Effect of human-biometric sensor interaction on fingerprint matching performance, image quality and minutiae count

Eric P. Kukula*, Christine R. Blomeke, Shimon K. Modi and Stephen J. Elliott

Biometric Standards, Performance and Assurance (BSPA) Laboratory,
Department of Industrial Technology,
Purdue University,
West Lafayette, Indiana, USA
E-mail: kukula@purdue.edu
E-mail: blomekec@purdue.edu
E-mail: modis@purdue.edu
E-mail: Elliott@purdue.edu
*Corresponding author

Abstract: This study investigated the effect of force levels (3, 5, 7, 9 and 11N) on fingerprint matching performance, image quality scores and minutiae count between optical and capacitance sensors. Three images were collected from the right index fingers of 75 participants for each sensing technology. Descriptive statistics analysis of variance and Kruskal-Wallis non-parametric tests were conducted to assess significant differences in minutiae counts and image quality scores, by force level. The results reveal a significant difference in image quality score by force level and sensor technology in contrast to minutiae count for the capacitance sensor. The image quality score is one of the many factors that influence the system matching performance, yet the removal of low quality images does not improve the system performance at each force level. Further research is needed to identify other manipulatable factors to improve the interaction between a user and device and the subsequent matching performance.

Keywords: biometrics; fingerprint recognition; human-biometric sensor interaction; HBSI; image quality; performance; computer security.

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Biographical notes: Eric P. Kukula received his PhD in Technology with a specialisation in Computational Science in 2008 and MS in Technology with specialisation in Information Security in 2004, both from Purdue University. He is a Visiting Assistant Professor and Senior Researcher in BSPA Laboratory and is currently teaching a graduate level course in AIDC Technologies and researches the HBSI which investigates the interaction between humans, sensors, systems and environmental conditions to determine the impact on performance and usability of biometric devices. He is an active member in developing biometric standards in the USA (INCITS M1) and internationally (ISO/IEC JTC1 SC37) in biometrics testing and reporting. In addition, he is a member of IEEE and HFES.

Christine R. Blomeke is a Graduate Research Assistant in the Biometric Standards, Performance, and Assurance Laboratory in the Department of Industrial Technology at Purdue University. She is pursuing her PhD in Technology. She has been involved with biometric research for three years and her research interests include: determining ways to improve fingerprint image quality in populations that typically have poor image quality, the perceptions and realities of the cleanliness of contact biometric devices and investigating the usability of devices by aging populations.

Shimon K. Modi is the Director of Research of the Biometric Standards, Performance and Assurance Laboratory at Purdue University and currently teaches a graduate level class on Application of Biometric Technologies. He received his PhD in Technology in 2008. His PhD dissertation was related to statistical testing and analysis of fingerprint sensor interoperability on system performance. He has a Masters in Technology with specialisation in Information Security from the Center for Education and Research in Information Assurance and Security (CERIAS) and Bachelor in Computer Science from Purdue University.

Stephen J. Elliott is an Associate Professor and Assistant Department Head of the Department of Industrial Technology at Purdue University and serves as the Director of the Biometric Standards, Performance and Assurance Lab (BSPA). His main interests include biometrics, security, biometric performance as well as pedagogical research in distance education. In those areas, he has published more than 15 journal articles and 35 conference proceedings. He is the Vice Chair of Ballots and Membership for INCITS M1 Biometrics Committee and has served on ISO IEC JTC1 SC37 Biometric Sub-committee.

1 Introduction

Biometric technology is defined as the automated recognition of behavioural and physiological characteristics of an individual (International Organization for Standardization, 2007). An important question that has received insufficient attention has to do with how individuals should interact with a biometric device to obtain the most suitable samples for matching with that particular system. A non-exhaustive list of factors that would likely influence users' behaviour includes information about the intended users themselves and their knowledge about the system, the environment, the application and the design of the system/device/sensor. Ultimately, the success of biometric technologies relies on the sensors' ability to collect and extract the biometric characteristics from different individuals. If most individuals experience failures during interaction, these failures may cause individuals, organisations and government to seek other security technologies.

The authors have undertaken the task of answering this important question through researching the human-biometric sensor interaction (HBSI). HBSI is an interdisciplinary research area within the field of biometrics that focuses on the interaction between the user and the biometric system to better understand how individuals use biometric devices to uncover the issues and errors users knowingly and unknowingly generate when attempting to use a particular biometric system (Elliott et al., 2007; Kukula, 2007; Kukula, 2008; Kukula et al., 2008; Kukula and Elliott, 2006; Kukula et al., 2007a, 2007b, 2007c). This research area attempts to understand the tasks, movements and behaviours users execute when they encounter different biometric modalities. This research area frames a challenge for the biometrics community: while the algorithms are continually improving, there remain individuals who cannot successfully interact with the biometric sensor(s) or provide the system with images or samples of sufficient quality to achieve satisfactory results. Therefore, the goal of HBSI research is to understand user movements, behaviours and problems so as to modify the user's interaction with the sensor through training and education with the objective of capturing better quality samples or recommend design alterations for biometric devices, processes or systems that better accommodate user limitations to reduce the quantity of unusable or unacquired biometric samples.

2 Motivation and previous literature

The motivation for this research is to determine the impact of human interaction with fingerprint sensors and the implications on image quality and subsequent algorithm performance. The significance of user interaction with various fingerprint recognition sensor technologies is apparent, given that fingerprint recognition is the most widely used of the biometric technologies, with popular applications in law enforcement [e.g., the integrated automated fingerprint identification system (IAFIS)], access control, time and attendance recordkeeping and personal computer/network access. The current biometrics industry report published by the IBG (2006) states that fingerprint recognition holds approximately 44% of the biometric market. Traditionally, this high market share has been attributed to law enforcement applications, but over the last two years, the list of applications for fingerprint recognition technologies has grown tremendously. This expansion is due, in part, to the rapid evolution of sensors and the expansion of applications beyond law enforcement and computer desktop single sign-on solutions to personal data assistants, mobile phones, laptop computers, desktop keyboards, mice and universal serial bus (USB) flash media drives, to name a few. In particular, the growth (in terms of volume) of one fingerprint vendor's sales reached new highs in fiscal year 2006 – shipping one million sensors between 1998–2003, four million between 2003–2005 and five million sensors in 2006 (Burke, 2006). As fingerprint recognition applications continue to become more pervasive, the biometric community must appreciate the impact that different types of human interaction have on performance of the biometric system, but also examine if there are differences in human interaction characteristics and system performance among the various fingerprint sensing technologies.

Original work by Kang et al. (2003) examined finger force and indicated that force does have an impact on quality, but did not specify quantitative measures. Instead, this research classified force as low (softly pressing), middle (normally pressing) and high (strongly pressing). Edwards et al. (2006) noted the relationship between finger contact area, pressure applied and other physical characteristics and stated that by analysing the finger pressure and contact area, it is possible to enhance fingerprint systems. Based on the work of Kang et al. (2003), the authors conducted experiments in Kukula et al. (2007) to quantitatively assess the impact of fingerprint pressing force on both image quality and the number of detected minutiae on fingerprint image quality as it is documented that image quality has an impact on the performance of biometric matching algorithms (Jain et al., 2005; Modi and Elliott, 2006; Tabassi and Wilson, 2005; Yao et al., 2004). Results of Kukula et al. (2007) revealed that there was no incremental benefit in terms of image quality when using more than 9N when interacting with an optical fingerprint sensor in one particular experiment. A second experiment further investigated the 3N–9N interval, with results indicating that optimal image quality scores were obtained with a subject pool of 43 people in the 5N–7N force level range. However, it should not be assumed that this force level range is optimal for other fingerprint sensing technologies, offering yet additional research opportunities.

3 The authors' approach

The purpose of this research was to perform a comparative evaluation of optical and capacitance fingerprint sensors to determine if fingerprint sensing technologies are affected by finger force, as discussed in Kang et al. (2003) and Kukula et al. (2007). The research conducted in this paper followed the methodology of experiment 2 in Kukula et al. (2007), but was modified to include the capacitance sensor. Five force levels were used and measured in Newtons (N): 3N, 5N, 7N, 9N and 11N. The force levels were measured with a dual-range force sensor. Interaction was limited to the subject's right index finger for both sensors to minimise the variability of measurement relative to dexterity and finger size. Variability that naturally occurs between individuals was treated as an uncontrollable factor. Once the fingerprint samples were collected, the prints were analysed using commercially available quality analysis software. The following variables were reported by the software: image quality score, minutiae and the number of core(s)/delta(s). The image quality score ranged from 0–99, with zero (0) being the lowest possible quality image score and 99 being the highest possible quality score. Fingerprint feature extraction and feature matching was performed using the Neurotechnologija VeriFinger 5.0 algorithm. Several different metrics can be used for analysing matching performance of a dataset; the authors used false non-match rates (FNMR) and false match rates (FMR) to determine the performance of different force levels. A combined graphical representation of FNMR and FMR can be created using detection error trade-off (DET) curves, which indicate a combination of FNMR and FMR at every possible threshold value of the fingerprint matcher. DET curves were created for fingerprints captured at each force level and then DET curves were created for fingerprint datasets that resulted by combining every possible pair of force levels. This methodology was performed separately for fingerprints collected from the optical and capacitive sensors.

4 Experimental design

To analyse the results, both parametric and non-parametric analysis of variance methods were used, based solely on model assumptions and the resulting diagnostics image quality scores and number of detected minutiae. Analysis of variance methods to compare the effect of multiple levels of one factor (force) on a response variable (image quality, number of minutiae) yielded a generalisation of the two-sample *t*-test.

4.1 Parametric – number of detected minutiae

The parametric method is known as analysis of variance or ANOVA. Parametric tests, like their non-parametric counterparts, involve hypothesis testing, but parametric tests require a stringent set of assumptions that must be met (NIST/SEMATECH, 2006). The ANOVA is partitioned into two segments: the variation that is explained by the model (1) and the variation that is not explained (the error) (2) which are both used to calculate the *F*-statistic (3) testing the hypothesis H_o: $\mu_1 = \mu_2 = \ldots = \mu_I$ and H_a: not all μ's are the same. In practice, *p* values are used, but the $F_{observed}$ test statistic can also be compared to the *F* distribution table, as shown in (4). Typically, when the H_o is rejected, the variation of the model (SSM) tends to be larger than the error (SSE), which corresponds to a larger *F* value. The number of detected minutiae was analysed using this methodology:

$$SSM = \sum\left(\hat{Y}_i - \overline{Y}\right)^2,\ dfM = 1,\ MSM = SSM/dfM \quad (1)$$

$$SSE = \sum\left(Y_i - \hat{Y}_i\right)^2,\ dfE = n-2,\ MSE = SSE/dfE \quad (2)$$

$$F = MSM/MSE \sim F(dfM, dfE) \quad (3)$$

$$F \geq F(1-\alpha, dfM, dfE) \quad (4)$$

4.2 Non-parametric – image quality score

According to Montgomery (1997), in situations where normality assumptions fail to be met, alternative statistical methods to the *F*-test analysis of variance can be used. Non-parametric methods are those that are distribution-free and are typically used when measurements are categorical, parametric model assumptions cannot be met or analysis requires investigation into features such as randomness, independence, symmetry or goodness of fit, rather than testing hypotheses about values of population parameters (NIST/SEMATECH, 2006).

One of the more common non-parametric methods was developed by Kruskal and Wallis (1952, 1953). The Kruskal-Wallis test examines the equality of medians for two or more populations and examines the hypotheses H_o (the population medians are all equal) and H_a (the medians are not all the same), with the assumption that samples taken from different populations are independent random samples from continuous distributions with similar shapes (Minitab, 2000). The Kruskal-Wallis test computes the *H* statistic, as shown in equation (5). Image quality scores were analysed with this method to address skewness of scores to the left.

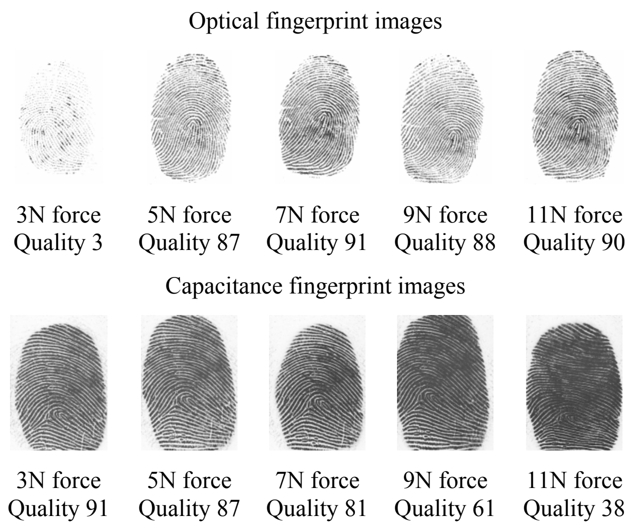
$$H = \left[\frac{12}{N(N+1)}\right]\sum_{i=1}^{a}\frac{R_i^2}{n_i} - 3\,(N+1)\,, \tag{5}$$

where a equals the number of samples (groups), n_i is the number of observations for the ith sample, N is the total number of observations and R_i is the sum of ranks for group i (NIST/SEMATECH, 2006).

5 Evaluation and experimental results

The evaluation consisted of 75 participants, 18–25 years old, and took place in October 2007. All participants used their right index finger and three images were collected at each force level and for both sensing technologies. The five force levels investigated were: 3N, 5N, 7N, 9N and 11N. Fingerprint images for two subjects at each of the corresponding force levels and the two sensing technologies can be seen in Figure 1.

Figure 1 Fingerprint images and quality scores for five force levels by sensor technology: optical (top) and capacitance (bottom)



Results are documented in terms of minutiae count analysis, image quality analysis and performance analysis.

5.1 Number of detected minutiae

The number of minutiae detected from a fingerprint image can vary according to the force applied by the finger on the surface of the sensor. An ANOVA test was performed at a significance level (α) of 0.05 to determine whether the average minutiae count between the force levels are statistically significant for the optical sensor. The p-value of less than 0.05 was observed, which indicated that the minutiae counts between the force levels were statistically different. In order to test which groups were significantly different, the Tukey test for pair-wise comparisons was performed. The results of the pair-wise comparisons and descriptive statistics are shown in Tables 1 and 2, respectively. The results showed that the 3N average minutiae count was significantly different from all the other force level average minutiae counts.

Table 1 Tukey pair-wise comparison results for optical sensor

	3N	*5N*	*7N*	*9N*	*11N*
3N	–	p < .05	p < .05	p < .05	p < .05
5N		–	p < .05	p < .05	p < .05
7N			–	n.s.	p < .05
9N				–	n.s.
11N					–

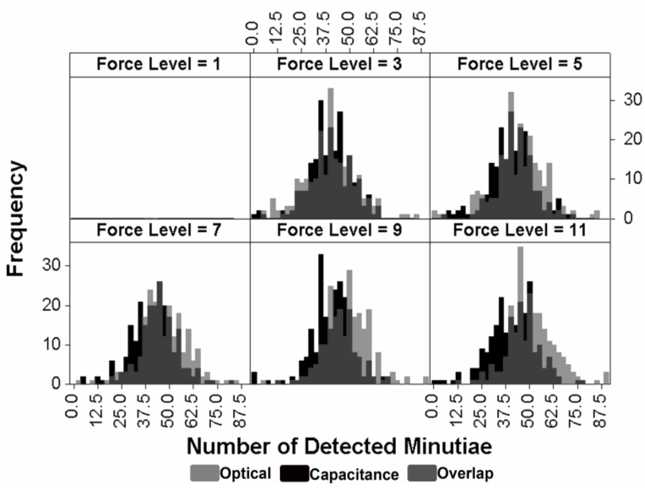
A similar ANOVA test was performed at a significance level of 0.05 to determine whether the average minutiae counts between the force levels are statistically significant for the capacitive sensor. The ANOVA test had a p-value = 0.387, which indicated that the minutiae counts between the force levels did not demonstrate a statistically significant difference. The descriptive statistics are presented in Table 2.

Table 2 Descriptive statistics for the number of detected minutiae by sensor type

Force level	*Optical*			*Capacitance*		
	N	*μ*	*σ*	*N*	*μ*	*σ*
3N	228	39.78	13.25	228	39.62	11.15
5N	228	43.72	13.12	224	40.76	11.40
7N	228	46.99	12.12	227	41.75	11.27
9N	228	48.61	11.77	228	41.01	10.96
11N	228	50.65	12.06	228	40.96	12.22

To further examine the differences in the number of detected minutiae across the optical and capacitance sensors, overlapping histograms were constructed, as shown in Figure 2.

Figure 2 Histogram of the number of detected minutiae by force level and sensor technology



5.2 Image quality

As described in the experimental design, image quality failed to meet the parametric ANOVA model assumptions due to skewness of the image quality scores. Thus, the authors used the non-parametric Kruskal-Wallis (*H*) test to analyse the image quality scores for both sensors.

The results of the non-parametric test for the image quality scores from the optical sensor revealed a statistically significant difference among the median image quality scores across the five force levels, $H(.95, 4) = 47.96$, resulting in a *p*-value less than 0.05. By examining the descriptive statistics for the optical image quality scores, as shown in Table 3, patterns can be found in the mean, median and standard deviation. The mean and median increase as force increases, while the variation between the image quality scores for a particular level decrease as force increases.

However, the descriptive statistics for the capacitance image quality scores exhibit the opposite behaviour, as shown in Table 4. For the capacitance image quality scores, the mean and median decrease as force increases, while the variation between the image quality scores for a particular level increases as force increases. The results for the non-parametric test for the capacitance image quality scores revealed the same thing; that is, there is a statistically significant difference among the median image quality score across the five force levels, $H(.95, 4) = 87.30$, resulting in a *p*-value less than 0.05.

Table 3 Descriptive statistics for optical image quality scores

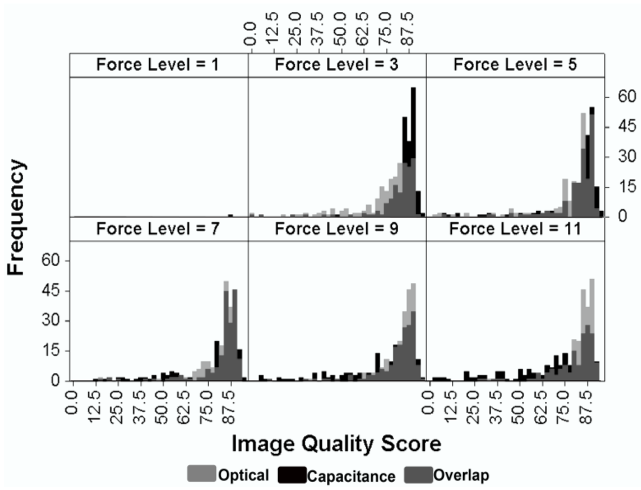
Force level	*N*	μ	$\tilde{x}$	σ
3N	228	75.25	80.0	17.05
5N	228	78.52	84.0	16.79
7N	228	81.15	86.0	13.15
9N	228	81.94	86.0	11.62
11N	228	82.25	86.0	10.95

Table 4 Descriptive statistics for capacitance image quality scores

Force level	*N*	μ	$\tilde{x}$	σ
3N	228	83.79	87.0	12.07
5N	224	80.87	87.0	16.31
7N	227	78.41	85.0	17.71
9N	228	74.26	82.5	20.30
11N	228	69.96	77.0	22.20

To further illustrate the different patterns in image quality data, histograms for the optical and capacitance sensor image quality scores were constructed by force level, shown in Figure 3.

Figure 3 Histogram of image quality scores by force level and sensor technology



5.3 Full dataset matching performance

Once the fingerprint image characteristics were analysed, performance of all the collected fingerprint images from different force levels was analysed using a minutiae-based matcher. DET curves were created to graphically represent the results.

Figure 4 shows the DET curves for fingerprint images from each force level on the optical sensor. Note the flatness of the DET curves for 5N, 9N and 11N is indicative of an optimal state. The DET curve for fingerprint images collected at 3N showed the poorest performance.

Figure 4 DET of the full set of optical images

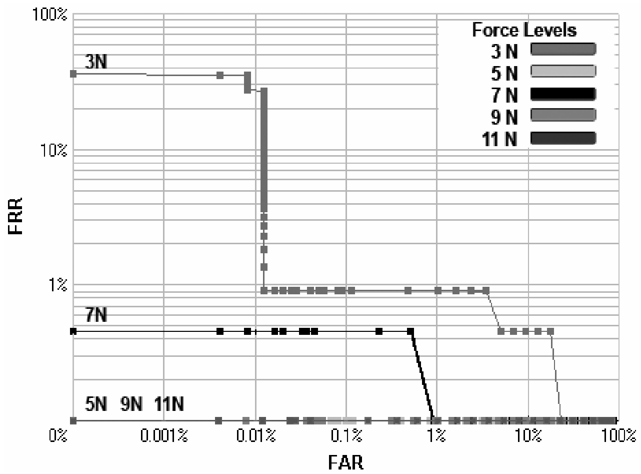
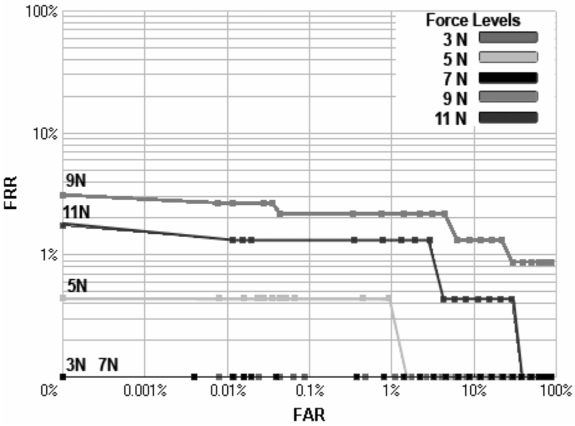


Figure 5 shows the DET curves for fingerprint images from each force level collected on the capacitive sensor. Note the flatness of the 3N and 7N DET curves is indicative of an optimal state, whereas performance deteriorates for force levels 5N, 11N and 9N.

Figure 5 DET of the full set of capacitance images



The full dataset DET for the optical and capacitive sensor indicated that performance varies for fingerprint images collected at different force levels. The optimal force level for matching performance is different for the two types of sensor.

5.4 *Lowest 5% quality removed matching performance*

Having established the impact of force levels on the different sensor technologies, the authors sought to study the impact of image quality on matching performance of the different force levels for the two sensors. Variations in the image quality score results for both sensor technologies and evidence of patterns in the descriptive data led the authors to hypothesise that performance might improve if some of the lowest quality images, in terms of reported image quality scores, were removed. The size of the dataset (n = 75) prompted the removal of images producing the lowest 5% quality scores for each force level; as such, 11 images were removed. Figure 6 shows two example images for each sensor type and force level combinations that were included in the lowest 5% category that did not achieve optimal matching accuracy and were removed from consideration for this particular analysis.

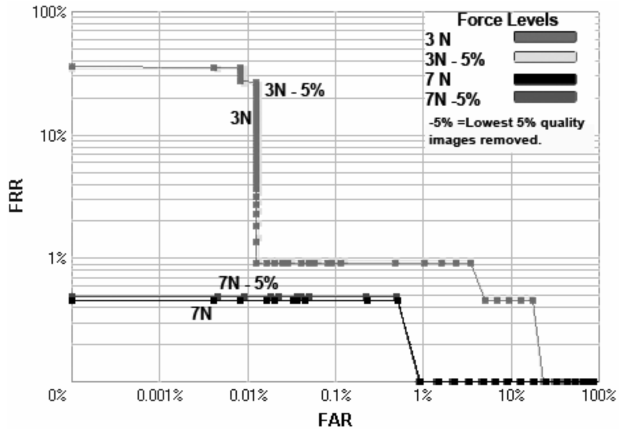
Figure 6 Selected images (two per force level and technology) removed as part of the 5% lowest quality bin

Optical 3N force Quality 29	Optical 3N force Quality 18	Optical 7N force Quality 21	Optical 7N force Quality 56	Capacitance 5N force Quality 32

Capacitance 5N force Quality 32	Capacitance 9N force Quality 10	Capacitance 9N force Quality 4	Capacitance 11N force Quality 19	Capacitance 11N force Quality 7

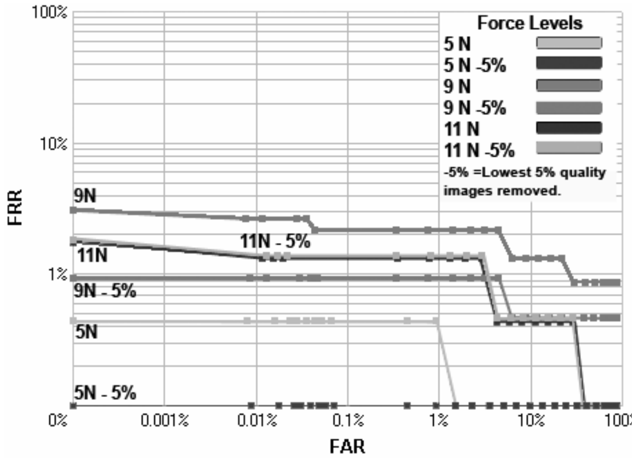
The DET curves in Figure 7 reveal that removal of the lowest 5% quality images collected on the optical sensor at force levels of 3N and 7N yielded negligible changes to system performance. An inward shift in the DET curve would have indicated an improvement in performance, which was not noticed for the 3N and 7N fingerprint datasets.

Figure 7 DET of optical images, lowest 5% quality images removed



However, the DET curves in Figure 8 reveal that the removal of the lowest 5% quality images for the capacitance force levels 5N, 9N and 11N resulted in shifts of the DET curves for two of the three force levels, 5N and 9N. In particular, the 5N DET curve shifted to reach optimal matching accuracy, as noted by the flattened curve. The 9N DET curve also demonstrated a noticeable improvement. There were negligible improvements to the DET curve for 11N when the lowest 5% quality images were removed.

Figure 8 DET of capacitance images, poorest 5% quality images removed



Removal of the lowest 5% quality images collected on the capacitive sensor showed a different behaviour compared to the optical sensor. Figure 8 shows that the DET curve for fingerprints collected at the 5N level was flat after the lowest quality images were removed. Removal of the lowest quality images resulted in optimal performance for fingerprints collected at the 5N level. It was also observed that removal of the lowest quality images at the 9N and 11N levels yielded an insignificant improvement in performance. Removal of the lowest quality images does not necessarily lead to an improvement in performance rates for all force levels. The inconsistent behaviour of image quality and performance rates at different levels of force was a surprising observation of this analysis.

6 Conclusions

The purpose of this study was to quantitatively compare the effect of force on the minutiae counts, image quality scores and fingerprint matching performance of optical and capacitance fingerprint sensors. Comparing these two sensor technologies reveals that increasing the amount of force applied to the sensor surface has an inverse impact on the quality scores. Images collected from a capacitance sensor are of a higher quality when captured at the lower end of the force range. In contrast, images collected from an optical sensor are of a higher quality when captured at the higher end of the force range. This is an important observation to consider when instructing individuals in how best to interact with a particular sensor technology, so that images captured by that technology have a quality score sufficiently high to optimise performance of the matching system. The minutiae counts significantly increased with increasing levels of force when using optical sensors, but the authors' research demonstrated no significant difference relative to this factor when using capacitance sensors.

Matching performance for the full dataset using optical and capacitive sensors showed very different performance levels for fingerprint images collected at different force levels. The optimal force level for matching performance is different for the two sensors and exhibits similar behaviours for the image quality analysis. Removal of low-quality images alone will not always improve the matching performance of a system. Further studies are needed to determine what other factors affect the system matching performance.

7 Recommendations and future work

The results of this research provided additional insight into human interaction with fingerprint sensor technologies, specifically the opposite effect of force level and image quality and the different behaviours of matching performance by force level. However, additional work is needed to further examine the impact of force on other fingerprint sensing technologies (e.g., thermal and ultrasonic sensors). Once the relationships of force level, image quality and matching performance are understood for these additional technologies, it would be interesting to perform an analysis with fingerprint templates consisting of images from multiple force levels to examine the effect on matching performance, with the overarching objective of further reducing matching errors due to HBSI.

References

Burke, J. (2006) *AuthenTec Ships Record 10 Million Biometric Fingerprint Sensors*, available at http://www.authentec.com/news.cfm?newsID=217 (accessed on 10 August 2006).

Edwards, M., Torrens, G. and Bhamra, T. (2006) 'The use of fingerprint contact area for biometric identification', *Proc. of the 2006 International Conference on Biometrics (ICB)*, Hong Kong, China, pp.341–347.

Elliott, S., Kukula, E. and Modi, S. (2007) 'Issues involving the human biometric sensor interface', in Yanushkevich, S., Wang, P., Gavrilova, M. and Srihari, S. (Eds.): *Image Pattern Recognition: Synthesis and Analysis in Biometrics*, Vol. 67, pp.339–363), World Scientific, Singapore.

International Biometric Group (IBG) (2006) *Biometrics Market and Industry Report 2006–2010*, available at http://www.biometricgroup.com/reports/public/market_report.html (accessed on 12 September 2006).

International Organization for Standardization (2007) *ISO/IEC JTC1/SC37 Standing Document 2 – Harmonized Biometric Vocabulary (WD 2.56)*.

Jain, A., Chen, Y. and Dass, S. (2005) 'Fingerprint quality indices for predicting authentication performance', *Proc. of the 5th International Conf. on Audio- and Video-Based Biometric Person Authentication*, Rye Brook, NY, pp.160–170.

Kang, H., Lee, B., Kim, H., Shin, D. and Kim, J. (2003), 'A study on performance evaluation of fingerprint sensors', in G. Goos, J. Hartmanis and J. van Leeuwen (Eds.): *Audio- and Video-Based Biometric Person Authentication*, pp.574–583, Springer, Berlin, Heidelberg.

Kruskal, W. and Wallis, W. (1952) 'Use of ranks on one-criterion variance analysis', *Journal of the American Statistical Association*, Vol. 47, pp.583–621.

Kruskal, W. and Wallis, W. (1953) 'Errata to use of ranks in one-criterion variance analysis', *Journal of the American Statistical Association*, Vol. 48, pp.907–911.

Kukula, E. (2007) 'Understanding the impact of the human-biometric sensor interaction and system design on biometric image quality', *NIST Biometric Quality Workshop II*, Gaithersburg, MD.

Kukula, E. (2008) *Design and Evaluation of the Human-Biometric Sensor Interaction Method,* p.510, Purdue University, West Lafayette.

Kukula, E. and Elliott, S. (2006) 'Implementing ergonomic principles in a biometric system: a look at the human biometric sensor interaction (HBSI)', *40th International IEEE Carnahan Conference on Security Technology*, Lexington, KY, pp.86–91.

Kukula, E., Elliott, S. and Duffy, V. (2007a) 'The effects of human interaction on biometric system performance', *12th International Conference on Human-Computer Interaction and 1st International Conference on Digital-Human Modeling*, Beijing, China, Vol. 12, pp.903–913.

Kukula, E., Elliott, S., Gresock, B. and Dunning, N. (2007b) 'Defining habituation using hand geometry', *5th IEEE Workshop on Automatic Identification Advanced Technologies*, Alghero, Italy, pp.242–246.

Kukula, E., Elliott, S., Kim, H. and San Martin, C. (2007c) 'The impact of fingerprint force on image quality and the detection of minutiae', *Proc. of the 2007 IEEE International Conference on Electro/Information Technology (EIT)*, Chicago, IL, pp.432–437.

Kukula, E., Blomeke, C., Modi, S. and Elliott, S. (2008) 'Effect of human interaction on fingerprint matching performance, image quality, and minutiae count', paper presented at the *Proceedings of the 5th International Conference on Information Technology and Applications (ICITA 2008)*, Cairns, Australia, pp.771–776.

Minitab (2000) *Minitab User's Guide 2. Release 13*, available at http://mathstat.carleton.ca/~help/minitab/STNONPAR.pdf (accessed on 7 June 2006).

Modi, S. and Elliott, S. (2006) 'Impact of image quality on performance: comparison of young and elderly fingerprints', *Proc. of the 6th International Conference on Recent Advances in Soft Computing (RASC 2006)*, Canterbury, UK, pp.449–454.

Montgomery, D. (1997) *Design and Analysis of Experiments*, 4th ed., John Wiley and Sons, New York.

NIST/SEMATECH (2006) *E-handbook of Statistical Methods*, available at http://www.itl.nist.gov/div898/handbook/ (accessed on 20 March 2007).

Tabassi, E. and Wilson, C.L. (2005) 'A novel approach to fingerprint image quality', *Proc. of the IEEE International Conference on Image Processing*, Genoa, Italy, pp.37–40.

Yao, M., Pankanti, S. and Haas, N. (2004) 'Fingerprint quality assessment', in N. Ratha and R. Bolle (Eds.): *Automatic Fingerprint Recognition Systems*, pp.55–66, Springer, New York.