the International Review Committee in the Brandon Mayfield case declared: "If the FBI had insisted on more information (.e.g., an image with scale for proper enlarging and an overall shot for orientation and proper finger determination), this error may have been avoided" (RB Stacey, A Report on the Erroneous Fingerprint Individualization in the Madrid Train Bombing case, JFI 54:712, 2004). Furthermore, this overall image will be useful in recognition of "non-recordable" areas. Moreover, this image is used to assess adequacy of hand positioning and to detect hand motion. This image will be displayed to the operator for initial "go/no-go" decisions and/or feedback to the user.

Palms: Six cameras will be used to acquire overlapping images that will span the potential palm area. These cameras will have little or no tilt angle relative to the plane of the hand. They will require sufficient distance from the palm to permit the depth of field needed.

Four long fingers: Six cameras will be used to acquire overlapping images of the four long fingers. Two sets of two cameras will provide for two fingers at a time. Four additional cameras at approximately 38^o angles will capture the sides and palmar aspects of the distal or proximal half of the length of two digits and part of the thumb. The more distal pair of cameras will require vertical tilting to permit capture of the fingertips.

Thumb: An additional camera will be required to acquire an additional overlapping image of the thumb. The thumb is anatomically positioned at right angle and rotated as compared to the other digits. Two cameras will capture the sides and palmar aspect of the thumb, but a third is required to capture the fingertip.

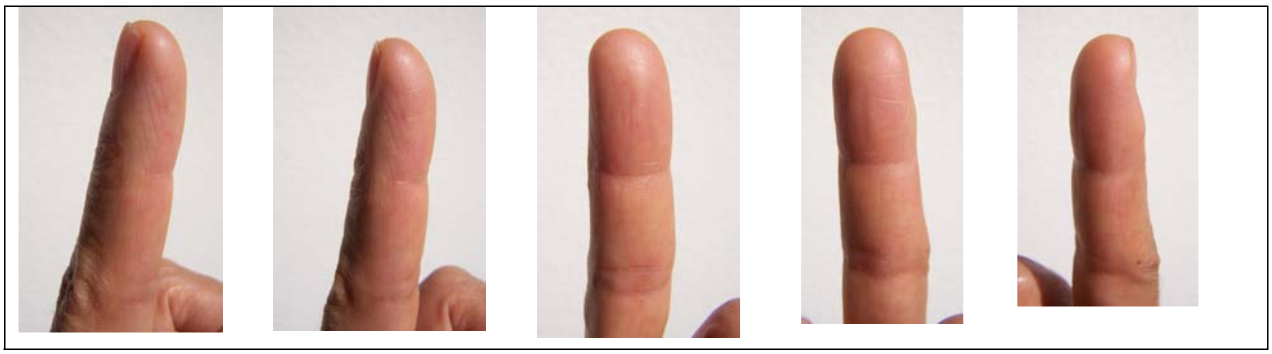


Figure 11. Demonstration of different camera views of the same finger. Notice also the varying shadow locations appearing in different images. Because the lights appear differently, we use carefully control shadowing and account for the curvature of the fingers and hands to compose a final image from multiple views that is rendered as a highly detailed "shadow less" image!

4.2.2. Camera Calibration

In order to extract 3D information from images, we have to be able to relate pixels in the image acquired by our capture device to real world coordinates. This can be achieved by a very well understood computer vision process called camera calibration [68]. During calibration both the extrinsic parameters (relating location and orientation of the camera reference frame to a know world reference frame) and intrinsic parameters (relating image pixel coordinates with corresponding coordinates in the camera reference frame) of the camera are computed. Assuming the camera positions inside the capturing device do not change, calibration has to be performed only once. Efficient algorithms are available to calibrate multiple cameras simultaneously [66].

4.2.3. Lighting Sub-System

Conventional light source considerations of interest to direct imaging have not appeared as an issue in current optical systems. It is our belief that insufficient attention has been given to this aspect of impression imaging systems. We particularly concern ourselves with three aspects:

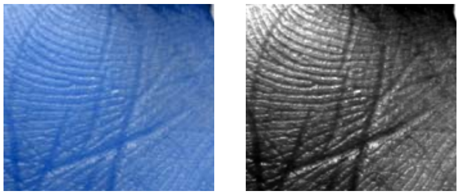
Wavelength: We will specifically use newly available blue light emitting diodes (LEDs). While such sources are both relatively cheap and reliable, they will enhance our ability to achieve contrast. Longer wavelengths (redder hues) will penetrate the skin tissue, whereas the shorter wavelengths (bluer hues) will not and hence better characterize surfaces. However, total greater skin reflectance generally increases at higher wavelengths because very little of the reflectance is due to the thin keratinous "stratum corneum" of the epidermal surface layer of the skin [see: http://www.cis.upenn.edu/~elli/tech-report.skin.pdf]. Also, brown melanocytic pigmentation is not consistent or uniform and thus may mask features of minutiae.

Monochromatic light will enhance sharpness, but we see no need for coherent or collimated light.

Directionality: We can take advantage of oblique lighting to produce shadows that will highlight the surface morphology and contrast ridges from valleys. This easily engineered by off-setting the light source from the camera-target axis. However, this will require off-setting in two directions to shadow each side of a ridge. Further, because not all ridges are unidirectional, we will offset in a total of four directions. Thus, we intend four sequential flashes from four different LEDs or LED banks. By controlling the use of shadows, we can produce higher quality, shadowless images.

Timing: Precisely because we wish to minimize potential motion distortion, we contemplate powerful, rapid flashes of light within milliseconds. Deployed light sources must be capable of such operations.

(a)



(b)

Figure 12. Example of viewing area (a) with magnification (b) under one illumination condition with blue light (on the left), which was subsequently converted to grayscale for palmprint extraction (on the right).

4.3. Print Acquisition

4.3.1. Hand Detection and Registration

A method to position and place the hands is needed to permit the cameras to properly focus on the hand topology, as well as to inhibit hand movement. Early efforts to use hand guides were often not wholly satisfactory. These systems have largely consisted of bars acting as finger guides. We believe that the most important and consistent landmark is the wrist. We envision the image capture station housing with a vertical rectangular slot in the front face, in which the hand is inserted, but with a semicircular cutout in the outer lip against which a person would fit his or her wrist. The back of the person's hand would rest against the inside of the outer wall of the image capture station housing. A post inside the image capture station housing against which the person would rest his or her thumb. We will explore the placement of an additional post inside the image capture station housing to limit the spread of the limit finger—although this would result in a small gap in the data acquisition of the side of this digit. We may also explore subtle surface molding to help guide fingers, but we would not want any such guides to obstruct camera views.

4.3.2. Multiple View Combination

While the physical setup of the capturing device considerably reduces the expected variability of hand positions in the captured images, it will not completely eliminate it. We anticipate small variations in hand orientation and finger positions (e.g. distances between the individual fingers). In order to precisely localize the hand and fingers in all images to pixel accuracy for rolled print extraction, we propose to employ a hand model based on Active Appearance Models (AAMs).

AAMs are generative parametric models that have been used successfully in the past to track faces and hands in image sequences [58, 59, 65]. AAMs combine separate linear models of hand shape and appearance, computed from labeled training images. The 2D shape model is defined by a 2D triangulated mesh and in particular the vertex locations of the mesh. See Figure 13.

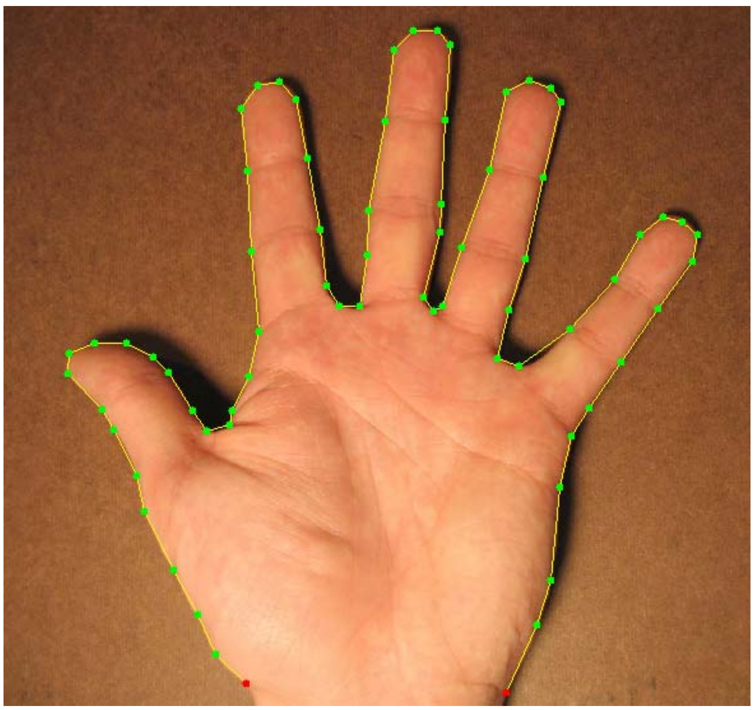


Figure 13. Hand with overlaid AAM vertices.

Using a set of training images in which the vertex locations of the mesh have been manually located and marked, a linear model describing the shape variations in the dataset is computed using Principal Component Analysis (PCA) [64]. The shape model then consists of the mean hand shape and the dominant modes of shape variations. The appearance of the AAM is defined as the pixel values within the normalized mean shape. Similar to the shape model, a linear model of the appearance variation is computed from the labeled training set, again using PCA. The combination of the shape and appearance models forms the Active Appearance Model. Once a model is computed from training data, it can be fitted to previously unseen hand images using the very efficient inverse compositional algorithm [65]. This algorithm has been shown to accuractly fit a face model to previously unseen images in less than 5 ms using standard

PC hardware [65]. Once fitted, the model can be used to accurately extract arbitrary portions of the hand, e.g. the fingertips and the palm.

A variety of extensions to the basic framework already exist for e.g. the extraction of 3D shapes (from single images) [70], for dealing with occlusions and missing data [60], and for fitting a single AAM simultaneously to multiple images/views [62]. In prior work we have also shown that we can compute accurate shape models for a large set of faces using labeled training data from only a small subset of subjects [61]. Due to the relatively small amount of shape variation expected in the image data acquired by our capturing device, these results directly apply here. As a consequence, a generic hand model trained off-line with independent training data can be used during on-line operation of the capturing device.

Active Appearance Models can be fitted very accurately provided that the fitting algorithm is initialized comparatively close to the true object location in the image [65]. We propose to use a background subtraction algorithm to approximately locate the hand in images acquired by the proposed capture device. Background subtraction is a well-studied problem in computer vision [67, 69]. The algorithms typically maintain a representation of the unoccupied scene (the background) and subtract it from images in which the object of interest, i.e. the hand, is visible. Pixels corresponding to the foreground object can then be identified. Using morphological image operations and connected component analysis [63] a continuous foreground region is extracted, which serves as initialization location for the AAM hand model. In the context of the proposed capturing device, background subtraction can be expected to perform extremely well, since the background is uniform and static, all light sources inside the device are tightly controlled, and all the cameras are static.

4.4. Image to Print Conversion

The final results from the HandShot ID System are images of prints for a variety of existing and new purposes. In order to be compliant with existing practices and uses, the HandShot ID System generates 10 rolled print equivalents. This is done by first using the active models to simulate the application of pressure to the 3-D model of the HandShot imaged hand. Simulating the application of pressure provides comparable distortion to that of rolling the print. We then use the shadowing appearing under different illumination effects to improve the ridge contrast information, thereby producing a composite image whose final resolution is improved by the knowledge acquired from the different shadow contrasts. The algorithm we use was created by Dr. Sweeney for this purpose. It uses a variable threshold voting system to binarize the image, where the threshold is based on an entropy measure of geographical similarity appearing in parts of the image that accounts for lighting effects and finger curvature. By removing these effects, we can get more significant contrast in different parts of different views and the combine those parts to construct a highly detailed “shadow free” image. The final composite can be rendered as a black/white print comparable to a rolled print.

5. Implications for Policy and Practice

We have stated in Section 3.7 that we will improve current fingerprint and palm print impression acquisition in several ways--to include increased quantity and quality of ridge data and do so in a faster, more convenient, operator-independent fashion.

By improving throughput and decreasing operator demand, we should improve electronic submissions to the FBI and state systems. Rapid electronic submission and database searching is key to law enforcement purposes. The Government Accounting Office (GAO) recently reported "maximizing the benefits of rapid responses under IAFIS depends largely on how quickly criminal fingerprints are submitted by local and state law enforcement agencies. Although, submission time had averaged 188 days seven years ago, it still averaged 40 days in the period between October 2002 and May 2003. Electronic fingerprint submissions continue to grow, but many jurisdictions lack resources to do this. In 1999 when IAFIS was implemented 45% of print submissions were electronic; in the first four months of 2003 70% were electronic. Only 30% of the fingerprints are currently submitted on the day of arrest. Many leads grow cold within hours of the perpetration of a crime.

High volume booking centers and border entry points can particularly benefit by a system that will acquire the finger and palm print data within seconds. This is not simply a matter of convenience, but translates into significant operator salary costs and improved flow of operations.

The elimination of an operator requirement and the near-instant data capture means that the HandShot ID system could be placed at entrance sites to secure buildings and premises as a more thorough and less vulnerable biometric access system. Operator independence, and particularly the elimination of the need for rolling fingers, paves the way for portable units. Although large, it is not hard to imagine such a machine in a police vehicle. Moreover, operator independence makes possible widespread deployed within general commerce. The prospect of replacing credit cards by a biometric device becomes more salient. The dollar impact of fraud and identity theft is measured in the billions of dollars, let alone the toll on innocent victims. The security infrastructure of the nation as a whole will improve if biometric identification and authentication devices become widespread and routine within the civilian community.

Perhaps most important is the improvement in the integrity of the entire print impression enterprise. We believe we will substantially improve FAR and FRR system performance characteristics. We specifically eliminate a significant source of error—the inadvertent print of a wrong finger by the officer or technician. We eliminate such sequencing errors through simultaneous capture of all 10 fingers and both palms. We also eliminate artifactual features from dirty or contaminated platens.

We will also improve the quantity and quality of data acquired which will also help prevent errors. It seems clear that the Brandon Mayfield case would not have occurred had the system had more data (and possibly better data) to compare. Palm prints have only recently been routinely taken and still not in all situations. By capturing palm prints routinely, we will substantially increase the information captured. We will eliminate platen smudging and and other obstructions that might potentially obscure some features. More significantly, we believe that we will enhance the resolution and coverage by use of multiple overlapping camera images and multiple flash exposures. We intend to capture increased minutiae data through higher contrast and higher resolution. Such a system will markedly increase robustness through redundancy and additional information. Poorer quality in one aspect of an image can be overcome by better quality from another overlapping image.

A possible impediment to broad impact could be an excessive instrumentation cost. Current scanners sell for approximately $30,000. Despite the many cameras used in this application we believe that the HandShot ID system could effectively compete in the marketplace. We believe this possible with current pricing structure, however there is every reason to believe that further dramatic price reductions in digital imaging chips will continue through the period of this project.

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