Palmprint Biometric Data Acquisition:
Extracting a consistent Region of Interest (ROI) for method evaluation

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Abstract

Traditionally personal identification was based on possessions. This could be in the form of a physical key, ID card, passport, or some kind of knowledge based entry system such as a password. All of these are prone to attack where impersonation of your identity for some kind of immediate financial gain, or the more serious identity theft, is possible simply by being in physical possession of an identity device or knowledge of a password.

In contrast biometric identification attempts to identify who you are. Iris or retina patterns, palmprint, fingerprint, face and voice recognition are well known examples of biometric attributes. Some biometrics such as fingerprints were established in the latter 19th century well before computers were commonplace. Others such as face, iris and voice recognition have emerged as computer technology and methodologies have developed. More recent research has also devoted attention to internal physiological biometrics based on brain (electroencephalogram), heart activity (electrocardiogram) and palm vein patterns. Even your personal gait based on how you walk has been investigated. Both security and forensic applications compete to find the best identification method trading off accuracy for performance depending on the intended application.

This thesis is a continuation of previous research to develop a tool for distributed palmprint image data gathering. This would enable researchers to concentrate on method evaluation whilst not losing valuable time in data validation. This simple tool will enable palmprint biometric diversity across continents to be gathered. This thesis continues by establishing how to extract a consistent region of interest in the acquired palmprint images from a mobile phone ,or statically mounted digital, camera.

The importance of establishing a consistent region of interest is considered by studying a simple existing identification method applied to a known palmprint database. In the discussions and conclusions the usefulness of this method is established and the final research outlined that is needed to finalize the palmprint acquisition tool for academic research.

Keywords:

Palmprint Acquisition, Biometric, ROI.

Acknowledgements

To my supervisors, Eleni Berki and Heikki Hyyrö. Without their persistence, target settings, and belief in me this would never have been finished. It has been a great learning experience and I want to take this opportunity to show my real appreciation and gratitude for their guidance and expertise. Thankyou!

I would also like to take the opportunity to thank the Hong-Kong University for their gracious help providing their database for my use. It enabled me to immediately look at the specific topic regarding region of interest without having to start gathering palmprint images. Hong Kong University [“Biometric Research Center - HK PolyU,” 2013] has contributed academic research, patents and publications to many areas of biometric research. Their database was used for initial method verification and investigation into region of interest problems.

Lastly I would like to thank my family. Without their support and encouragement I would never have managed to combine family life, work and University at the same time.

Tampere, December 2014

Andrew Cox

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List of Abbreviations

ROI	Region of interest
DCT	Discrete Cosine Transformation
FFT	Fast Fourier Transform
ROC	Receiver Operating Curve
HOG	Histogram of Orientated Gradients
SVM	Support Vector Machine
HSV	Color space, alternative to RGB, which stands for Hue Saturation and Value.
DG	Directional Gradient
LBP	Local Binary Pattern

1 Introduction

Identification theft is often big news. The effects are very personal and impact can range from inconvenient to potentially devastating. Personal identification is traditionally based on possessions such as a key, an ID card, a passport or a password. These are prone to attack when a person has physical possession of an identity device or knowledge of a password.

Biometric identification identifies who you are rather than believing you are the person simply by being in possession of personal effects or knowledge. Iris or retina patterns, palmprint, fingerprint, face and voice recognition are well known examples of well established biometric attributes.

This thesis concentrates on palmprint data collection to further academic research into recognition methods. The aim is to create a tool that can be distributed anywhere and be used by almost anyone without the need to train them. We are becoming a world where travel knows no bounds and larger cities are now multicultural. Databases of palmprints often concentrate on small local sample sets in the country where the respective research is being undertaken. The aim of this tool being developed is to gather images from around the world to create a truly world wide database that can be used to further research and not be restricted to small local sample sets.

After an introduction to biometric palmprint recognition with a Bachelor's thesis study, a tool for collecting palmprint images had been developed that encrypted and sent images to a secure server. The developed tool works and has been demonstrated. This is briefly mentioned in Appendix 1: Stage 1 palmprint database: An android tool for distributed palmprint image collection, along with a summary of the security implications tackled in the section 3.1 Ethical and security considerations.

The initial implementation of this tool took no account of how distortion effects of the acquired image and had no techniques working to verify that those images could be used in practice. This thesis attempts to understand two issues:

1. The role and challenges of identifying a region of interest (ROI) in palmprint recognition.
2. Quantifying the impact of ROI extraction by implementing an already established texture based recognition algorithm.

First a literature review walks through some basic concepts of what techniques are generally around, method comparison, acquisition techniques, background extraction. A small area of interest about identical twins and impact on result sets is included.

The second part of this thesis implements a technique to verify images acquired using a mobile device. In the implementation an attempt is made to understand the two questions described above. This is done in two stages. The first stage is to use an established database of palmprints and an established palm recognition technique. An application is developed that implements and verifies the results. The second stage is capturing a new database using a mobile device from randomly selected anonymous people and applying the method developed in the first stage. This requires using more detailed background extraction as the images are taken using a standard mobile phone in a normal office setting or university building. During the development the methods are explained. The results and modified findings are discussed and reviewed in detail.

The final topic is conclusions and further steps. A conclusion is drawn on the success of the implementation and investigations, and how the development of this tool can continue to reach the stated goal.

It is assumed and hoped that following this thesis the next steps can be followed and this tool deployed and be used in practice by any academic researchers anywhere in the world to help further palmprint methods and techniques.

2 Literature review

Traditionally personal identification was based on what you have. These would come in the form of physical key, an ID card, passport, or some kind of knowledge based entry system like a password. All of these are prone to attack where impersonation of your identity for some kind of immediate financial gain, or the more serious identity theft, is possible simply by being in physical possession of an identity device or knowledge of a password.

Biometric identification attempts to identify who you are rather than what you have. Iris or retina pattern, palmprint, fingerprint, face and voice recognition are well known biometric attributes. Some biometrics like fingerprints have been established for a period in the latter 19th century well before computers were commonplace. Others like face, Iris and Voice recognition have emerged as computer technology and methodologies have developed. More recent research has also devoted attention to internal physiological biometrics based on brain (electroencephalogram) [Paranjape et al., 2001] heart activity (electrocardiogram) [Wübbeler et al., 2007] and palm vein patterns [Wang et al., 2007]. Even your personal gait based on how you walk have been investigated [Derawi et al., 2010]. These are just come examples.

A comparison of state of the art recognition techniques was conducted [Zhang et al., 2012]. Competitive code, ordinal code, Derivative of the Gaussian (*DoG*) *code, robust line orientation code (RLOC), Wide Line Detector (WLD), FisherPalms and Discrete Line Transform (DCT) + Linear* Discriminant Analysis (LDA) were studied. Performance and error correlation are highlighted as the key comparison measurements with an eye on practical implementation in industry as the trade-off against intensive forensic accuracy.

Categorization of general palmprint classification techniques can be grouped into three areas [Imitas & Fattah, 2010], structural, texture and algebraic. The following loosely groups information into these three categories, although mixing best practices and methods can cross these boundaries.

Structural techniques look for winkles, lines, edges, their construction and phase. Predominantly Gabor filters are used in palmprint recognition [Imitas & Fattah, 2010]. Image representation using Gabor filters has been proposed for many years [Tai Sing Lee, 1996]. There are many papers that develop techniques for recording line and orientation information from Gabor filters, how to classify and compare the features for palmprint detection.

The human visual system does not suffer from problems detecting edges and lines that are very close or intersect. Hence the motivation is to model event detection on the human visual system that does not suffer from this problem [Van Deemter, 2000]. Gabor wavelets were the result of findings from neurophysiology research [Hubel & Wiesel, 1959]. Exploiting the phase of these Gabor wavelets enables extraction of simultaneous lines and edges obtaining the polarity, removing the dependency on contrast variations. This eliminated the need for separate detectors, for example Canny detector for lines and another for edges. Biological constraints are used to simplify the Gabor function [Van Deemter, 2000] .

Palm code uses Gabor filters to extract phase information [Zhang et al., 2003]. A coding method to quantize in two levels images based on the Gabor filters along six different orientations called Binary Co-Variance Vector (BOCV) was proposed [Yue et al., 2009]. An alternative proposal used the simplified Gabor wavelets as an efficient binary method to represent palm maps [Wei et al., 2009] .

Neurophysiology based Gabor filter creating a competitive code scheme that extracts the line and orientation information can be used [A.-K. Kong & Zhang, 2004]. Claims of Genuine Acceptance Rate of 98.4% are achieved using this method.

An extension of line information (Fusion Code) with the orientation information (Orientation Code) forms Palmprint Phase Orientation Code (PPOC) [Xiangqian Wu et al., 2005]. Using a modified Hamming distance to measure similarity of PPOC the method improves on fusion code for recognition.

Palmprint verification using consistent orientation coding can be compared to competitive code (CompCode) and Orthogonal Line Ordinal Features (OLOF) [Zhenhua Guo et al., 2009]. The claim is high accuracy and fast matching speed. CompCode utilizes six Gabor filters to work out the orientation information. OLOF utilizes ordinal filters in exactly the same way to get orientation information. Both represent the stable features in a palmprint, namely principle lines and wrinkles. Using both methods and only using the strong consistent areas a more robust detection method is gained, so called Strong Fusion technique.

Gabor wavelets are used in many areas of identification, not just palmprints. The same methods can be used in face recognition as one simple example amongst many [Choi et al., 2008].

Robust Line Orientation Code (RLOC) is another encoding method to code local orientation information, based on the Radon transform [Jia et al., 2008]. The difference between two orthogonal Gaussian's can be used to calculate local ordinal measures from palmprints [Sun et al., 2005] .

Band Limited Phase Only Correlation (BPOC) concept was introduced [Iitsuka et al., 2008]. Phase Only Correlation (POC) does not perform well when there is non-linear distortion. High frequency information is removed from the results of the block 2D DFT so a complete 130 pixel phase representation of each palm image is produced. This is the palmprint feature which is used for recognition. Non-Linear distortion is represented by hand translation in images. BPLOC is used to estimate and take care of this distortion so that the phase representation is generated for the comparison.

In low resolution images it is difficult to obtain a high recognition rate using only principle lines because of their similarity among different people. Texture representation for coarse level palmprint classification provides a much more effective approach [Zhang et al., 2003].

Fourier transform takes the time domain image and translates it into the frequency domain. Using standard formula magnitude and angular information can be extracted. After changing the coordinate system to polar,select eight distinct magnitude rings, along with 8 distinct angular regions. An increase in magnitude showed creases being more dominant, and angular information increasing showed the direction of the creases [Li et al., 2002]. Features were then classified by magnitude and angular information where matching is the distance between two palmprint feature sets.

Discriminant Discrete Cosine Transform (DCT) feature extraction can provide improved recognition [Jing & Zhang, 2004]. After DCT frequency band extraction and selection Linear discriminative features are extracted using Fisher Linear Discriminant technique to obtain a vector, called a Fisherpalm [Xiangqian Wu et al., 2003]. The combination of the two techniques are claimed to be improvements on Eigenface [G. Lu et al., 2003], Fisherface [Belhumeur et al., 1997] and Direct Linear Discriminant Analysis (DLDA) [Yu & Yang, 2001].

Hand geometry can be combined with palmprint and fingerprint texture matching [Ferrer et al., 2007]. The texture is based on Gabor filters which have been tuned. Results for correct identification using Geometry, fingerprint, palmprint and fusion of the three show that geometry is clearly worse than texture identification. However fusion gives the best acceptable results for commercial usage, although further larger scale testing was suggested.

Unlike fingerprints with uniform structure the palmprints irregular lines flow in many directions. Local Binary Pattern (LBP) can be used on a region of interest (ROI) for palmprint recognition [Ong Michael et al, 2008]. When the ROI is available, Laplacian isotopic derivative filter is used to enhance contrast and sharpness. A Gaussian Low Pass Filter (LPF) smooths any gaps. The result is an enhanced region of interest. Prewitt and Sobel operators were used to get directional responses. A modified probabilistic neural network (PNN) was employed in the texture description stage. Hamming distance of the LBP was used for feature comparison. The correct recognition rate achieved is 98.6%.

Segmentation of a palmprint image with DCT and standard deviation feature vector is a simplified method for palmprint recognition [Dale et al., 2009]. The palmprint image is split into 4 sub images. Each sub image is transformed to the frequency domain and split into four quadrants, the first top left quadrant is split into a further four, and then again the top left into four again. In this way there will be 9 quadrants of varying size for each sub frequency image, as the top left smallest quadrant is not used. Each of the nine quadrants from the frequency domain has the standard deviation taken and a 36 byte feature vector is obtained (Each of the 9 quadrants are four bytes each giving 36 bytes in total). A float of 144 bytes represents the palmprint image when the four sub-image vectors are combined. This single floating point number representing a single palmprint of a person provides a compact and efficient database entry. Canberra distance [Emran & Ye, 2001] is used to calculate the distance between two vectors in space, so recognition is fast and provides an experimentally proven General Acceptance Rate (GAR) of 97.5%.

Band segmentation is an alternative to quadrants [Imitas & Fattah, 2010]. The palmprint image is segmented into several narrow bands, and two dimensional FFT is used to record features about the palmprint using dominant spectral feature extraction. Using publicly available databases good recognition accuracy was achieved. Comparing previous results a much simplified DCT algorithm and feature vector extraction [Dale et al., 2009] achieve 97.5% accuracy whilst 98% is achieved using enhanced Gabor filters [J. Lu et al., 2009]. The results of using image segmentation with FFT dominant spectral feature extraction achieved 99.94% accuracy [Imitas & Fattah, 2010].

A palmprint image can be split into uniform blocks, where the blocks are described by local binary patterns [Mu et al., 2010]. By calculating the patterns distributions statistical features based on the texture of the blocks can be described. From this Discriminative Common Vectors are formed (DCV) which allow Euclidean distance of DCV and nearest neighbor classifier for palmprint classification. Speed and accuracy using low resolution images outperforms Gabor texture based classification in the tests conducted. The speed improvement is based on the fact that Gabor filter convolutions are CPU intensive operations in comparison. Texture based methods were less prone to distortion and lighting variation in the acquisition methods used. The reason given is that the texture based methods are more robust to lighting and contrast variations.

Symbolic Representation of Sequential Data (SAX) has been successfully used for palmprint image recognition [J. Chen et al., 2010]. 1D SAX has been used for data mining purposes, so extending to 2D has been applied to palmprint images. Reducing the time data, called SAX level, and SAX length, a 2D matrix of symbols is generated. Given an $m \times n$ size image I, an i size matrix then represents the new image. It is then converted into a symbol matrix, SAX representation. Euclidean distance is extended for this symbol matrix to find the minimum distance match for similarity. Vertical and horizontal translation are used to find the minimum distance and reduce any translational distortion. Comparisons between SAX, competitive code, palm code and fusion code are made where SAX out performs palm code and fusion code. Although verification is similar to competitive code, the trade-off of performance, little training and storage size are considered benefits for SAX in this case. Identification accuracy depending on the database used is 99% or 99.9%.

2.1 Measurements for method comparison

The most discussed measurement technique for method comparison through all papers is Receiver Operating Characteristic (ROC). Depending on the palmprint end operating environment the trade-off between security and performance is used to determine a threshold. This threshold relates False Non-Match Rate (FNMR) and False Match Rate (FMR) which ultimately allows selection of the correct technique for the final target application needing palmprint recognition [Franzgrote et al., 2011; Jain et al., 2004; Zhang et al., 2012].

This ROC graph is FMR (False Match Rate) vs FNMR (False Non-Match Rate). FMR is defined as the rate at which two different people are identified to be the same person (False match). FNMR is defined as the rate at which two biometric properties from the same person are mistakingly thought to be from two different people (False non match). Both of these are functions of system threshold. Reducing the system threshold reduces noise but increases FMR. Similarly increasing the threshold increases noise and detail and therefore increases FNMR. Civilian applications trade FMR and FNMR against each other along with performance as shown in Fig 1

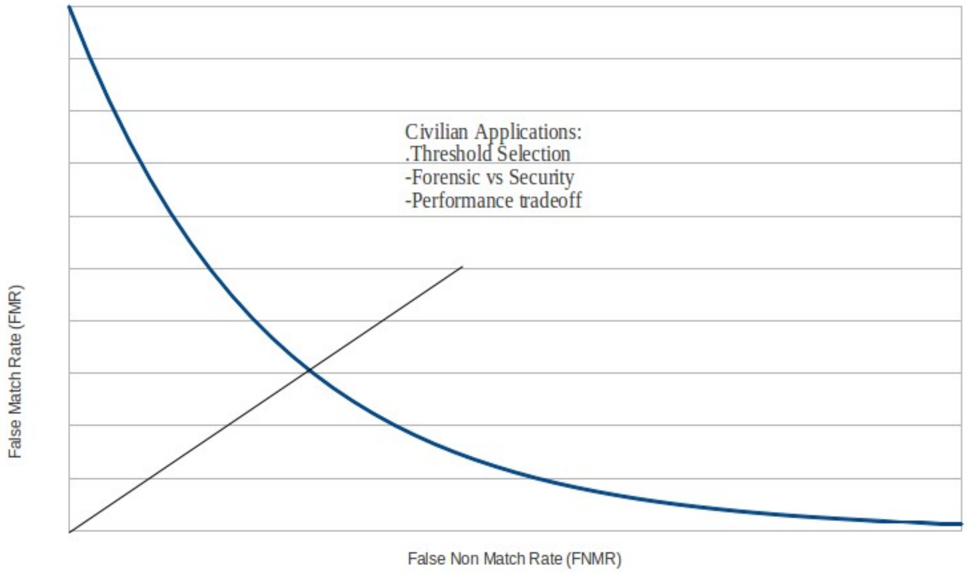


Fig 1. ROC curve

FMR can be replaced with Genuine Acceptance Rate (GAR), and FNMR with False Acceptance Rate (FAR). These can be used in the same way to give the ROC curve [Franzgrote et al., 2011; Zhang et al., 2003, 2012].

Genuine acceptance rate is defined as the ratio of properly matched samples vs the total number of samples being tested. False acceptance rate is defined as the number of correctly non-matching samples vs the total number of samples tested.

Whether using FMR/FNMR or GAR/FAR to represent the ROC curve, optimization is referred to as Equal Error Rate (EER) [Derawi et al., 2010; Yue et al., 2009]. A line is taken from the origin and where the line crosses the curve is the EER. This EER threshold is the point which is used to compare different palmprint recognition techniques.

2.2 Acquisition and application

A simple scanner can be used for collecting biometric palm prints allowing a high contrast palmprint to background image [Ferrer et al., 2007]. This means that extra background extraction processing is based on simple thresholding and the palmprint itself remains the focus of attention.

Another approach is to use a touch-less acquisition technique such as a low resolution CMOS camera, where the hand can be held a small distance away from a device [Ong Michael et al., 2008]. The purpose built device meant this was more acceptable to people and reduced contamination of a touch device. Using a color camera, skin color was used to detect the palmprint and allow tracking as the palm moved. Background extraction could then take place before the region of interest is found by finding the gaps between the fingers using competitive valley detection. The region of interest was then found and used in Local Binary Patterns (LBP) where results achieved were as good as 98% correct identification. Measurements on distance from the camera showed in this case the optimal recognition is at 45cm, quickly falling off as the distance becomes greater or smaller. Long term tests also showed some deterioration in recognition results.

More elaborate custom palmprint capture equipment has been developed. An example is where a ring of illuminated light is used, a CCD camera and a few pegs in a semi enclosed box to provide palmprint images [Zhang et al., 2003]. The image size is 384x284 and 768x568 giving around 75dpi for identification using palmprint texture methods. A coordinate system was used to align different palmprints for effective feature extraction using the gaps between the fingers as reference points. The central part of the palmprint could then be extracted once the coordinate system has been established. 2D Gabor phase coding is used to extract texture features from the palmprints. A normalized hamming distance is used to determine the similarity between two palmprint feature vectors. Lighting and camera focus were extensively altered to simulate capturing by different devices. Experimental results showed robustness against lighting and focus. Using false acceptance rate vs genuine acceptance rate a 98% genuine acceptance rate was achieved, along with a 0.04% false acceptance rate. A performance measurement was given that using Visual C++ on a 500MHz Pentium, 100 registered images within the database the total identification time was 1.1 seconds. This was without optimization of the code. This is a little difficult to make a comparison in absolute terms with other reported performance measurements.

Manual alignment where the user has to have three palm-images taken has been tested [Han et al., 2007]. The person aligns the finger gaps with the top of the image whilst the three images are taken. The ROI is then a fixed area. Only if the Hamming distance between the trained images is below a defined threshold are the images used as templates. Poor results on manual alignment occurred, meaning the users would need to retrain the system if this stage failed.

Dedicated hardware using an ARM processor and DSP chip with a USB camera connected to a common Linux platform to perform palmprint recognition has been demonstrated [Yuan Cui & Bo-nian Li, 2010]. The technique used for recognition is based on local DCT and Wavelet reconstruction.

Touch-less method of fingerprint acquisition using multiple cameras to create 3D type representation of fingerprints has been explored [Parziale et al., 2005]. A touch-less setup using the hybrid client server architecture can be used [Franzgrote et al., 2011]. Any security issues with possible data interception and misuse were avoided. Initially the mobile capture has to be robust, detect orientation and take care of lighting and background issues. For this the flash is utilized to light up the foreground of the palmprint, and the background appears darker. Hand segmentation uses a 13x13 set of squares from the image which are used to compute the median and variance. From this individual pixels can be assigned to the hand or background. A low accuracy initial rotation of the hand is detected and the image rotated so the fingers are pointing upwards before drawing a line across the image to detect eight transitions showing the four top fingers. More detailed honing occurs to detect the lowest points of background and hence the troughs between the fingers. Normalization of this image also occurs during this process so that varying distances between hand and camera can be removed and a region of interest defined. Six Gabor filters are used and the competitive rule applied. The winning index is represented by three bits, and the image region of interest is coded into three bit planes for efficiency. A sample set of thirty people with six hundred palmprint images were used with an Apple iPhone. Without accelerated coding using special CPU operations, and without using Accelerated Gabor filtering the matching would take 4.2 seconds. With both of these techniques the time was reduced to 0.116 seconds. Accuracy is reported to be good, given by recorded false acceptance rate and genuine acceptance rates. However it is impossible to extract the true comparison of GAR/FAR from the graph as there are no reported values or tables to use and compare with other literature.

A comparison of a flatbed scanner, high quality cameras, and a contact-less devices using hand-shape and palmprint feature extraction have been compared [Morales et al., 2012]. Contact methods such as scanners need to cope with errors in pressure altering the shape and dimensions. In contrast contact-less methods need to cope with projection, illumination and blurriness caused by movement. Conclusions stated that interoperability is possible between contact-less and contact methods of acquisition. Surveying users there seems no real preference between contactless (46%) and contact acquisition (54%). When considering the acquisition methods the users predominantly preferred scanner. The responses were: web-cam (18%), scanner (45%), specially developed scanner called RPM (9%), contactless at 5-10cm (3%) and contactless at 10-30cm (25%).

2.3 Identical twins

Two types of identical twins are possible. The first is where two separate eggs are fertilized resulting in twins with different DNA. The second possibility is where a single egg splits into two and two individuals develop with almost identical DNA. The frequency in a population is 0.4%, which some researchers believe is the performance limit on some biometric systems. For example face recognition of identical twins [Phillips et al., 2000]. Empirical testing using competitive code as the test method with sets of identical twins has been conducted [A. W.-K. Kong et al., 2006]. It was indicated in the tests that strong lines including principle lines and some weak lines are genetically related features. Ignoring these principle lines in results meant identical twins could be separately identified.

Identical twins in general were not taken into account. This might represent a slight skew on recognition method comparison when specific error rates are quoted. It has been suggested that recognition performance is limited when 0.4% of the population are identical twins, so if this is not taken into the sample set for method comparison then a skewed result will be present [Phillips et al., 2000] .

2.4 Background extraction

When establishing a region of interest it is important to focus methods on the palmprint. The ROI can only be extracted if the background has been removed from the image containing the palmprint. When producing a database of images consideration on how to take an image and extract the background is needed. The following literature briefly explores this need.

An extended set of Haar-like Features can be used for rapid object detection [Lienhart & Maydt, 2002; Viola & Jones, 2001]. A simple small set of rotated rectangles can be trained so that quick detection of objects is possible. A simplified set of edge, line and center surround features are established. A cascaded series of classifiers are used as a degenerated decision tree. At any point fast failure is promoted so that quick detection occurs. The simple algorithm is boosted by AdaBoost classification and other optimizations have been exploited [Lienhart et al., 2003].

Haar-Like feature training has been implemented for person recognition in crowded streets successfully [Munder & Gavrila, 2006], and in gesture recognition [Q. Chen et al., 2008]. Databases of positive images with the features within them clearly identifiable, and a database of negative images with the features not present, must be constructed. Many thousands of images make the detection better. No similar databases of positive and negative images for palmprint extraction were found.

A survey of skin color modeling and detection methods was conducted [Kakumanu et al., 2007]. When training using HSV color space thresholds defining skin color can be used to remove the background, especially if the background is selected to be far away in the HSV space from the skin color. It is not known to the author how this can be used when considering different races with different skin colors in comparison with backgrounds to be extracted, so something to be considered with further investigation.

The methods to extract the palm-image from the background can be complex and detailed, and a topic for a masters thesis in itself. So a combination of the above techniques and manual selection are used, as described in further detail in Background extraction section following later.

2.5 Extracting a consistent ROI for method evaluation

Continuing from background extraction of a palmprint from an image, a Region of Interest (ROI) must be extracted from the palmprint to be used in matching algorithms. The following literature discusses this in a little more detail.

When a mobile phone is used to take three consecutive images using an Android mobile phone with manual user alignment is time consuming and difficult [Han et al., 2007]. If it fails the system must be retrained. A region of interest (ROI) can be automatically extracted using a mobile phone to remove rotation, translation and scale variation [Aoyama et al., 2013]. Capturing an image of the left hand at a resolution of 640x480 background extraction is done using HSV skin color thresholding followed by a region growing technique until a binary representation of the hand is achieved. Using a radial distance function the gaps between the fingers can be found [Yoruk et al., 2006]. From the three finger points a perpendicular line drawn onto the palm identifies an ROI. To correct non-linear distortion Band Limited Phase Only Correlation (BLPOC) is used to calculate matching scores. Comparing different databases with CompCode, OrdiCode, BLPOC the results look good. However the ROI extraction is only correct 80.5% of the time and needs to be improved. Work was limited to the left hand only.

Alternatively using a document scanner the target is to combine hand features with texture feature information [Ferrer et al., 2007]. Work is limited to the right hand only. As the contrast in the acquired image is high, a simple threshold is used to extract only the palmprint from the background. Using peak and valley information the fingers can be found and a simple triangle represents each finger dimension. Using the valleys a circle is calculated to minimize the square error on the palm area. The ROI is then this circle extracted from the palmprint image. It is stated that this is a translation and rotation invariant ROI. Gabor filters are used for the texture information of this ROI and fingers. Recognition is done in two parts. A Scalar Vector Machine (SVM) to match the measurement information, and Hamming distance. Fusing the two together gives the matching results for measurement of hand and the palmprint recognition.

Palmprint authentication using a symbolic representation of images (SAX) is texture based matching after identifying a region of interest [J. Chen et al., 2010]. The palm is extracted from the background using using simple thresholding, followed by morphological operations to remove small unwanted background information left over. Utilizing a curvature maximum finding algorithm two points between fingers are found. A simple perpendicular line is then extended from the line between the two fingers, and an ROI formed in the palm area. Non uniform illumination correction is then applied.

Morales et al. [Morales et al., 2012], in addition to acquisition methods look at ROI extraction. Instead of using two point square ROI based on points between two outside fingers

[Zhang et al., 2003], ROI positioning is extended to 3 points [Morales et al., 2012]. First the center and size are found by locating a circle at the center of the palm which is established with minimized error but maximized diameter. This is followed by two coordinates of the outside finger valleys being established so that the image can be rotated to the point where the finger coordinates form a vertical line. An ROI three quarters the size of the radius of the circle forms the square ROI. With this method location, size scalability between devices and test sets of data can be eliminated.

2.6 Literature summary

In the literature review a brief outline of biometrics was given and how palmprint verification can be used in identifying who you are rather than what you have. Even in the case of identical twins, you can be identified.

An introduction was also given to biometric palmprint recognition followed by some time-line descriptions of techniques that have been developed, along with some findings the authors had observed. A very loose categorization was used of structural, algebraic or texture, and a walk-through of some research has been given. A brief discussion on methods used for comparison of palmprint techniques has been discussed and that most papers were not using the same measurement, and what this meant in practice.

Table 1 Gives the referenced techniques in the review in chronological order.

Reference	**Title**
[Hubel & Wiesel, 1959]	Receptive fields of single neurones in the cat’s striate cortex
[Tai Sing Lee, 1996]	Image representation using 2D Gabor wavelets
[Belhumeur et al., 1997]	Eigenfaces vs. Fisherfaces: recognition using class specific linear projection.
[Van Deemter, 2000]	Simultaneous detection of lines and edges using compound Gabor filters
[Yu & Yang, 2001]	A direct LDA algorithm for high-dimensional data—with application to face recognition
[Emran & Ye, 2001]	Robustness of Canberra metric in computer intrusion detection
[Li et al., 2002]	Palmprint identification by Fourier transform
[Zhang et al., 2003]	Online palmprint identification

[G. Lu et al., 2003]	Palmprint recognition using eigenpalms features
[A.-K. Kong & Zhang, 2004]	Competitive coding scheme for palmprint verification
[Xiangqian Wu et al., 2005]	Fusion of phase and orientation information for palmprint authentication
[Sun et al., 2005]	Ordinal palmprint represention for personal identification
[Ferrer et al., 2007]	Low cost multimodal biometric identification system based on hand Geometry, palm and fingerprint texture
[Choi et al., 2008]	Simplified Gabor wavelets for human face recognition
[Iitsuka et al., 2008]	practical palmprint recognition algorithm using phase information
[Ong Michael et al., 2008]	Touch-less palm print biometrics
[Yue et al., 2009]	Orientation selection using modified FCM for competitive code-based palmprint recognition
[Wei et al., 2009]	Improved competitive code for palmprint recognition using simplified Gabor filter
[Zhenhua Guo et al., 2009]	Palmprint verification using consistent orientation coding
[Dale et al., 2009]	Texture based palmprint identification using DCT features
[J. Lu et al., 2009]	Enhanced Gabor-based region covariance matrices for palmprint recognition
[Imitas & Fattah, 2010]	A spectral domain feature extraction scheme for palmprint recognition
[Mu et al., 2010]	Palmprint recognition based on discriminative local binary patterns statistic feature
[J. Chen et al., 2010]	Palmprint authentication using a symbolic representation of images
[Zhang et al., 2012]	A comparative study of palmprint recognition algorithms

Table 1: Referenced Methods Evolution in Chronological Order

A survey of palmprint acquisition methods, and background extraction is also explored as these are the basis for any palmprint tool that will acquire images for further palmprint method evaluation.

Table 2 shows acquisition methods cross referenced to the material referenced in the literature review.

Reference	**Acquisition Method(s)**
[Ferrer et al., 2007]	Normal scanner
[Ong Michael et al., 2008]	Low resolution CMOS camera
[Zhang et al., 2003]	Ring light, pegs, box and CMOS camera
[Yuan Cui & Bo-nian Li, 2010]	USB Camera
[Franzgrote et al., 2011]	Mobile Phone Camera
[Morales et al., 2012]	Flatbed scanner, high quality camera, Webcam, IR Webcam, PRM Biometric scanner.
[Parziale et al., 2005]	Multiple surround cameras

Table 2: Acquisition methods cross reference

Finally a survey was presented of how Region of Interest (ROI) had been extracted in a number of papers to focus on the area of the palmprint that will be evaluated for identification purposes.

Every part of this information is relevant and applicable. The following sections first acquire an image from a database or from a camera, the latter requiring some knowledge on pre-processing to extract the background from the palmprint image. A method is chosen from the discussed techniques to explore and verify the images acquired. The ROI is of particular importance in the performance and accuracy that can be achieved, as will be discussed.

3 Implementation of palmprint recognition for mobile phone data collection

3.1 Ethical and security considerations

3.1.1 Personal data

Security and personal data is a very important topic. It covers a multitude of issues from personal, moral, to legal. Within the development of this data gathering tool security and personal privacy has been thought about carefully. This section tries to cover some of those issues. Concern is raised regarding privacy in Norway where names were asked to be deleted, leaving only Biometric data for research [Yang et al., 2012]. Identification was permitted only by using unique identifiers. Some further checks before deployment of this generic tool will need to be made depending on the country where information is gathered and stored. In this thesis the PolyU palmprint database [“PolyU Palmprint Database,” Retrieved December 8, 2013] followed these rules where anonymity was guaranteed by unique identifiers that are not related to specific people. Also trust that ethical considerations were followed has been assumed with regards to this database. Regarding section 3.3.3, Establishing an independent dataset for ROI extraction evaluation, the same anonymity whilst gathering a new palmprint database was guaranteed with the same unique identifiers that are not connected to specific individuals.

Android security is carefully considered in the documentation [“Android Security Overview | Android Developers,” 2013]. Throughout the development these guidelines were followed. Specifically no data was stored on a removable storage area. The application itself runs within a Java Virtual machine which is run separately in a sandbox from other applications. Data regarding an individual is only stored for the minimum period in a local sand-boxed non-removable storage area within the phone and then immediately deleted when the data is stored for analysis on the authors own secure machine. The data is not shared, copied or visible anywhere else. No names are recorded at all. All data is also deleted on submission of this thesis.

3.1.2 Overall architectural security considerations

The previous study (Appendix 1) considered a client server architecture towards the final goal of a data gathering tool for palmprint collection. Pam2Palm refers to the name of the original study tool that was implemented to gather palmprint images into a database. To reiterate the importance of security these details follow as the current study will be combined with the Palm2Palm tool in the next steps.

Deployment was on an Ubuntu system. Ubuntu is installed with a firewall as default, which can be configured to increase security. The firewall should be set up for “no bind requests”. This means that any computer externally polling this computer asking for information will be ignored so that they will not know that there is a Tomcat server or Palm2Palm service present.

Tomcat can be configured to change ports used from standard 8080 as the default setting to something else. Linux is covered by the fact that users need authentication and access to login. So a person trying to access the system either remotely or locally will need to have been given authority. Even then they would need to be given read/write access on the file system to access any data. Additionally passwords are hard coded into the Server deployed on this file system, which are used to access the MySQL database. MySql has its own security restrictions, and its own guidance on how to handle this [“MySQL :: MySQL 5.0 Reference Manual :: 6 Security,” 2013]. Only the server is given access to the data and programs written to access it. So the password for database access is not visible which means no-one can access it unless this is compromised by giving the password out. Even if the person knows the password he/she would need access onto the Ubuntu installation. No retrieval of information has been coded into the server to access the database meaning that even if the server were hacked it will be secure.

MySQL is a server in it's own right, listening on port 3306. This leaves it open to attacks externally, when we only connect to it on localhost from TomCat. External access to the database and table was therefore prevented. This means that the database and all tables are only available on the local computer, namely the Palm2Palm service hosed by Tomcat.

Organizations deploying this server will have to think carefully about security policies and the governmental guidance on data protection. As such the server could also be deployed so that it is accessed only on intra-net with secure access. And then only accessed externally using private VPN (Virtual Private Network).

Personal data collection and usage is a very big issue. All security issues already discussed above must be implemented to ensure only the right people have access to the data. Further to this anonymity must be guaranteed to the data. As such the Android application should not send the information unless consent is given to do so. In all cases the implications and usage of the data should be given to the user before it is submitted to the database.

One issue might be data interception, or sniffing. If data goes through any intermediate point with the PC or the Internet then the data becomes potentially visible. If this becomes an issue it is a simple matter to take the HTTP Put message body, and encrypt it using the Java Cipher encryption [“Java SE Security,” 2013]. In the Palm2Palm tool both client and server have encryption/decryption classes written to encode/decode the message body before it is handled. The client and server implementation for the Palm2Palm implementation have the class Crypt.java which utilizes the Java SE Cypher [“Java SE Security,” 2013], a standard way recommended to ensure secure data transmission.

Future security enhancements could be server/client authentication, although this could be solved using Open VPN. Within Tomcat a war file is placed where it is then automatically unzipped if it is changed to form its original folder structure running the server solution. A war file is simply a compressed file structure containing the server code to execute and any associated resources. A very tough security measure to detect hacking is to provide a checksum for the war file using sha256sum in Ubuntu. A linux cron job, a background process running, could be set to periodically detect and verify that this has not been compromised, and if it has then remove the installation.

3.1.3 Ethical and security consideration, summary

In summary there are many security measures that were implemented in the original study as default and can be used as a system wide solution as described. A security risk analysis should be conducted once the system is deployed to ensure all ethical and legal requirements are met.

Within this Masters Thesis every consideration to personal anonymity and protection is provided. All contributors notified of the implications. No data is shared or exposed. All data submitted was deleted on completion of this thesis.

3.2 Problem statement

When studying palmprint biometrics, there are a vast array of methods. When setting out to compare these methods or develop new methods the first major obstacle is to identify a non biased dataset. There are palmprint databases available for research purposes [“Biometric Research Center - HK PolyU,” 2013 ; “CASIA Palm Image Database,” Retrieved June 30, 2014].

Appendix 1 shows an android phone client/server tool called Palm2Palm. This allows high resolution palmprint images to be obtained, encrypted and sent to a secure storage area. This allows privacy issues to be addressed. To make this tool useful researchers should be able to concentrate on method evaluation whilst not losing valuable time in validating the palm-images obtained.

This thesis continues by looking into establishing how to extract a consistent region of interest in the acquired palmprint images from a mobile or static camera. To understand the ROI a simple existing identification method is chosen and applied to a known palmprint database. To deepen the understanding and confirm results a database from new individuals is also constructed and tested.

Later in the discussions and conclusions the usefulness of this method is established and the final research outlined defining further required research and development to make the tool viable.

3.3 Methodology and findings

3.3.1 Palmprint database: texture based palmprint identification

3.3.2 DCT features to evaluate image region of interest (ROI)

To investigate palmprint acquisition a method is needed to understand what constitutes a good image. Hong Kong University Biometric Research Center [“Biometric Research Center - HK PolyU,” 2013] has published papers on palmprint identification. For academic research Hong Kong University provides a database of prepared palmprints [“PolyU Palmprint Database,” Retrieved December 8, 2013]. The method section below describes a palmprint texture based recognition technique [Dale et al., 2009] that is used on the provided database. The findings section describes the implementation, and the results that were obtained using this technique and the database. This will be followed by conclusions that describe what we can extract from the practical implementation.

Method

For academic research the Hong Kong University provided a database of prepared palmprints [“PolyU Palmprint Database,” Retrieved December 8, 2013]. Upon request Version 2 was supplied, providing a zip file with 7752 images. This corresponds to 386 different people, with images from two sessions. Each session had the same palmprint image taken between eight and ten times. Each image is 384x284 pixels. The images remain anonymous although they are easily identified with the following file naming convention:

PolyU_xxx_L_NN.bmp

xxx – the person, ranging from 001 to 386

L – Either 'F' or 'S' representing first or second session

NN – the image number from 01 to 10

No information is supplied as to how the palmprint database images have been prepared. The fingers have been cropped off, and some form of template between the fingers has masked the parts between the fingers. The image has been cropped before the start of the wrist.

Dale et al. [Dale et al., 2009] describe a method that uses the palmprint database provided.

The steps involved are:

1. palmprint cropping
2. Feature Extraction using DCT

3. Training and Measurement

A description of the practical implementation of the described method is given in the following sections for each of these steps.

Palmprint cropping

A Java desktop program was written to automatically run through all the images within the palmprint database folder. A memory map is constructed that identifies a person by a numerical number ranging from 001 to 386. Each person in this memory map has information

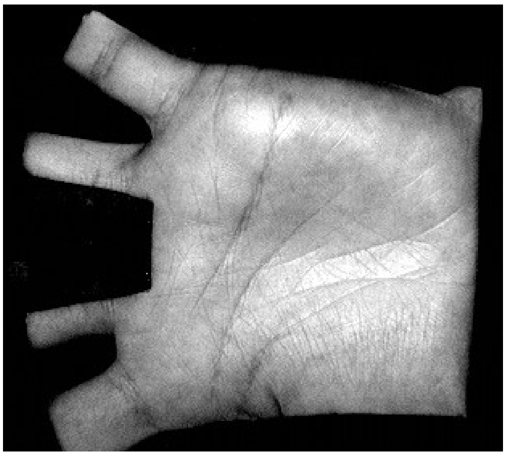


Fig 2. Example palmprint from PolyU university database

about the palmprint sessions along with the names of all the filenames for the images associated with the session.

The palmprint database has already been set up where most background noise along with thumb and fingers have been removed, or blocked out. Fig 2 shows one such example from the database.

OpenCV [“OpenCV 2.4.6.0 documentation, open source image processing library,” 2013] is used for all generic image processing. Where the algorithms are not available they have been written. This allows the focus to be on palmprint research rather than spending time developing already existing standard image processing code.

Palmprint ROI extraction is done in four stages [Dale et al., 2009]

1. Low Pass Filtering to smooth the image
2. Obtaining the external boundary of the palmprint and identifying the corners which are used to anchor the ROI, near the wrist.
3. Joining the corner wrist points, from the center project a perpendicular line across the palm

4. Defining a Region of Interest (ROI) which is 128x128 pixels.

Fig 3 shows the same palmprint with the corners identified by circles. Between the two is drawn a straight line, and a centerline perpendicular to that. From this a ROI is defined which is 128x128 pixels. This is the region that will be used for Feature Extraction.

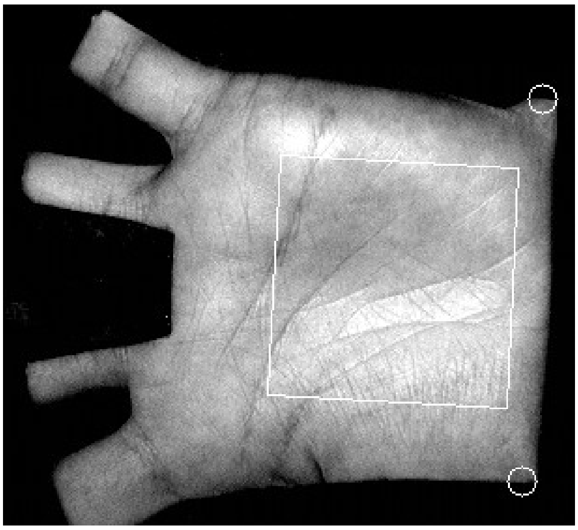


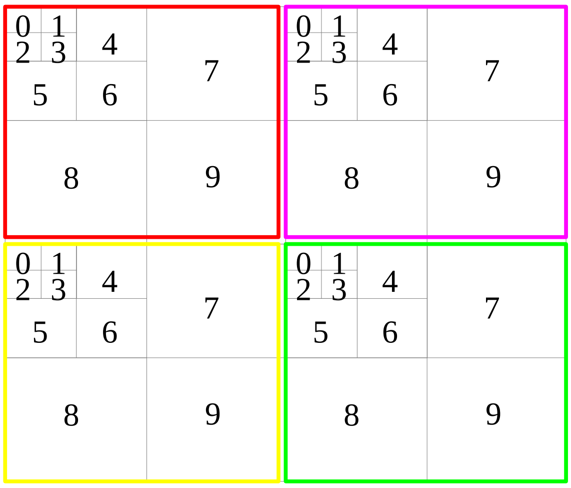
Fig 3. Palmprint with ROI and corner identification markers

Feature extraction using DCT

The extracted ROI is used to construct a feature vector of 36 values representing the image. The ROI is subdivided into four areas are given in red, purple, yellow and green as shown in Drawing 1.

Each of these four regions is 64x64 pixels in size. The Discrete Cosine Transformation (DCT) is taken on each of these four colored regions in turn. The DCT image for each region is then divided into ten sub regions as shown, numbered 0 to 9. Subregion 0 is ignored, whilst for the rest a 2D Standard Deviation (STDev) is taken to represent that region. Each of the four colored areas can then be represented by nine standard deviation values, so the total image is represented by 36 distinct values. This is a vector of 36 values representing this 128x128 pixel image. It is this vector that is used for training and validation later and is called the feature vector for this palmprint.

Fig 4 shows an extracted ROI with the Feature vector segmentation shown.



Drawing 1: Feature vector segmentation of palmprint ROI

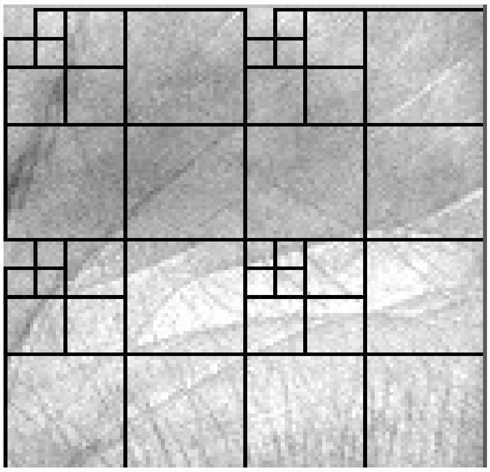


Fig 4. ROI with feature vector segmentation lines showing

Training and measurement

In construction of the PolyU database each person had attended two sessions, the first and second. Each session had a number of images, nominally ten. Each image had a feature vector generated, and each person can have an average feature vector representing that person. In this way a database of palmprint Feature Vectors was created for identification purposes.

A test set was chosen that represents the person. A single session was chosen for training and testing feature vectors that represent each person. The details of how the test set was chosen are not explicitly explained [Dale et al., 2009]. The total number of people in the test and training set was fifty. *K* represents the number of images used for training of a single person's feature vector. The total number of images will be five hundred irrespective of the value of *K*, so that the number in the testing set will reduce as the number in the training set is increased.

Table 3: Training set and image information (PolyU Database) shows that as *K* increased for the training set, the sum of the training set and test set was always five hundred. The trained feature vector is the average vector of the training image set feature vectors. Each trained feature vector was compared against all trained feature vectors representing all fifty people. Canberra distance was used to check for the best match.

K	**Training Set**	**Testing Set**
2	2x50=100	8x50=400
4	4x50=200	6x50=300
6	6x50=300	4x50=200

Table 3: Training set and image information (PolyU Database)

The logic used for comparison can be summarized best in pseudo code as follows:

Total number of images: 50 people, 10 images each, so total is 500

*Training images = K *50, where K = 2 ,4, 6 respectively.*

For each of the 50 people, average the first K vectors, and store as trained feature vector.

Number of Test images = 500 – Training Images

For each of the test images:

Check the Canberra distance of the feature vector to all trained feature vectors

Order the Canberra distance results in ascending order

The smallest Canberra distance can then be tested:

True positive if the same person produced the test and trained image feature vectors

False positive if the person producing the test image feature vector is not the same person as the the person that produced the trained image feature vector

A measurement of the Percentage Genuine Acceptance Rate is then calculated as the total number of true positive matches as a percentage of the total number of images tested.

Findings

A program called 'processPalms' was written in Java. The entire database of images was cataloged and a memory database of the images obtained. The results are shown as follows:

Number of files = '7153'.

Number of people = '356', number of images = '7153''.

Each person should have two sessions, and roughly ten images in each session.

The program is written to allow visual representation of the palmprint images, related information about them as well as turning on and off various metrics or algorithm visualization of the image processing. In this way the images, algorithms and results can be analyzed. The following describes each process acting on the database images, showing what was done and why.

All the following algorithms are available in OpenCV ["OpenCV 2.4.6.0 documentation, open source image processing library," 2013] unless specifically stated.

Extracting the ROI

The first process is to low pass filter the image. This will blur the image and aid in production of a solid palmprint for boundary identification. This was achieved using the Median Blur function which replaces a pixel with the median of surrounding pixels. A kernel size of 3 worked well and experimental changes did not effect results.

Once the low pass filter has prepared and removed any high frequency items in the image, thresholding occurs. Turning the image into binary is done using a threshold value of 32. Any pixel above is set to 255, and any pixel below set to 0. Once a binary representation of the palmprint is available dilation and erosion are used to filter out any small artifacts from the image. A Morph ellipse is created with a kernel size of 7. The kernel size and thresholds were experimentally changed to find the optimal for the image set. A typical binary palmprint can be seen in Fig 6

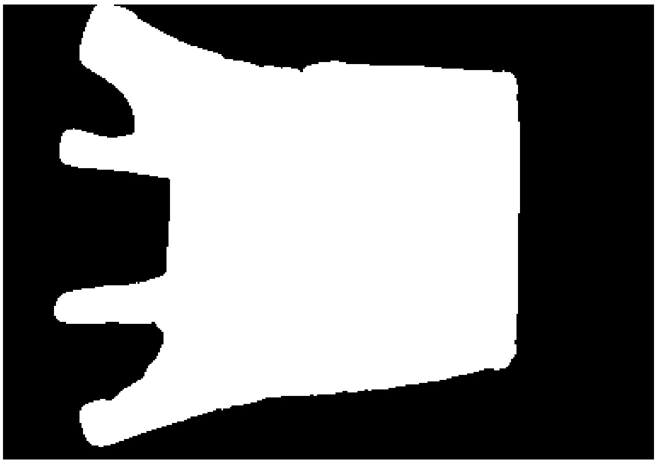


Fig 6. Binary palmprint used for contour extraction

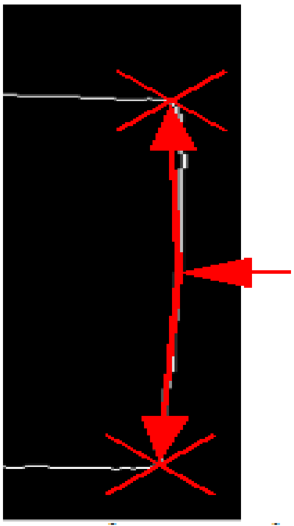


Fig 5. Palmprint corner detection

OpenCV supplies a contour method that will trace all internal and external binary edges. Asking this method to do simple chain approximation and only detect external contours it will find a list of all contours. Sometimes, due to dilation and erosion, fingers may be separated from the main palm, or there are background artifacts that are too big to be removed. In these cases multiple contours may be found. Each contour is a vector of points. OpenCV provides functionality to take an array of points and return a single minimum bounding rectangle that contains all the points. In this way we can find a bounding rectangle for all contours. Only the largest is chosen to represent the main Palm area. This can be seen as in Fig 7.

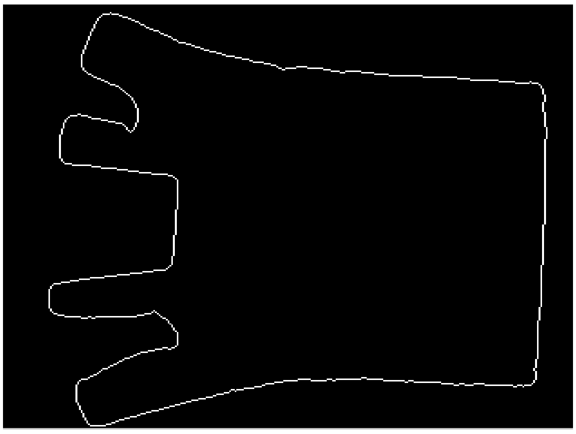


Fig 7. Palmprint with boundary contour shown

First the corners should be found, from which a center point and an ROI can be extracted for the method to work on [Dale et al., 2009]. There are many techniques for finding corners. Due to the clean nature of the contour a simple algorithm was developed. The method is described by the pseudo code below and shown in Fig 5:

Start from the right hand edge, center position

Work left until the contour is found.

Simultaneously work up and down until the next pixel is more than three pixels to the left along the x-axis, this will be the corner

The simplicity of this method works well in most cases. Alternatives, for example Harris Corners were tried, however extra complexity appeared to be added with no additional advantage or improvement in accuracy.

The ROI is found by projecting a line that is perpendicular to the line between the two corners, starting at the center-point of that line. At a predefined distance from the starting point a rectangle which is 128x128 pixels in size will represent the ROI. Note that the vertical edges of the rectangle are parallel with the line extending between the two corner points. In the same manner the horizontal rectangle edges are perpendicular to the line between the two corner points. OpenCV did not provide functionality for this purpose, so methods using a mixture of Polar and Cartesian coordinates were developed. Fig 8 shows the ROI extracted from the 'processPalms' program.

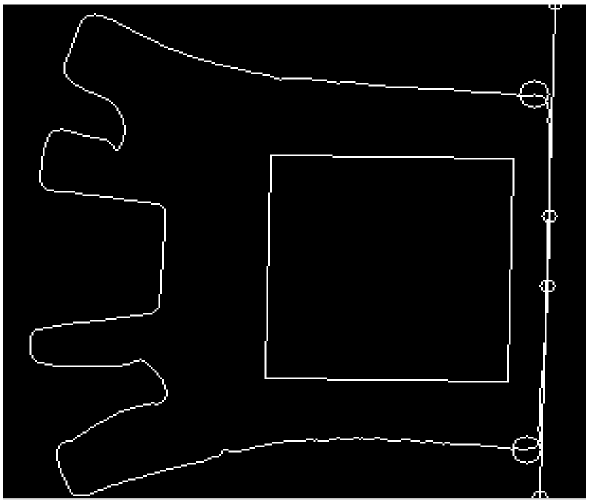


Fig 8. Palmprint contour with ROI and corner markers

Once the four corners of the ROI are known, OpenCV offers the methods that when combined extract the rotated area into a separate image that is parallel with the Cartesian axes. The following pseudo code describes the process:

Create a rotation matrix centered on the ROI (getRotationMatrix)

Create a new target image the same as the original

Use Affine transformation to rotate the whole palm image (warpAffine)

Use the OpenCV sub matrix to extract the 128x128 ROI into separate image

In the recognition algorithm tests that follow the ROI is the image that represents the palmprint. The rotation and extraction of the ROI is done on the original palmprint image. Fig. 9, shows the ROI before, followed by rotation and extraction.

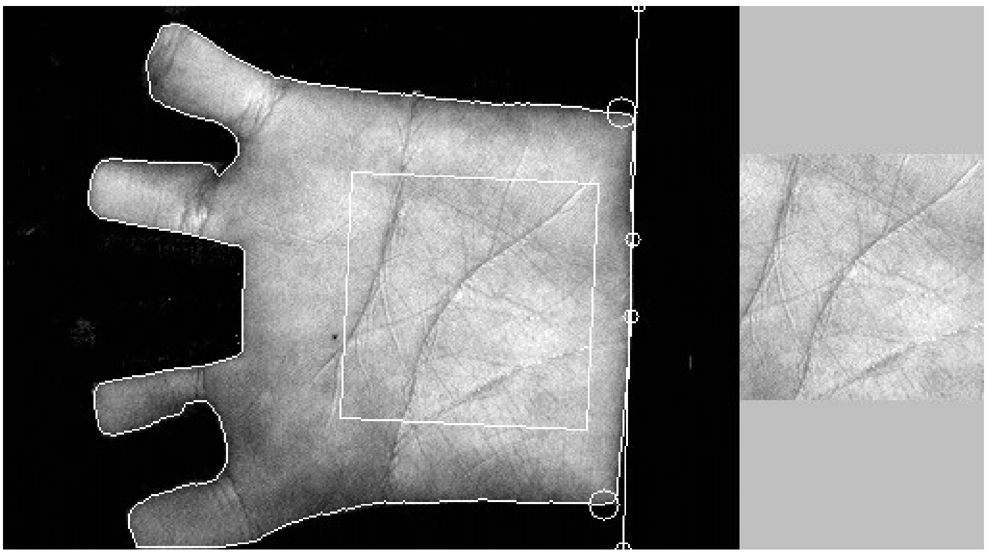


Fig 9. ROI rotation and extraction ready for feature vector analysis

The last stage of training is to construct the feature vector from the extracted ROI.

As explained, in the section entitled Feature extraction using DCT, the ROI is broken into four distinct areas which are 64x64 pixels in size. Each one has the Discrete Cosine Transform taken. Each of these areas has nine boxed sub-areas having the standard deviation taken. There are nine standard deviation values representing each of the four areas. A 36 value feature vector represents this ROI.

One such example for person 38, second session, the tenth image looks as follows:

'S':'PolyU_338_S_10.bmp':[7.99172088755395, 10.677375802018895, 7.692784592622819, 13.5965084263125, 17.303553806203464, 12.223486503838624, 36.74711935425035, 42.62042165860556, 23.675355257491358, 7.7926736462260395, 12.307641715587762, 7.919321859480516, 11.72385110956761, 20.809393598317307, 12.540450298257545, 29.756962452831026, 41.64707065687327, 20.713391258064302, 7.614929909709018, 7.185989634695335, 6.74576473936209, 12.687948090582992, 13.337576073220793, 12.101668430659092, 29.29210857134562, 27.71725030193739, 21.202233617207195, 7.86006806445765, 7.279881877249804, 5.896174350503509, 12.545172921706545, 12.96890239405446, 9.523874992252571, 30.73843182853471, 23.51401693948089, 19.065396558210907]

At this point 386 people were in the database of palmprints. The assumption was that each and every image could be used, so 7752 feature vectors. When running the 'processPalms' program using visual analysis of the images along with feature vector checks some problems were observed.

As there were so many images manual inspection is time consuming. For this reason various checks were built in. One check is for Null Feature Vectors. This means that a feature vector could not be obtained. Fig 10 is a good representation as to why:

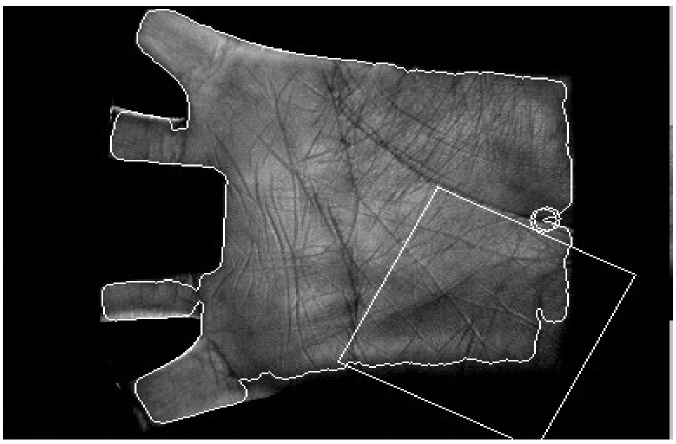


Fig 10. Palmprint with ROI out of bounds due to incorrect corner detection

The corner finding algorithm failed, so the corresponding ROI stepped outside the boundaries of the image, so the vector creation failed causing the exception. It is difficult to see how any corner algorithm can easily find projected corners without more advanced image processing in this case.

Null feature vectors opened up many more issues when examining almost all the images one by one. Some examples follow (Figs 12 - 14):

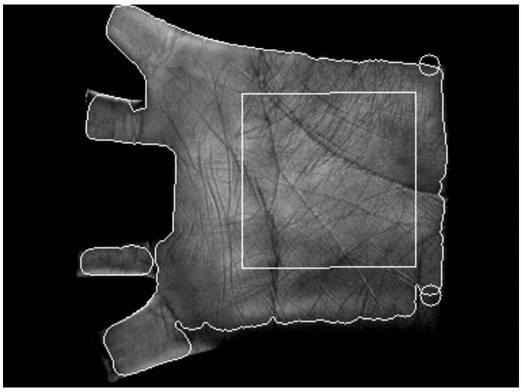


Fig 12. Offset ROI on palmprint due to incorrect corner detection

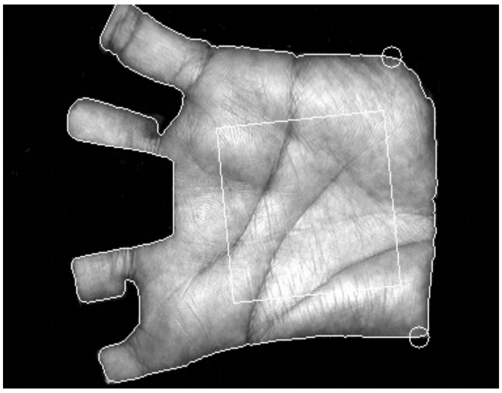


Fig 11. Rotated ROI on palmprint due to large curve caused by corner detection problems.

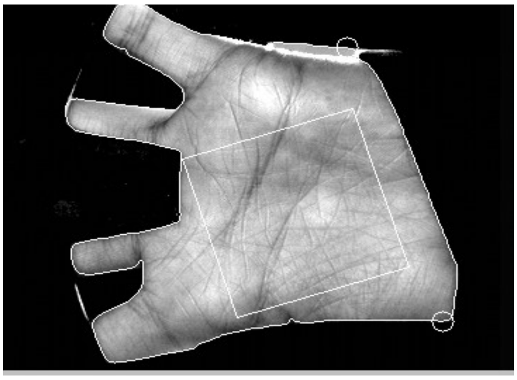


Fig 13. Rotated and offset ROI due to corners can't be found with missing wrist area

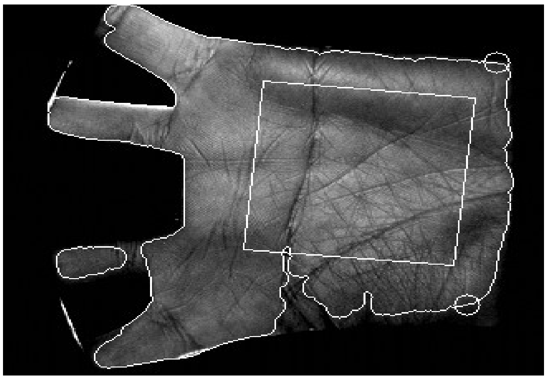


Fig 14. Incorrect ROI due to poor palmprint image

When studied the same person can have a very clean palmprint and unusable palmprints simply by releasing pressure of the hand on the device taking the image. In this way the threshold being used can move considerably as shown in Figs 11 to 13. The amount of this change depends on the hand, whether it is wrinkled, has loose skin, is made up of fatty tissues or is very lean, whether one side of the hand is lifted more than the other. These are only the obvious change factors. Variable thresholding was considered and briefly studied. As the variation was great and uneven across the palm it was found not to add value or improve the situation in finding the corners. A more advanced method would be needed.

Whilst studying the images for problems in establishing consistent corner points to base the ROI on, saturation problems were noticed. An example is shown in Fig 15:

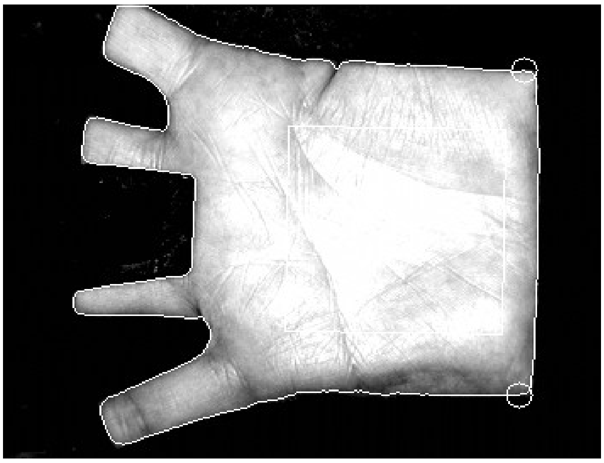


Fig 15. Example of good ROI placement with saturated ROI

It can be seen that although a ROI is found from well established corners, the ROI itself is saturated. This means a large proportion of the pixels are white or near white. The reality of this is that the feature vector cannot reliably represent the palmprint as valuable information has been lost by saturation.

It was found that although there is a consistency between images in the same session, they can differ between sessions. For example the following images show the same person where one palmprint is taken from the first session, and the other from the second session (Figs 16 and 17):

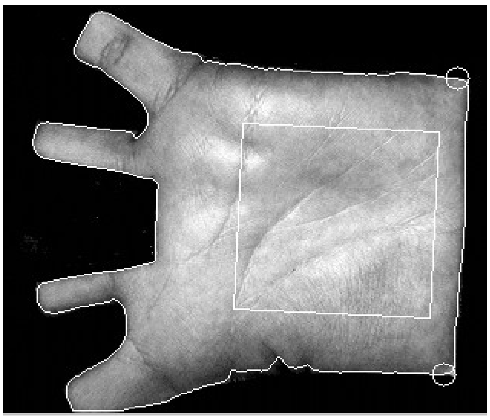


Fig 16. Example where the first session palmprint taken is good.

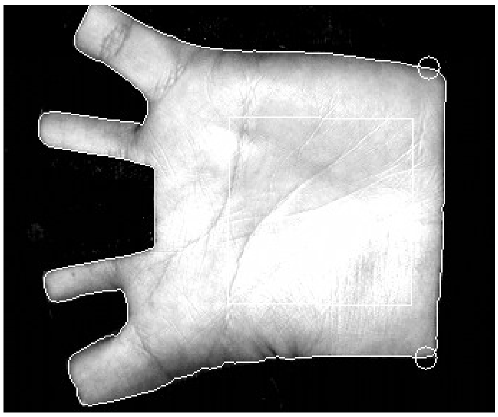


Fig 17. Example where the second session palmprint taken over saturated and not good

The Canberra distance between the two average vectors for the two sessions would be quite large, and yet this is the same person. The slight variation should not affect the feature vector distance, but the saturation loses information which increases the distance between them.

A simple manual study related to the mentioned problems within some images led to 582 images associated with 30 people being removed from the sample set just based on the visual analysis and null feature vectors as described. The original starting point was 386 people, so this is why all tests were done with the remaining 356 people.

Testing the ROI

The samples from 50 people were taken and tested [Dale et al., 2009]. The original paper does not describe how the 50 people were chosen from the whole set of people. So in this thesis, in addition to testing the whole set of 356 people, two sets of 50 people were separated to test as in the original paper. The method to extract the two sets of fifty people is described in the following pseudo code:

Iterate through each of the 356 people

For each person test the first session, then the second session calculating the session deviation.

Once a list of a person's name, first session and second deviation are calculated sort ALL session deviations by the first session placing in ascending order.

'Session deviation' is calculated by

Calculating the average feature vector for the session

Measuring the Canberra distance for each image feature vector in relation to the average session feature vector, finding the max and min deviation.

Calculating the session deviation which is : max – min deviation.

The output from this calculation is a list of all the people tested, sorted by the first session deviation. The first has the least deviation from all images to the average feature vector. Selecting the first fifty people makes up the first top 50 images, whilst the next 50 make up the second top 50 people. We now have three different sample sets. The complete population of the database, then the best and second best 50 palmprints. Some sample measurements are shown in Appendix 2–Selection of sample palmprints using session deviation. to show the method used in more detail.

The results of palmprint recognition described using feature vectors are shown in the table 4:

Test Set	**Total**	**True Positive**	**False Positive**	**K**	**%GAR**	**Results [Dale et al., 2009]**
Good Image Set 356 People	2871	2598	273	2	90.49	-
Good Image Set 356 People	2159	2046	113	4	94.8	-

Good Image Set 356 People	1447	1400	47	6	96.75	-
Top 50	400	399	1	2	99.75	93.3
Second Top 50	404	404	0	2	100	
Top 50	300	300	0	4	100	95
Second Top 50	304	304	0	4	100	
Top 50	200	200	0	6	100	97.5
Second Top 50	204	204	0	6	100	

Table 4: Palmprint database person feature vector identification results (PolyU Database)

These results can now be compared with those found from Dale et al. [Dale et al., 2009] as seen in the last column. Using the whole set of people there are similar results when K= 2,4,6. The closest match is when K=4. When selecting the test sets for the least session feature vector deviation then very good results verging on 100% genuine acceptance rate are achieved.

Discussions

The purpose of implementing the method described, Texture Based Palm Print Identification Using DCT Features to Evaluate Image Region of Interest (ROI) [Dale et al., 2009], has been successful. The successful points are now be discussed.

Table 4 shows that using the PolyU palmprint database ["PolyU Palmprint Database," Retrieved December 8, 2013] similar results can be achieved. Using the whole database of good images, totaling 356 people, the figure of 95% GAR for K=4 directly matches the results. The measured vs reported results for K=2 are 93.3% compared to 90.49% and then K=6 is 97.5% compared to 96.75%. Therefore these results would be considered acceptable when the methods for finding corners, thresholding and other image processing methods can vary depending on implementation and choices.

Taking the tests further 50 sampled people were selected from the entire database set to run the tests [Dale et al., 2009]. In the Findings, session deviation is discussed. For every person in the whole database the minimum deviations in the first session were ordered in a list. This enabled a first and second set of 50 people to be chosen with the minimal session deviation between all palmprints taken; the idea being to see the best results that can be achieved. Table 4 shows that with K=2, 4, 6 then 100% GAR can be achieved. This is somewhat artificial and contrived. This proves that with careful selection, results could be molded and improved, even though they were not in the paper studied. The test would also show that results quickly decrease %GAR if larger session deviation sets were also used. It was not thought to be useful to continue these tests, but rather move onto the next stages. The claim is that preprocessing will improve %GAR [Dale et al., 2009] which the results do indicate to be the case.

As demonstrated in the section Findings, there were 30 images completely discarded. The main issue is that the ROI could not be found due to thresholding problems as one example. As a palm is pressed down on glass it flattens and moves depending for example on how flexible or how stretchy the skin is. It does not take much to consider that if the image were taken without pressing down and altering the external shape of the palm a more consistent ROI might mean these could be used as valid images. This would also represent real world results better. It was considered to try and use Haarcascades [Lienhart & Maydt, 2002], Histogram of Gradiants (HOG) training [Dalal & Triggs, 2005] and contours to detect convex hull shapes which show where the fingers are positioned. Once the fingers could be found accurately then it is believed a consistent ROI could be found. Studying the PolyU database of palmprints it was determined that the images could not be used as the hull shapes between the fingers are masked off. The wrist area has also been chopped off. There are no other areas that could be used to detect and create a consistent ROI. Although the database represents real world image acquisition using a palmprint device that is made for the purpose and with a hand placed in it, the method could not be used in the context of palmprint detection using mobile phones for further studies as described in the Appendix 1.

All the database palmprint images have already been prepared using a set resolution of 368x284. Therefore rotation of the ROI is the only point where the database images have a possible change in pixel information. OpenCV offers a rotation and interpolation function using cubic interpolation to try and make certain as much of the information as possible is not lost. Using a mobile camera image resolution would vary considerably depending on the distance from the palmprint. This database does not represent the real situation when taking palmprint images with a mobile phone.

Saturation issues were noticed in many of the images that were removed from the test set as well as within images that remained. As the focus at this point was on the ROI extraction this was left to a later stage. A simple measurement of percentage of saturated pixels could be made to quantify the quality of the image. This will be done at a future stage.

During this exploration the results from Dale et al. [Dale et al., 2009] have been verified. Some issues related to the selection of images, image quality and region of Interest extraction have been brought into question regarding how they would behave if used when a camera phone is used rather than on a static data set. With this in mind the next exploration will be tackling the area of how to extract a consistent ROI within palmprints from images taken with mobile phones, and brought together by using the same feature extraction technique already tested.

3.3.3 Establishing an independent dataset for ROI extraction evaluation

The PolyU database has clipped wrist and fingers, being placed on a jig before the image is captured. As the intention is to take images on a normal mobile device, a Palm Database of full hand images is required to evaluate methods for ROI extraction. Taking hand images and establishing a collection of full hand images is presented here. Evaluating the dataset with respect to ROI extraction and suitability for the evaluation is discussed.

First the general method is explained, before the measurements and findings are discussed.

Method

An anonymous set of hand images were gathered. The dataset was collected for testing and then deleted to comply with data collection laws in Finland. Friends, family, random students and University staff contributed to hand images. One session was held, collecting ten images of the left hand. No attention was taken on geographical location of origin, or age group. The images taken were as follows:

English Man	1
German	1
Finnish Men	29
Finnish Ladies	6
Italian Lady	1
French	1

Of these three children, two boys and one girl, were also included in the above.

Total number of people was 39. Total number of images was 3900.

The data was collected to conform to the way the PolyU data was presented. The filenames in this case to make them anonymous were as follows:

ANDYSDB_xxx_L_NN.jpg

xxx – the person, ranging from 001 to 039

L – Either 'F' or 'S' representing first or second session. In this case only 'F'

NN – the image number from 01 to 10

The Region of Interest (ROI) described in the section Extracting the ROI (29), was concentrated on the PolyU Database where fingers and the palm had been cropped. The image was already in gray-scale. Therefore there is no prior knowledge of whether gray-scale images were taken or converted from color in the PolyU database. The assumption is that the Palm image data set is well formed as far as can be known.

Within the new data set the whole palm is present as shown in Fig 18. Anonymous person example1, and in Fig 19. Anonymous person example2.

Fig 18. Anonymous person example1

Fig 19. Anonymous person example2

The images shown are from the same person. A concerted effort to not bias results was taken. The images are positioned off center, different scales in the Z-Axis, and partial rotation deliberately included in the images. The reason is to simulate real world situations where a person is taking a dataset located anywhere outside controlled environments. A high resolution mobile phone is used.

Background extraction techniques were needed to be able to separate the real palm image from the background of where the images have been taken. The background is set to zero, so that all processing only then includes the Palm Image itself.

With the palm separated from background the finger valleys, sometimes referred to as inter-digital folds, can be identified. A consistent region of interest can be established in relation to these inter-digital folds which is consistent for each individual as shown in Fig 20. Interdigital fold, and ROI extraction.

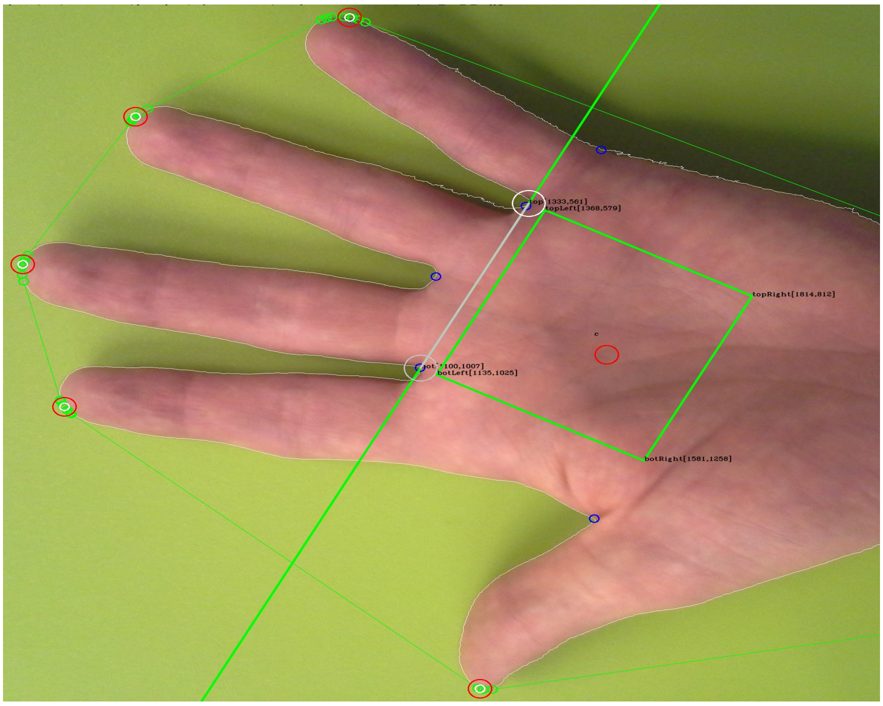


Fig 20. Interdigital fold, and ROI extraction.

The ROI is now extracted, and rotated about the center. Non-lossy format of bitmaps is used for the ROI storage, and bi-linear interpolation is used to keep as much of the pixel information integrity as possible.

Each ROI can be different in size depending on the rotation and how close or far away the image was taken.

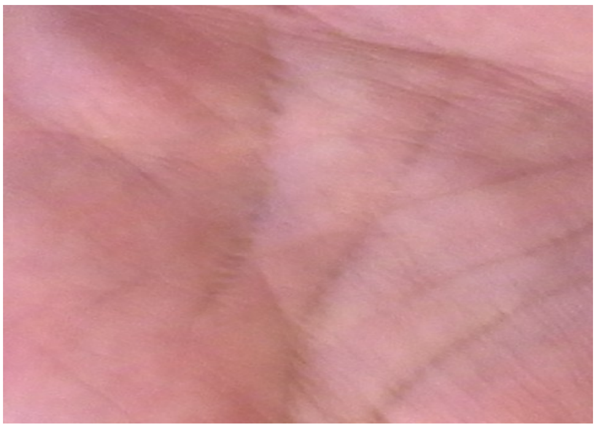


Fig 22. andysdb_004_f_06.bmp - 480x480 pixels

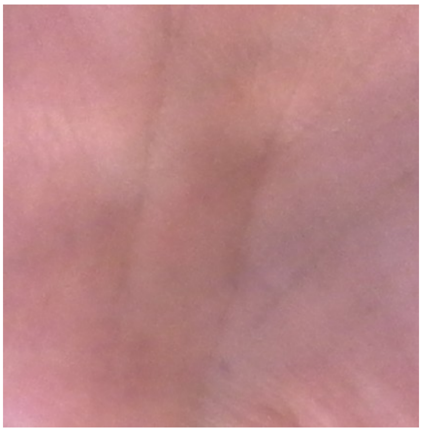


Fig 21. andysdb_009_f_09.bmp - 430x430 pixels

Fig 21. andysdb_009_f_09.bmp - 430x430 pixels and Fig 22. andysdb_004_f_06.bmp - 480x480 pixels show the ROI extracted and the difference in the sizes depending on the scale distortion, i.e. how far away the camera is from the palm when the image is taken.

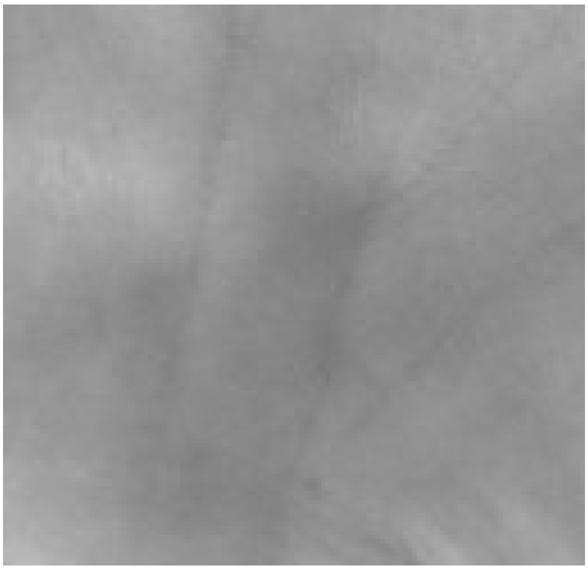


Fig 23. Grayscale andysdb_009_f_09.bmp 128x128

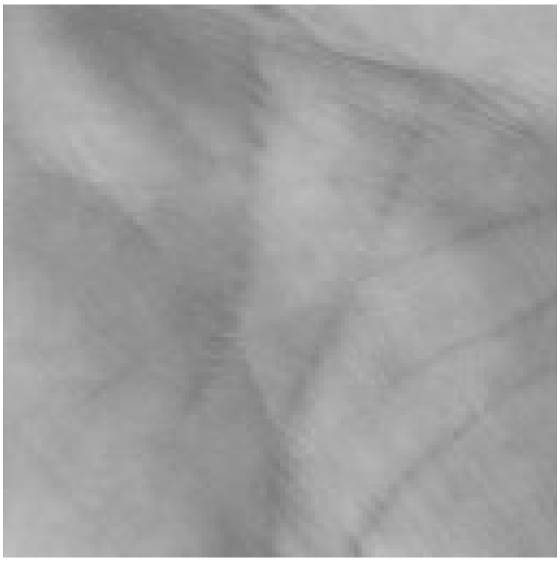


Fig 24. Grayscale andysdb_004_f_06.bmp 128x128

To use the same comparison as with the PolyU database defined in Testing the ROI findings, the ROI is converted to gray-scale and scaled to a size of 128x128.

The examples then become Fig 24. Grayscale andysdb_004_f_06.bmp 128x128 and Fig 23. Grayscale andysdb_009_f_09.bmp 128x128 respectively.

From this point onwards the same software and methodology, as defined in Feature extraction using DCT and described in detail in Testing the ROI, is used for feature extraction and comparison.

Findings describe how this was implemented, followed by a discussion of the results obtained.

Findings

The images are taken with a Samsung Galaxy XCover 2 [“Samsung Galaxy XCover 2 - Android 4.1, 1GHz, 4” TFT WVGA, 5MP Camera,” 2013]. The images are all 2560x1920 pixels, and color.

The following sections deal with background removal, extraction of the ROI followed by the testing the ROI

Background extraction

Academic research has been looking into background removal for many years. Some of these have been described in section 2.4 Background extraction in the literature review. Histogram back projection and color space conversion are discussed there in more detail.

An automated background extraction technique was initially developed using Hue Saturation Variance (HSV) color space. Hue is kept, whilst trying to ignore value and saturation. This acts as a filter. Using a green place mat, the green clearly stands out from any color in a Palm image, as shown in Fig 18. Anonymous person example1. Converting from RGB to color space using OpenCV library, the hue is normalized to construct an 8 bin histogram. This can be seen in Fig 25. HSV 8 bin histogram of palm image for andysdb_000_f_001.jpg.

Fig 25. HSV 8 bin histogram of palm image for andysdb_000_f_001.jpg

Histogram back projection, [“Back Projection — OpenCV 2.4.9.0 documentation,” Retrieved June 1, 2014], is used on the original image so that the present colors are enhanced, and others filtered away. An image without most background noise is produced as in Fig 26. Histogram back projection andysdb_000_f_01.bmp.

Fig 26. Histogram back projection andysdb_000_f_01.bmp

From this a binary image is produced using thresholding shown in Fig 27. Thresholded image andysdb_000_f_01.bmp.

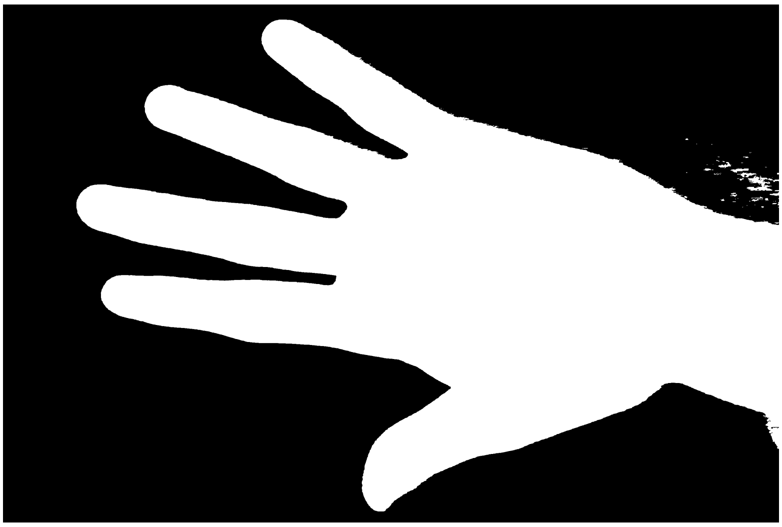


Fig 27. Thresholded image andysdb_000_f_01.bmp

The fact that there are artifacts in the background of the image does not matter. Using the OpenCV contour to find the largest external contour, the outline of the palm is found, filtering out all other artifacts. Everything else is rejected. A single image with the contour is produced, and has been drawn around the palm image for clarity in Fig 20. Interdigital fold, and ROI extraction.. The white outline tightly hugs the contour of the hand.

To find the inter-digital folds, there are two more stages using more common OpenCV functionality. A convex hull will take a full set of vectors in the contour and reduce them to a subset which will surround the hand in an external hull shape joining the extremities. A minimal set is given which are shown in green within Fig 28. Convex hull and convexity

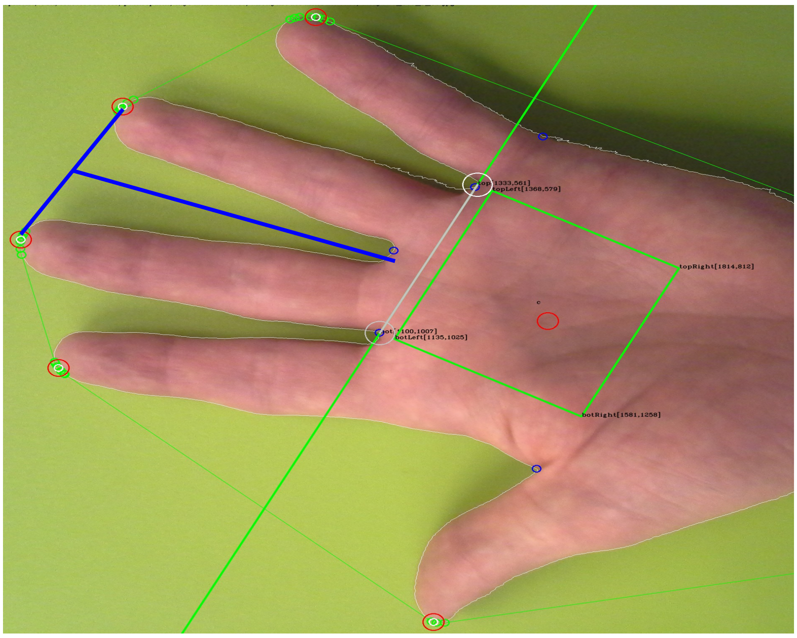


Fig 28. Convex hull and convexity defects

defects. There are multiple green circles that indicate the individual external vectors. The red circle indicates a central single point that is the average of all of those at the end of the fingers. This is to get a further reduced set of points that represent the ends of the fingers.

Using the contour points and the reduced finger tip points, Convexity Defects [“Structural Analysis and Shape Descriptors — OpenCV 2.4.9.0 documentation, Convex Hull.,” Retrieved June 1, 2014] are calculated [Kulkarni & Kopanar, 2013 ; Banu, 2012]. Fig 28. Convex hull and convexity defects shows in blue how this works. Although done mathematically, visually it can be seen that a line is drawn between the ends of the two finger points. Using the contour points each point is used to calculate the maximum distance from that initial line between the fingers to the hull defect point. The maximum distance from that line is then noted as the convexity defect, or what is called the inter-digital fold. This is shown by the second ,almost perpendicular, blue line extending to the inter-digital fold. One convex hull point is obtained for each inter-digital fold. As can be seen in Fig 28. Convex hull and convexity defects only two of these are chosen, represented by large white circles and a line drawn between them. An ROI can then be referenced from this two points and extracted, rotated, and stored for evaluation.

As there are 39 people, 3900 separate ROI images are stored under the name of the original image as bitmaps. Each ROI only differs in size and content now. Examples of a small part of the database is as follows:

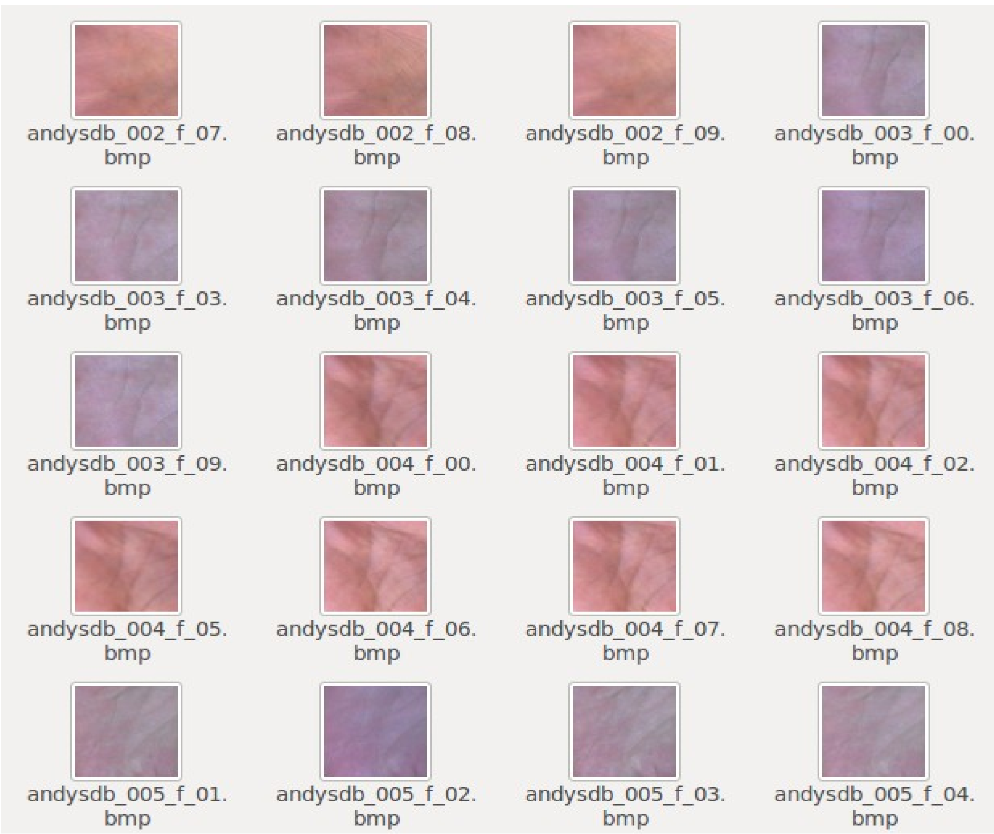


Fig 29. Example palm database extracted ROI

This technique worked well under good lighting, no shadows and indoors. However when outside, when shadows could not be eliminated, this did not work well. For that reason a combination of automated and manually picked inter-digital folds allowed the focus of the thesis to stay with the evaluation of the ROI rather than background extraction. The background extraction and lighting must be continued at a later stage and research is needed in this area to make this robust and usable.

Preparation of ROI

A generic conversion application was developed to read in all the ROI bitmaps, convert to gray-scale, and resize them. Multiple outputs were generated. For example 128x128, 256x256 and so on. Only image sizes of 128x128, at this point, was used as in the original PolyU database software to match and compare the results. In the future resolution and interpolation effects could be checked. Conversion used was bilinear interpolation.

Testing ROI data set

As previously described Dale et al. [Dale et al., 2009] took 50 sampled people and tested those. In this case there are only 39 sampled people. Unlike before there is no need to sort for the best 50 people.

The test and training set are defined in Table 5: Training set and image information (Own database results).

K	Training Set	Testing Set
2	2x39=78	8x39=312
4	4x39=156	6x39=234
6	6x39=234	4x39=156

Table 5: Training set and image information (Own database results)

The results of palmprint recognition described using feature vectors are shown in Table 6: Palmprint database person feature vector identification results (Own database results):

Total Images (39 People)	True Positive	False Positive	K	%GAR	%GAR 356 People PolyU DB	(Dale et al., 2009) Results
314	266	48	2	**84%**	90.49%	93.3%
236	198	38	4	**84%**	94.8%	95%
158	139	19	6	**88%**	96.75%	97.5%

Table 6: Palmprint database person feature vector identification results (Own database results)

From the results we can see that the %GAR is poor compared with the PolyU Database. The approximate difference depends on the training set (K) varying between 6.49% and 10.8% difference.

Discussions

The expectations were that with careful ROI extraction the %GAR would compare with, or improve on, the results from the Hong Kong database. Some further analysis follows on from the following set of questions.

1. How accurate does the ROI placement need to be? Or what is the tolerance of translational movement of the ROI for comparison and correct identification to work. A dither test (Translational (dither) test analysis) was devised to try and understand this question and the impacts on the results.

2. Are all the images for a single person good? Not knowing if one image of a set is poor may significantly affect results of what constitutes a good set of images for a person. This is discussed in Person to person Canberra distance comparison.

3. Comparing average feature vectors, do we see better results? This is followed up in Average feature vector comparison .

4. Can we visualize and understand the approximate 6-8% errors when we consider K training set vs all other images? Error: Reference source not found explores this further.

The results of these tests follow, and their impact on the results obtained. We also explore some literature in the 2.5, Extracting a consistent ROI for method evaluation, section that account for the results obtained.

Translational (dither) test analysis

The question is how accurate does the ROI placement need to be? Or what is the tolerance of translational movement of the ROI for comparison and correct identification to work.

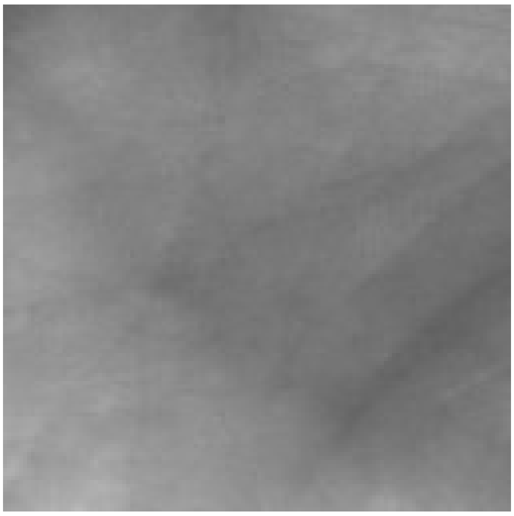


Fig 30.
andysdb_000_f_00_x_000_y_000.bmp
Dithered +/-20 stepsize 2

For this a single ROI image was taken from a single persons palm image. The 36 value feature vector established from this ROI. From the top left (x,y) position of where this reference ROI was taken in the palm-image, 400 other ROI images were taken. This was called dithering where x and y were varied from -20 to +20 in steps of 2 pixels. Each ROI had its 36 value feature vector established. Fig 30. andysdb_000_f_00_x_000_y_000.bmp Dithered +/-20 stepsize 2 demonstrates a single extracted ROI where the filename reflects the x/y dither value.

Using Matlab a surface can be drawn indicating the dither value along the x/y axis. The Z axis represents the Canberra distance between each one.

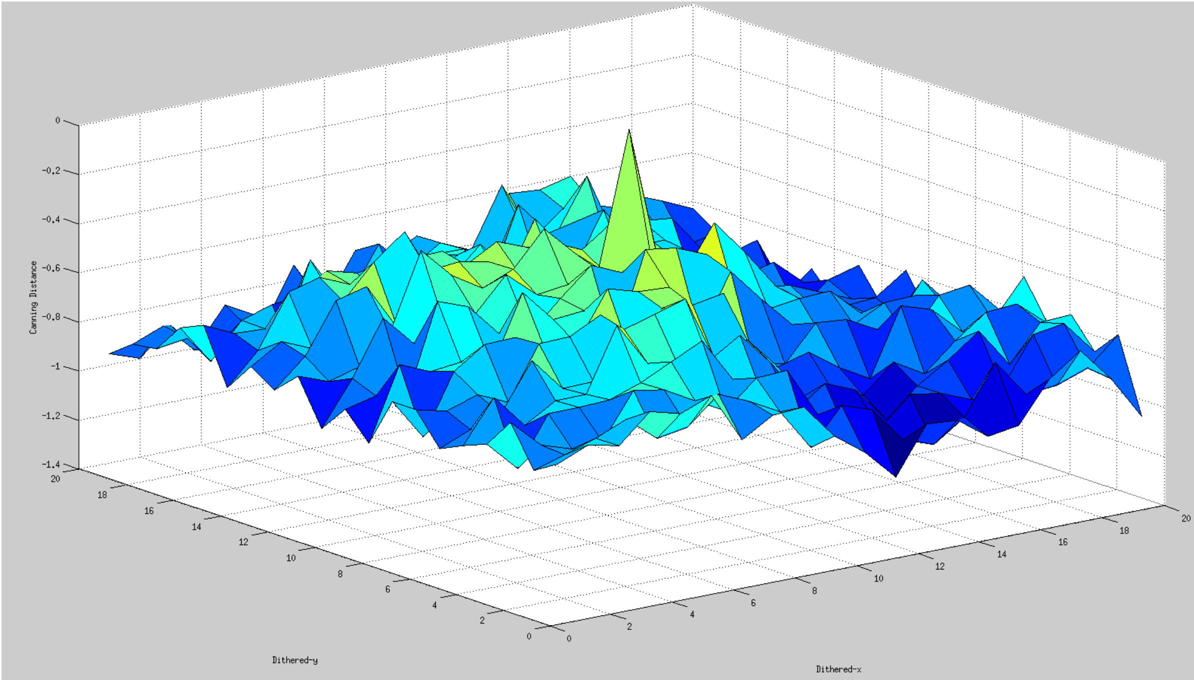


Fig 31. X-Y dithering vs Canberra distance between them

It is easy to see that there is variation, and that the largest peak is where there is no dithering, in other words the x/y dither is zero and hence the same image as the reference image where the Canberra distance is zero.

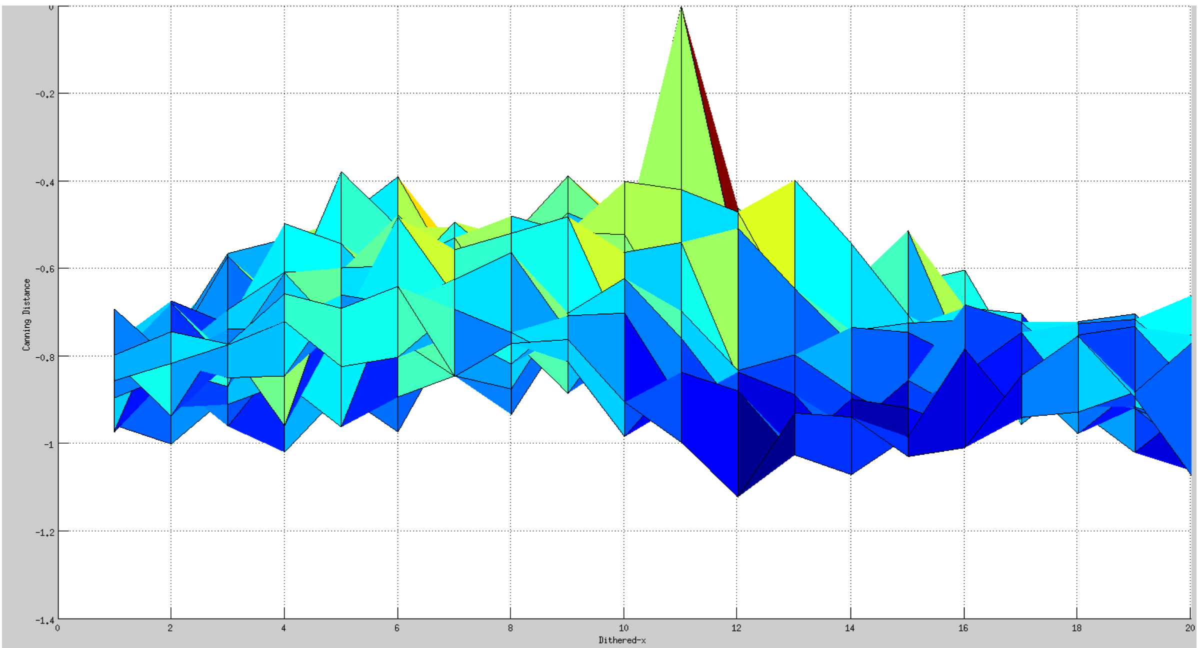


Fig 32. X-Z View

Looking from the Y or X axis we can take a look at these from the side to try and get a better understanding (Fig 32. X-Z View, Fig 33. Y-Z View).

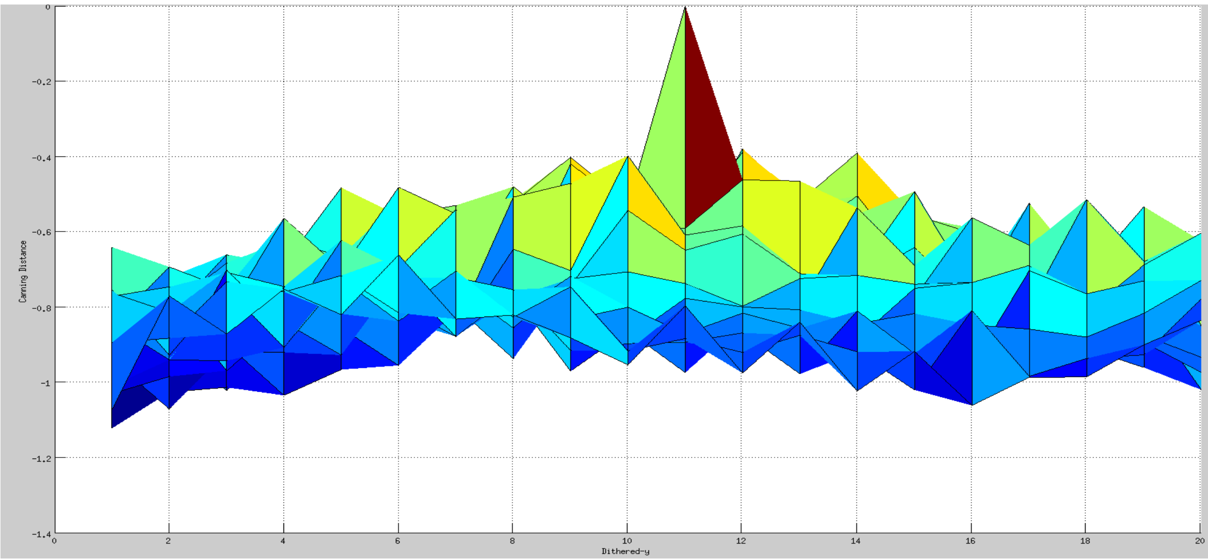


Fig 33. Y-Z View

Each feature vector standard deviation varies between each dithered image, and hence the feature vector changes. When the Canberra distances are computed we get a large variation as shown in these images, although the peak quickly appears when there is no dithering. This suggests that the further away from the correct ROI the deterioration by measuring the Canberra distance is quick. And the difference from the other peoples feature vectors quickly reduces too.

Finally a slice through column 11 which shows a single feature vectors Canberra distance with respect to all the other dithered images (Fig 34. Slice column 11 through self comparison peak). Y extends along the horizontal axis whilst the vertical axis is Canberra distance.This ROI selection with translational error is one contributing factor for the error seen.

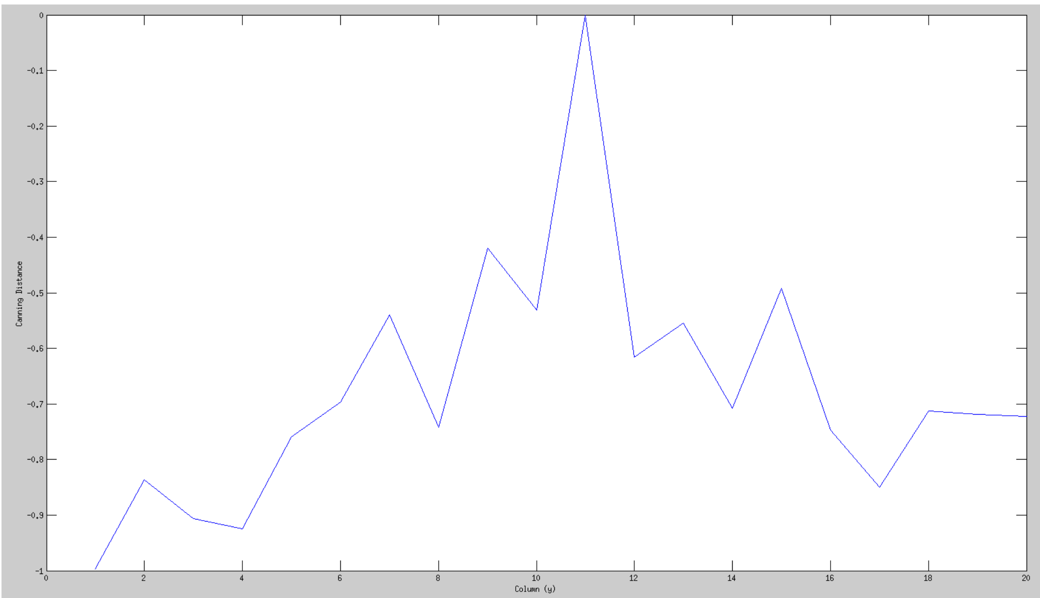


Fig 34. Slice column 11 through self comparison peak

This suggests, without being quantified mathematically at this point, that session deviation does needs to be minimized so that the Canberra distance of other peoples feature vectors is maximised.

Person to person Canberra distance comparison

Are all the images for a single person good? Not knowing if one image may throw the whole results out and what constitutes a good set of images for a person.

For this purpose the variation in a single persons set of images is measured. For each person take the average feature vector, and measure against all of that persons own images, of which there are ten. The results can be seen in Fig 35. Average feature vector vs Canberra distance for own Image set.

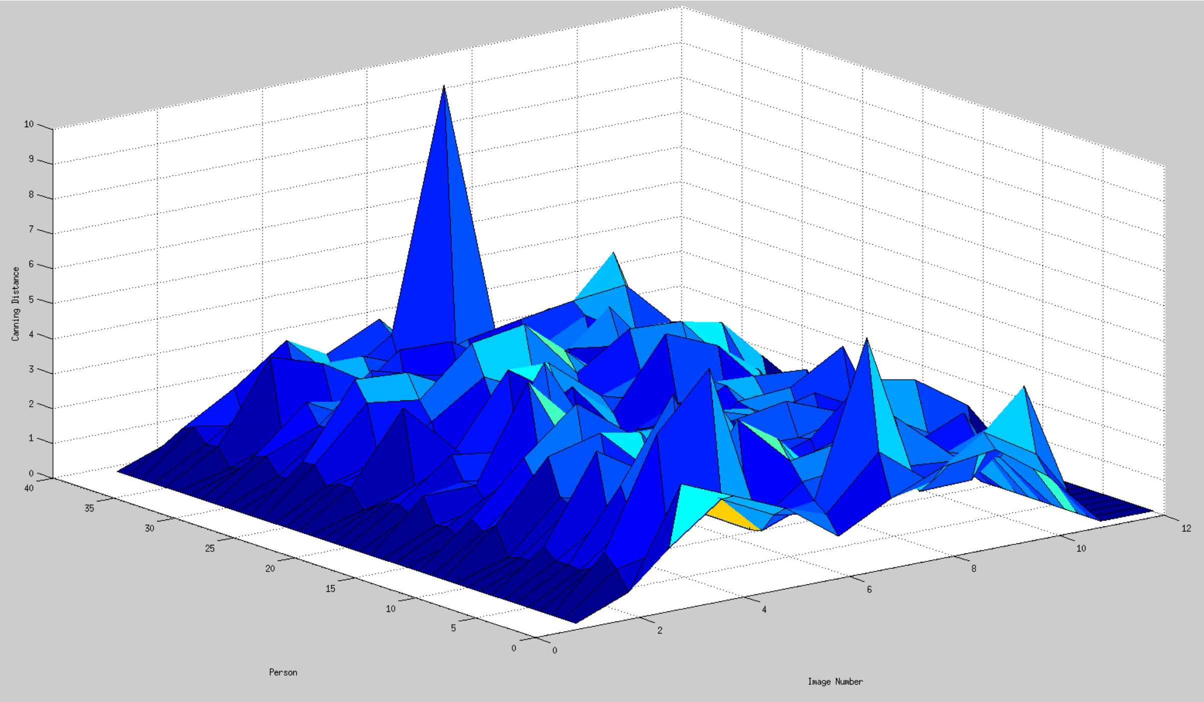


Fig 35. Average feature vector vs Canberra distance for own Image set

The X-Axis shows the images from 1-10 for each persons session images. The Y-Axis represents each of the 39 people that the image sets were taken from. Vertically shows the Canberra distance value for each persons image vs the average feature vector for that person.

The expectation is that there is a tight distribution for the same person vs its average feature vector. However there is one, and several other large peaks indicating that the set of images for each person may not be so good as was originally thought. Person 38 is where the largest peak occurs.

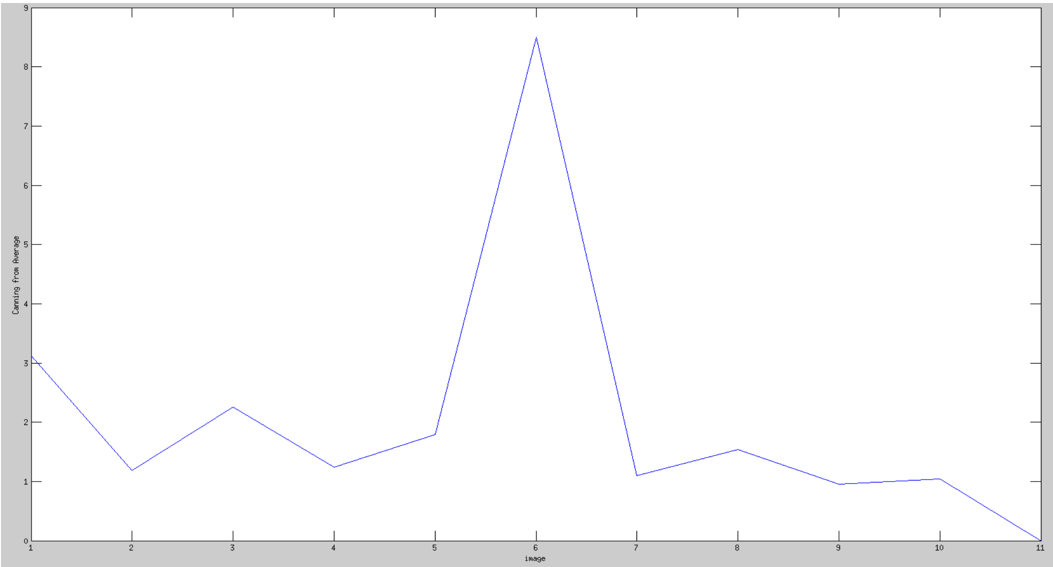


Fig 36. Average vs each image feature vector Canberra distance

There are at least 3 major peaks with a high Canberra distance away from the others, meaning large session deviation. This is a significant contribution to the errors that were in the results. The significance could increase depending on K chosen for the training set and whether there are large deviations in the distance within those.

Average feature vector comparison

Does average feature comparison artificially improve results? Do we see better discrimination between Canberra distances?

To look at this the average feature vector for each of the 39 people were taken, and a matrix of Canberra distance comparing all with all was visually presented. The results can be seen in Fig 37. Person av feature vector vs person av feature vector (view 1). and Fig 38. Person av feature vector vs person av feature vector (view 2).

View 1 is the 3D view with the graph rotated so that the self average feature Canberra distance is central showing a distance of zero.

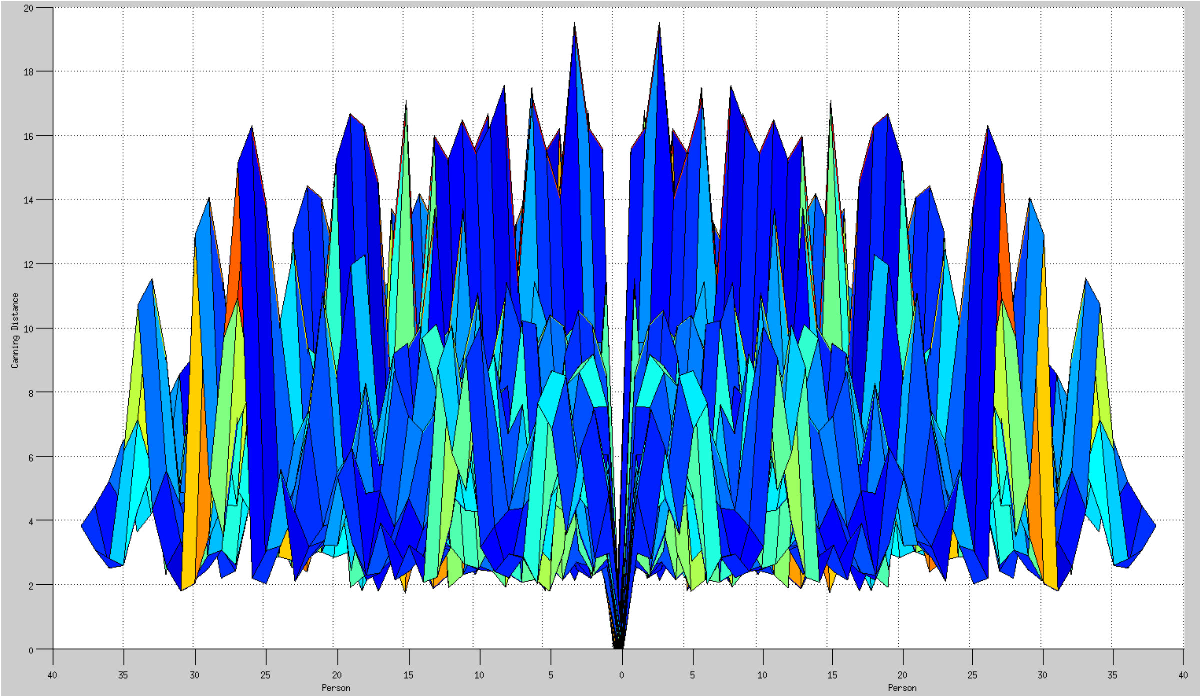


Fig 37. Person av feature vector vs person av feature vector (view 1).

View 2 is a top view where you can see the same orientation and the zero Canberra distance running from top to bottom corners.

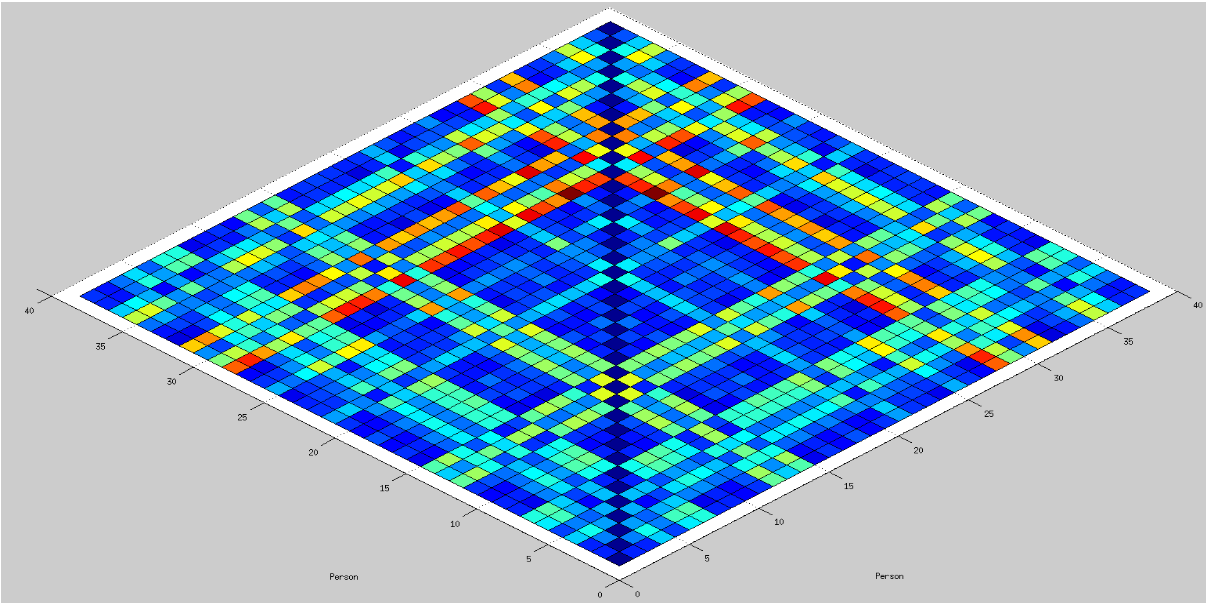


Fig 38. Person av feature vector vs person av feature vector (view 2).

View 3 shown in Fig 39. Person av feature vector vs person av feature vector (view 3). is the alternative representation as shown in view 1.

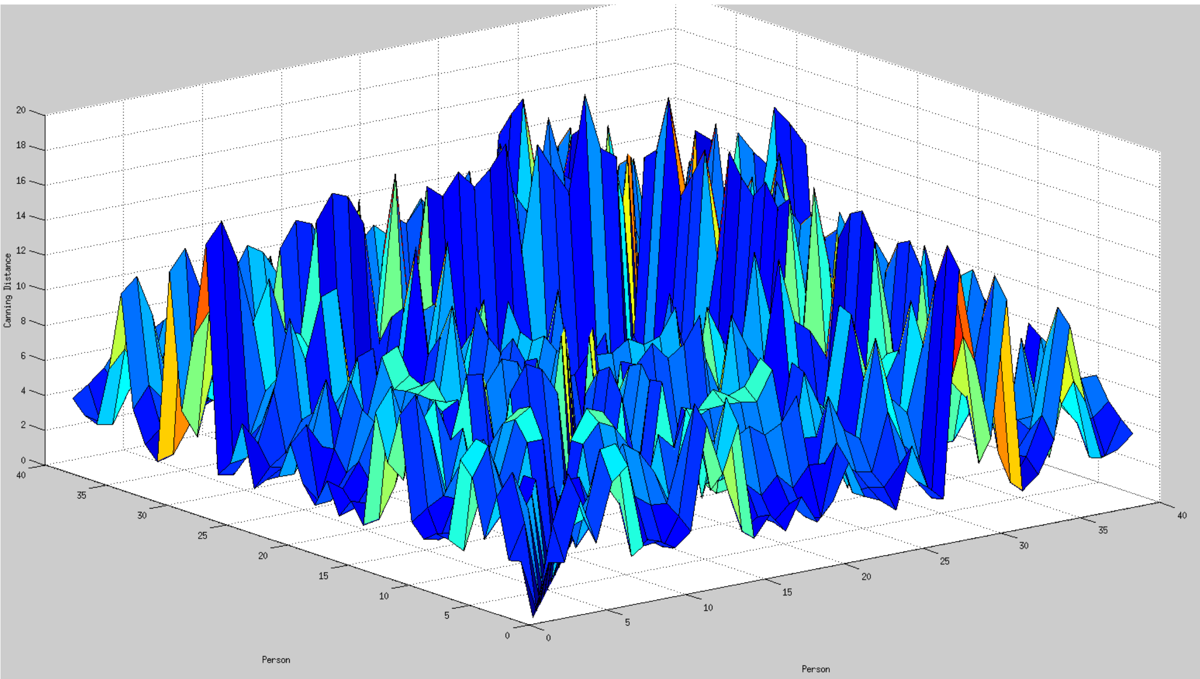


Fig 39. Person av feature vector vs person av feature vector (view 3).

The results of this seem to clearly indicate that in this unreal test situation the average feature vector for each person when measured by Canberra distance with all other average feature vectors is unique. However this is unrealistic. The discrimination between them is not improved in any way, and cannot really contribute to the understanding of the error values obtained.

Trained sets for K images vs all other images

K is the number of images taken from each person and an average taken. So for K=2 then two images make an average feature vector to represent the person. If there were 10 images taken in a set of images for the person, then there are 8 images left to add to the total test images. If the Canberra distance of a test image to another persons trained image is the smallest, this then represents a false positive. Each time the Canberra distance to its own trained feature vector is smallest and selected, then this is a true positive.

This can be visualized in Fig 42. Person trained image average vs all non trained images K=2.

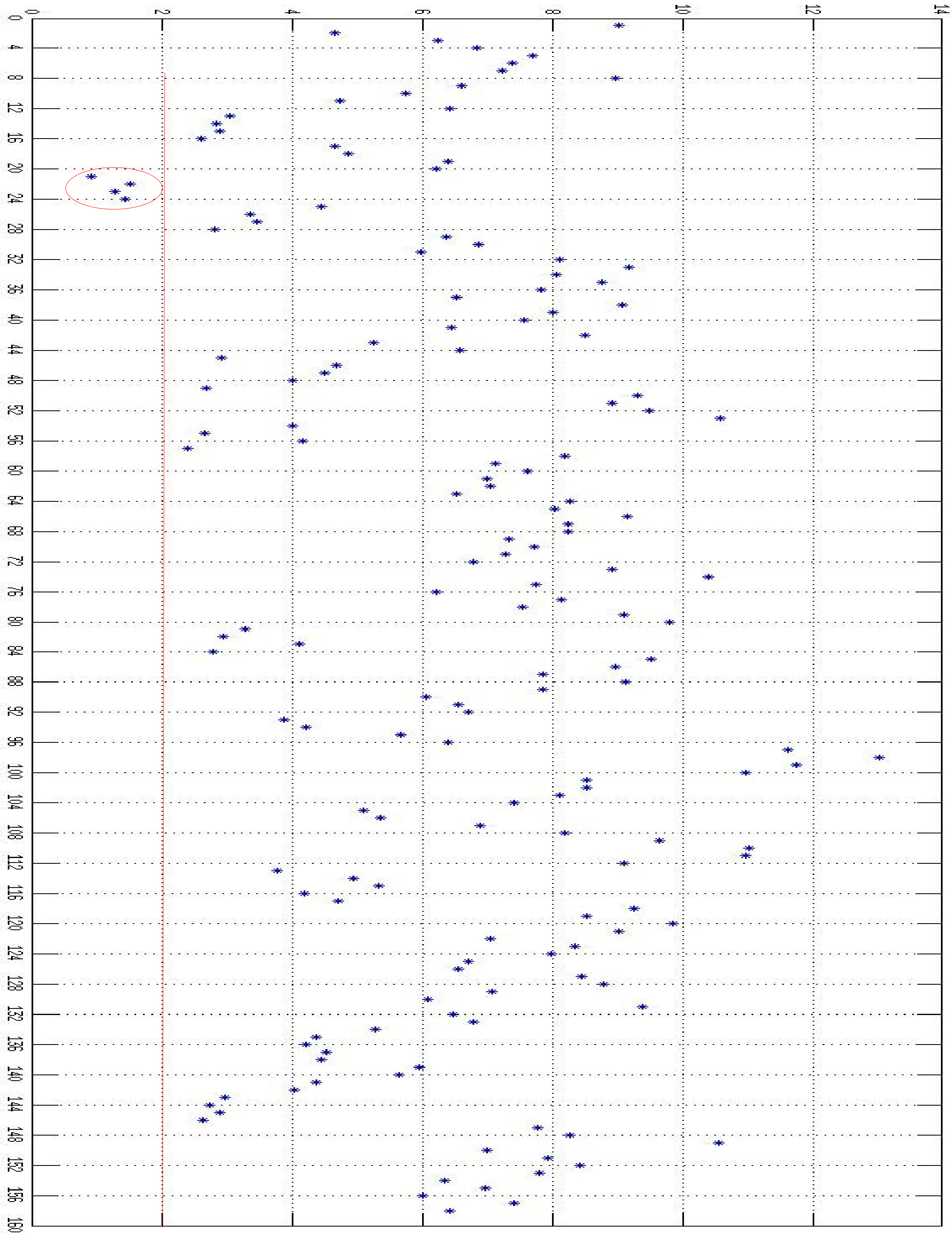


Fig 40. Person set vs all trained sets K=6

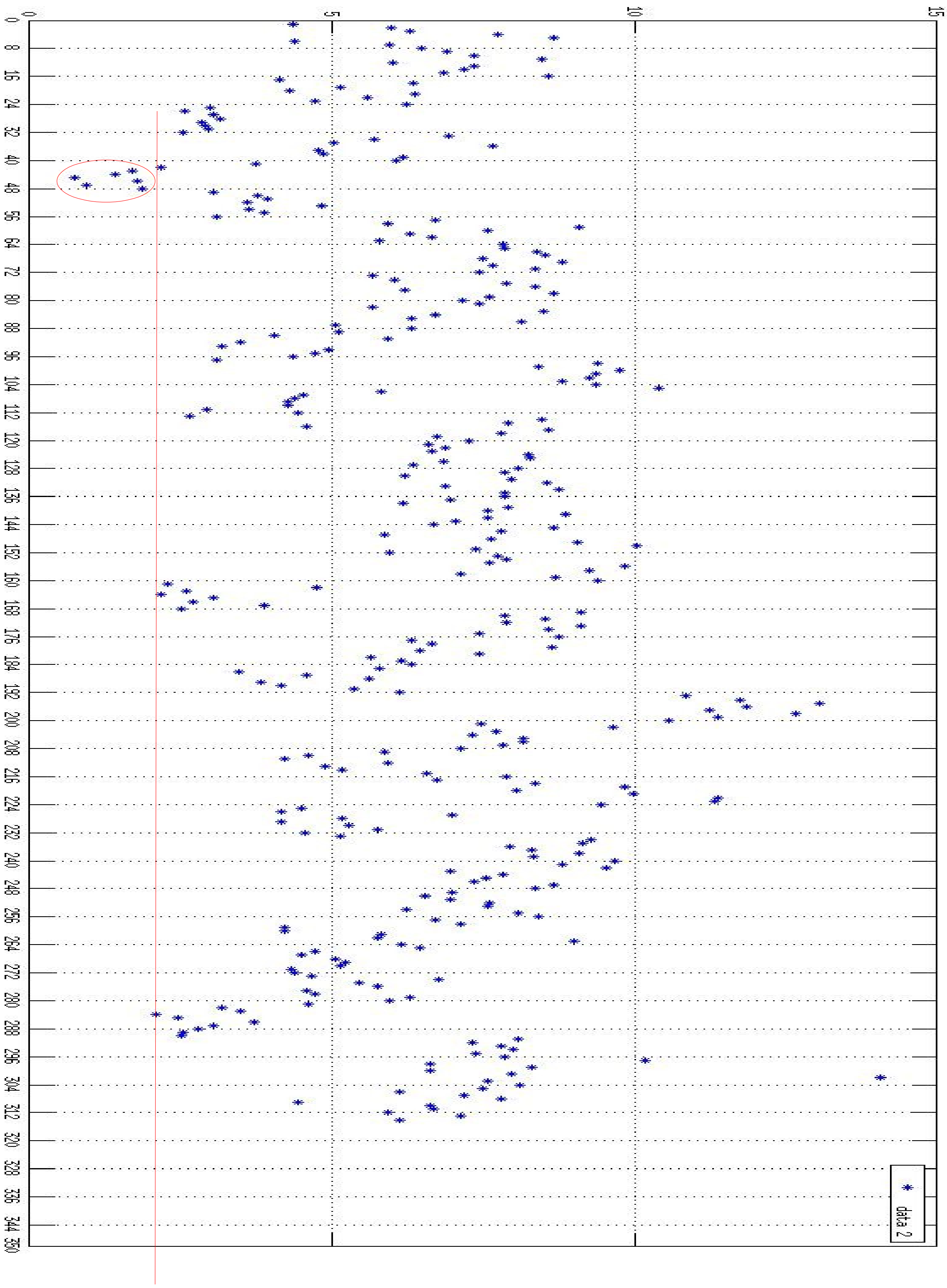


Fig 41. Person 6 vs all trained sets K=2

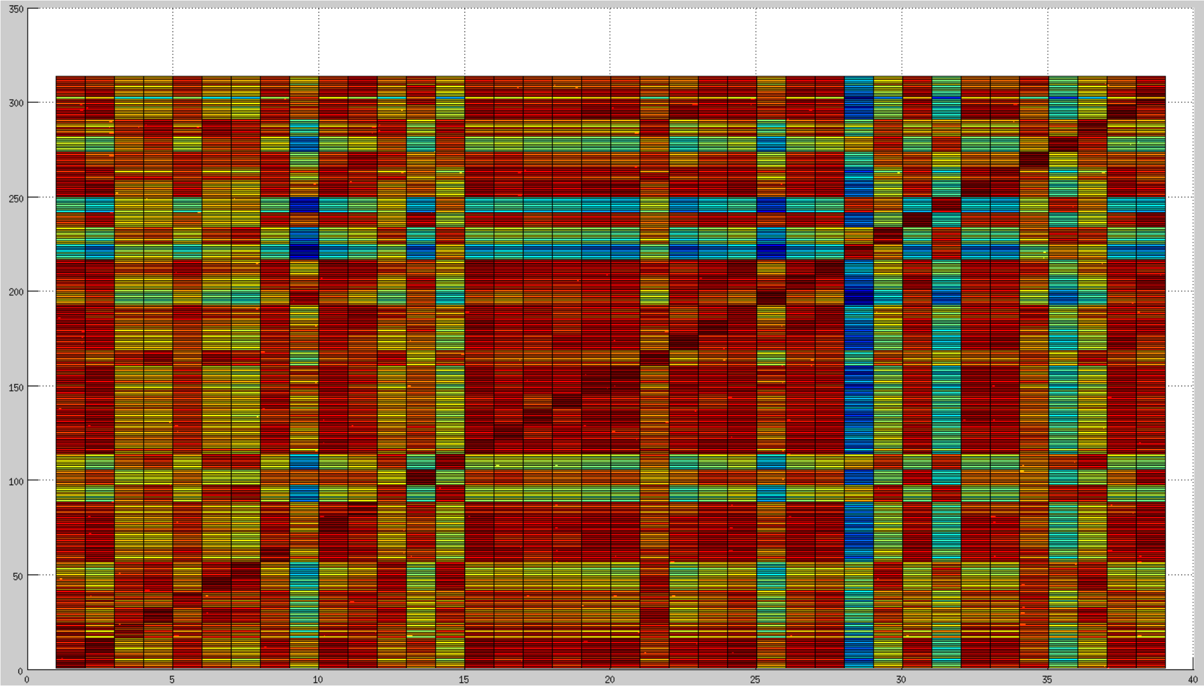


Fig 42. Person trained image average vs all non trained images K=2

Vertically is shown the test images which totals 314, as described in Table 6: Palmprint database person feature vector identification results (Own database results). Horizontally are the 39 peoples trained feature vector, where K=2. The diagonal from bottom left to top right shows mostly in dark red where the trained feature vector for the person correctly identifies the test image of the same person.

Notice this is weak in a lot of places where false positives are evident, and shown in the results in Table 6: Palmprint database person feature vector identification results (Own database results), 6 to 8.4% less than in the PolyU result set. This clearly shows visually the problem, although does not indicate the reason.

If we increase to K=6, then Fig 43. Person trained image average vs all non trained images K=6 shows a much darker and defined diagonal, which is not reflected in the results of Table 6: Palmprint database person feature vector identification results (Own database results). K=2 has a closer %GAR than K=6 compared with the PolyU database. However by the coloring it can be clearly seen the whole result set is different.

Digging a little deeper person 6 was chosen at random,Fig 41. Person 6 vs all trained sets K=2. Vertically are the 314 test images, whilst across the horizontal is the Canberra distance from person 6 trained feature vector with K=2.

The circle represents clearly identifiable person 6 images, which total 6. The 7th is border line indicated by the vertical red line. Following this line shows that there are two possible other people that can be very similar Canberra distances and represents potential false positives. The 8th image is definitely a false positive as another person is incorrectly identified.

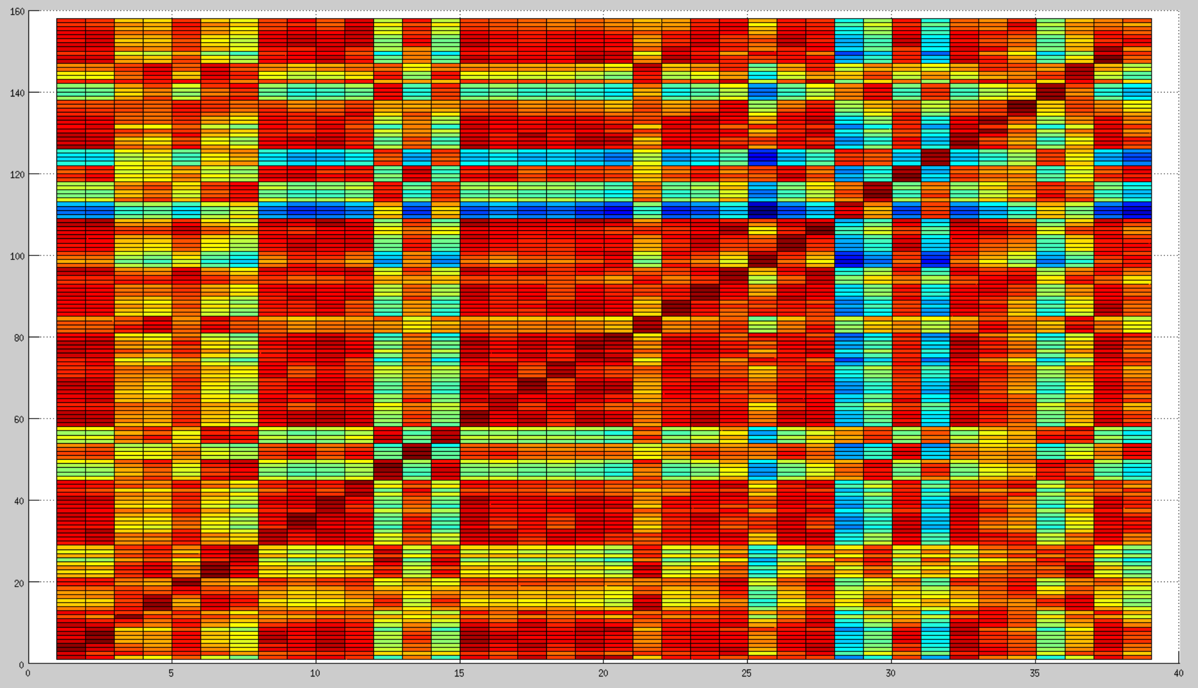


Fig 43. Person trained image average vs all non trained images K=6

Fig 40. Person set vs all trained sets K=6 Demonstrates the results for K=6 where the test images for person 6 is 4. Notice with the red circle that all four are correctly identified and the red line shows clearly there are no other images that might be chosen instead of these.

Although this does not show the reason for the incorrect identification, it does show in more detail the problem already defined regarding ROI detection and positioning (Translational error) along with large image set deviations for a number of people.

4 Conclusions and recommendations

4.1 Conclusions

The aim of this thesis is to move from taking images of palmprints towards enabling this tool to verify palmprint images are suitable for research purposes already at the point where they are taken. This will establish a tool for world wide palmprint data collection using both academic and non-trained personnel. Those collecting data would not be trained, and outsourced or crowd sourcing data collection may be possible. The first stage of taking images without validation was already completed as defined in Appendix 1: Stage 1 palmprint database: An android tool for distributed palmprint image collection.

In the Introduction it was stated the following two issues should be understood:

1. The role and challenges of identifying a region of interest (ROI) in palmprint recognition.
2. Quantifying the impact of ROI extraction by implementing an already established texture based recognition algorithm.

Simple recognition techniques need to have a consistent ROI extracted. A very simple texture based recognition system was chosen with ROI extraction and implemented in section 3, Implementation of palmprint recognition for mobile phone data collection. An established PolyU database was used, as this had been used in many research papers [Zhang et al., 2003; J. Chen et al., 2010; Dale et al., 2009]. As the results were reproducible a new database was constructed with random anonymous people using the same method in section 3.3.3, Establishing an independent dataset for ROI extraction evaluation, although results were not so reproducible as described in section 3 Discussions.

An attempt to establish the reason for the results being approximately 10% worse for a real life database set was discussed in section 3.3.3 - Discussions. A set of four questions were posed. It was established that the role of extracting the ROI is critical for palmprint identification. Minimizing session deviation for each person gave much better results reducing the number of false positives. This session deviation, or deviation between all images for a person, is key to successfully and correctly identifying a person by his or her palmprint image.

At the start of the thesis it was thought extracting a consistent and repeatable ROI from palmprint images was relatively simple. The role and challenges of ROI extraction as already described is not only critical to successful identification but also difficult. The factors affecting the ROI extraction were quantified and discussed. The following sections further discuss the importance of Acquisition, ROI extraction and possible ways to improve. It is then followed by recommendations on how to proceed.

4.1.1 Acquisition

Acquisition is important in preparing the palmprint image for ROI extraction. There are many methods for acquiring palmprint images as identified in the literature review section 2.2 Acquisition and application . It does not matter which acquisition method is used, the quality of the image contributes to how good the ROI will be.

For camera acquisition the distance of the palm from the camera, for example, directly affects pixel density, scale, rotational and translational movement. In addition if we assume a camera sensor is parallel to the palm, we have the best scenario. It is likely that with camera acquisition this may not be the case causing one side of the palmprint to be closer to the camera than the other, producing non linear distortion.

For scanner acquisition this distance is fixed and controlled. Problems occur with greasy or dirty images. Rotation and translation can be a problem. This can be overcome, as in the PolyU palmprint database [“PolyU Palmprint Database,” Retrieved December 8, 2013], where pegs are positioned between the fingers to try and reduce this positioning challenge. However the technique suffers, as identified in Fig. 10 - 15, where pressure of the palm on the scanning surface makes a large difference in ROI position and exposure.

A 5-step process similar to those discussed to gain an ROI based on the gaps between the fingers may produce improved results [Zhang et al., 2003]. Pegs are used to get the PolyU database images. No discussion on accuracy is given based on the ROI selection. Instead of Canberra distance, Hamming distance is used. It is also concluded that Gabor phase filtering is used to extract texture features from the image as some palm images do not have clear wrinkles. Some indications are given that it is considered necessary to enhance or use a combination of techniques to improve the image information.

Preparation of the images due to dirt, injuries and camera noise were considered problematic in some papers discussed. This is in addition to the rotational, translational and non linear distortions. Considering that the intention is to migrate towards a palmprint image gathering tool where no preprocessing of gathered images should be done, this thesis had only considered the ROI extraction and verification without preprocessing. No dirt of grease was seen in any samples, but this should be considered.

4.1.2 Extraction of ROI

The assumption here is that acquisition of the image has been done well as described above. An attempt to review ROI extraction and discuss potential solutions follows.

The first challenge when using palmprint images from a phone is extraction of the background. Scanned images are better as the background is usually very dark and consistent, in which case thresholding is usually adequate. When images taken with a camera the background can be complex and varied. Background extraction was only briefly discussed in section 3.3.3. Skin color thresholding and region growing for background extraction can be used [Aoyama et al., 2013]. In this thesis HSV color thresholding was used to filter color. Due to scope and time further development was not done in the context of this thesis regarding background extraction. It would benefit greatly to explore HSV color separation using skin color thresholding to automate background extraction. Consideration on different races and skin colors needs to be thoroughly investigated and understood before this could be used.

Once the background behind the palm has been extracted the second challenge is establishing a reference point which allows the ROI to be established, as described in section 3.3.3. Rather than using the Convex Hull to calculate the finger gaps as was implemented, a radial distance function might provide improvements [Aoyama et al., 2013]. Using a center point the radial distance is calculated. Valleys between the fingers are used to estimate the rotation and the image can then be rotated accordingly [Ferrer et al., 2007]. The center of the palm may be obtained and by using least square minimization a circle maximized to fit within the palm. This creates a round ROI. The claim is that this ROI is rotation and translation invariant.

Other publications also extract an ROI from a complete palm using the same points between two of the fingers [J. Chen et al., 2010]. There are discussions on blurring, lateral movement and scale distortions being present in the images which the ROI extraction should be able to compensate for. Preprocessing of the image is done using 1D average filter so that dirt, injuries and camera noise can be removed. Using generated SAX templates MINDIST is used for measuring the difference between two palmprints. As stated no alignment algorithm is perfect to extract an ROI from the palmprint, so the MINDIST value is calculated using translation of the original image in the horizontal and vertical axis. This is used to remove the translation elements and ROI scaling removes the scale problem. This SAX and MINDIST method also demonstrated higher robustness towards blurring.

Utilizing Band Limited Phase Only Correlation (BLPOC) for score matching can take into account non-linear distortion [Aoyama et al., 2013]. A comparison between a non pre-processed ROI extraction, and the method proposed using radial growing is made. Both use skin color thresholding. The first without region growing achieved 80.5% correct ROI extraction, and with region growing found 93.0% were extracted correctly. This appears to be in line with the results found in the first evaluation in Extracting the ROI and shown in Figs 10 to 14, where incorrect ROI can be obtained due to distortions caused in finger placement and pressure. Distortion due to finger spread is also mentioned in other papers [Ferrer et al., 2007].

Revisiting Dale et al. [Dale et al., 2009], on which the implementation of this thesis was taken, the main claim is that no preprocessing enhancement is done, except a low pass filter at the initial stages. No classification or mapping techniques were used. In comparison with other methods this produced good results as well as being faster. This thesis manages to reproduce the results effectively. There is no mention of the problems within the paper, yet we show problems in the section Extracting the ROI, which is visible in Figs 10 to 14. To achieve the same results each persons feature set was used to calculate a min and max Canberra distance from a mean feature vector of that person. Sorting into ascending order the top 50 people's feature sets with minimal Canberra session deviation were chosen. This would match the discussions above where pressure of the palm on a scanning device, or finger spread, rotational and translation movement when the images are taken all indicate that a more complex method is required to extract a consistent and achievable ROI. The ROI would then be without distortions affecting the results, as discussed in the section 3.3.3 Establishing an independent dataset for ROI extraction evaluation - Discussions, which tried to understand why the results had been approximately 8% less GAR than in the section: Implementation of palmprint recognition for mobile phone data collection based on the paper by Dale et al. [Dale et al., 2009].

4.2 Recommendations

An understanding of the problems and pitfalls regarding Aquisition, ROI extraction and various distortion effects has been gained. With the literature review, the practical implementation and previous work on the capturing and storage of the images in a secure environment the main parts of the palmprint data gathering tool are forming. There are two major items still missing. First is the quality measurement of the images taken, so that we know the images taken are good enough to use for method research into palmprint recognition. The second is improving the palmprint verification method that will confirm images taken in a database are really acceptable in a real academic research environment or even in a real world application.

With these items in mind the next steps towards a common academic tool for gathering of palmprint images based on a normal mobile phone can continue. The next steps are discussed in the following sections.

4.2.1 Translation, rotation and nonlinear distortion

Further consideration and literature review is needed looking at translation, rotation and non linear distortion tolerant methods for use in image acquisition and verification. Consider if there are some checks that can be done using, but not limited to, width of the palm as an example. Asking the person having their palmprint image taken to slightly rotate it so that the palm is considered flat and parallel to the CCD when the maximum is reached, an automated calibration and positioning procedure could be developed.

Removing or minimizing these identified distortion factors is the major work in establishing how to take and store images that are unprocessed so that any palmprint method can use the captured images without bias.

4.2.2 Preprocessing for correct ROI

Some methods claim that ROI can be rotational invariant by using, for example, the expanding radial distance ROI rather than square. Evaluation of this and a search for additional literature is needed to consider whether in the verification stages this could be used or whether there is a more appropriate validation method. Enhancement of the image is discussed many times, although the details are often left vague. Exploration of this topic, only for the purposes of the verification of the gathered images, should be considered.

4.2.3 Alternative or more complex methods for ROI selection

With verification that the gathered images are acceptable it should be considered whether the BLPOC, or some other phase orientation scheme might be a better verification scheme as they do not require ROI extraction. Alternatively it should be considered if improvements in ROI extraction, using preprocessing enhancements, the current method can be enhanced and exceed the results already achieved. The purpose behind this is only to verify and check images whilst not influencing or changing captured and stored images.

4.2.4 Summary

In summary this thesis has successfully answered the question about the role and challenges of identifying a region of interest (ROI) in palmprint recognition. This thesis also successfully quantified ROI extraction results by showing the effects on correct identification.

Recommendations on how to proceed have been given. This is based on the need to acquire palmprint images and extract the background with minimized distortion. Identifying if ROI extraction can be made consistent enough to use simplified recognition techniques for validation has been questioned. Alternative search methods, as provided in the literature review, that do not need ROI extraction and are based on phase orientation information appear to promise better tolerance for verification purposes.

The next steps for the academic palmprint data collection tool have been defined and can proceed. Establishing these facts means the data collection tool can be automated for use by non trained outsourced or crowd sourced individuals across the world, hence contributing to a truly worldwide multicultural dataset which in turn can be used to further research of palmprint recognition methods.

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6 Appendices

6.1 Appendix 1: Stage 1 palmprint database: An android tool for distributed palmprint image collection

This appendix describes the initial research done during a bachelors thesis, upon which the masters thesis has been based.

6.1.1 Abstract

The palmprint database is essential for research, verification, and general work in this area. The database needs to be trusted, allowing focus to be on the methodologies rather than on how to ensure the data is valid. The image quality and/or that the region of interest can be repeated between images ensuring the focus is entirely on the research topic.

Due to the depth of knowledge and information needed the Bachelors thesis was restricted to a palmprint database. A commonly available mobile phone for collection of palmprints was chosen. The idea was that in stage 2 and beyond, the Masters Thesis, the data validation and quality metrics could be developed to ensure that at the palmprint gathering stage the images would be repeatable and trustworthy.

The target was to avoid security issues as discussed in Franzgrote et al. [Franzgrote et al., 2011]. The standard client server architecture was exploited to resolve the security issues. Although the security issues and personal data, were considered and described, they will not be covered here. A summary of the palmprint database and mobile gathering tool is included here give the entire picture of where the tool is intending to be developed and what has been achieved so far.

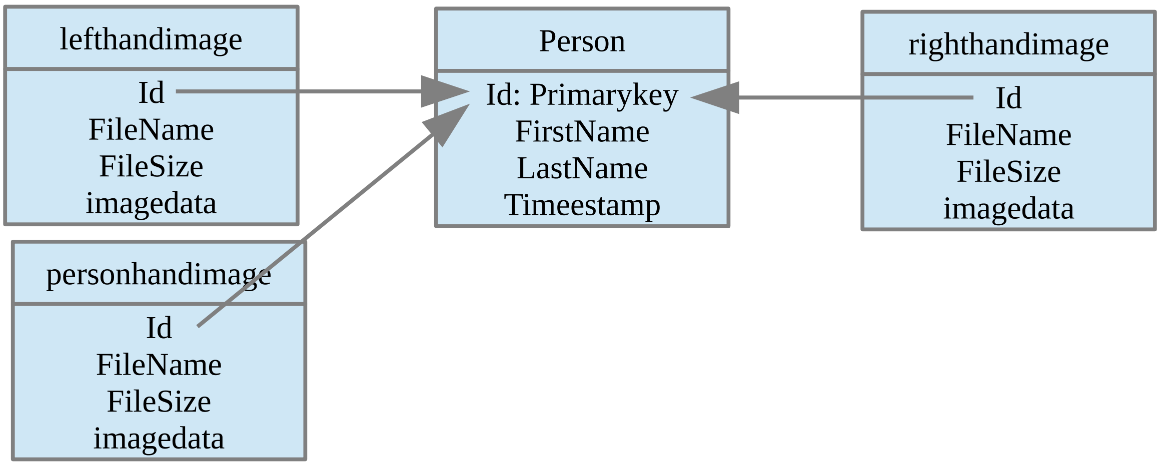
6.1.2 Methods

Database

The database chosen was MySQL [“MySQL Community Edition :: www.mysql.com/,” 2013]. When using Ubuntu [“Ubuntu - www.ubuntu.com/,” 2013] development environment for the server, this is simple a matter of package installation, as follows:

```
sudo apt-get install mysql-server mysql-client
```

An overview of the database tables is as follows:



Drawing 2: Palm2Palm database schema

With these tables one or many people can be studied. Each person can have their palmprints taken once, twice or multiple times over a short period of one session or over several years. This will allow short and much longer term research to be undertaken.

System overview

The demands on the server are that it can be deployed anywhere in the world. The server must be able to collect palmprint Data from one to many devices, mobile or PC based. The system setup is shown for an Android mobile device and the Palm2Palm server:

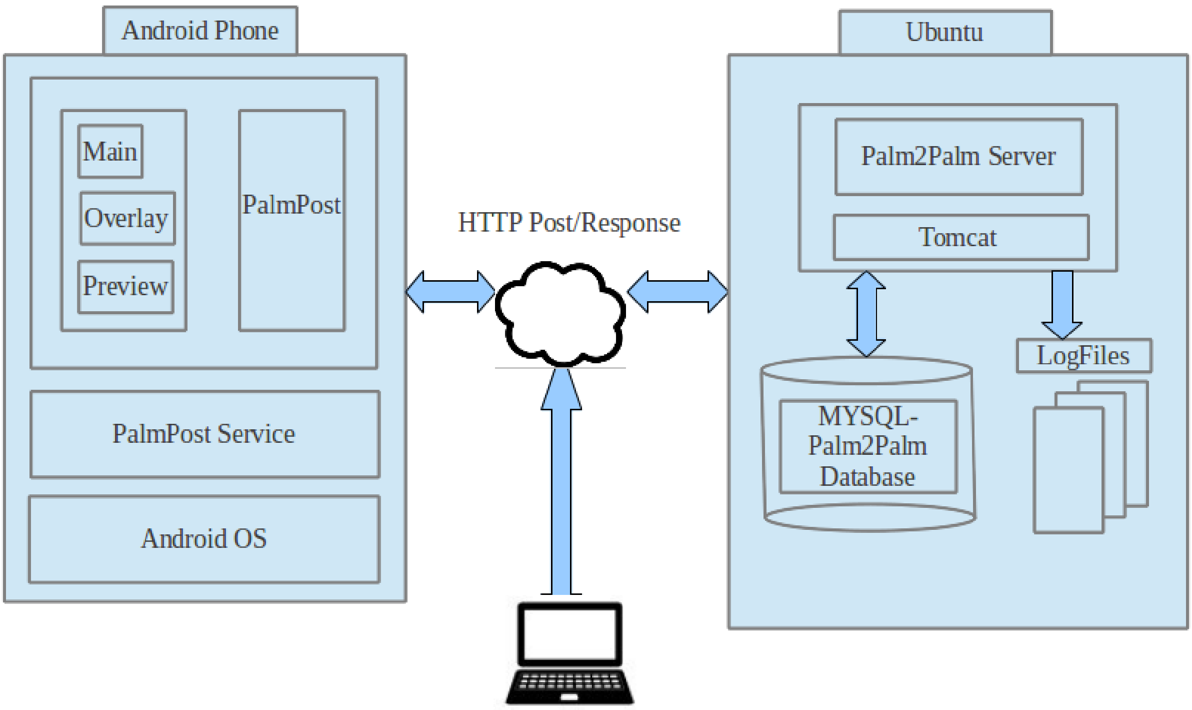


Fig 44. Palm2Palm system overview

PC/Laptop palmprint image collection

Palm images of an individual can be entered and posted to the Palm2Palm server database with the following simple form.

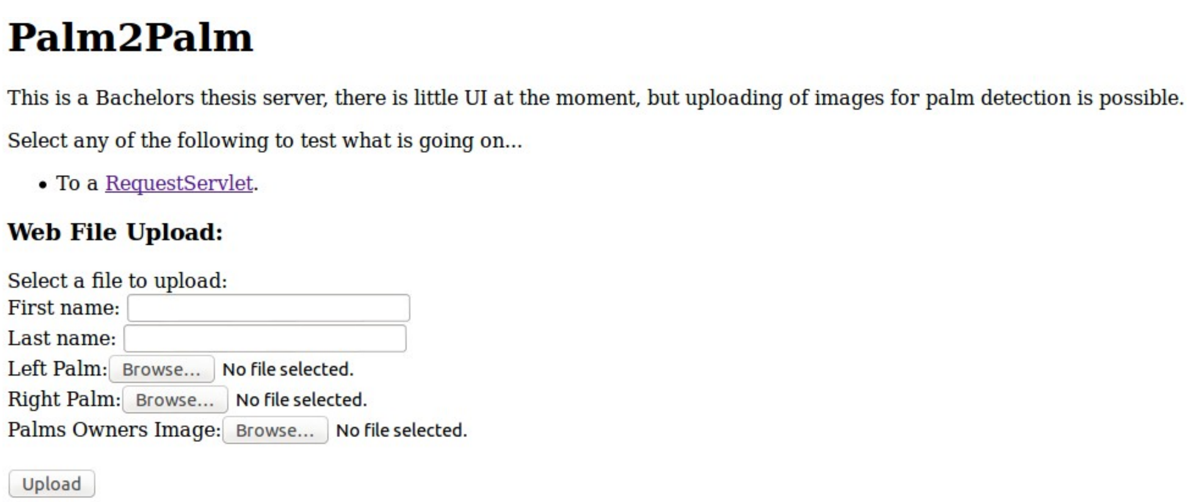


Fig 45. Palm2Palm upload form

The “Upload” button allows this to connect to the server sending the images and all personal meta-data. A response is received and displayed confirming if the operation is successful.

This enables any researcher sitting anywhere in the world with a laptop or PC to interview candidates for palmprint Registration in the database collecting relevant data for research. No data is stored locally on the PC removing many security issues with respect to the host computer.

Android handset palmprint data gathering

There are many choices for mobile devices that could be used for standard palm image collection. Android handsets [“Android,” 2013] were chosen due to their mass availability, ease of use, and high resolutions cameras. The device used in development was a Samsung Xcover 2 [“Samsung Galaxy Xcover 2 - Android 4.1, 1GHz, 4” TFT WVGA, 5MP Camera,” 2013].

UI – Single use case walk through

Launching

The product has been called “Palm2Palm”. The icon on the launch screen is a simple hand which immediately launches a splash-screen showing hands indicating the reason for the application.

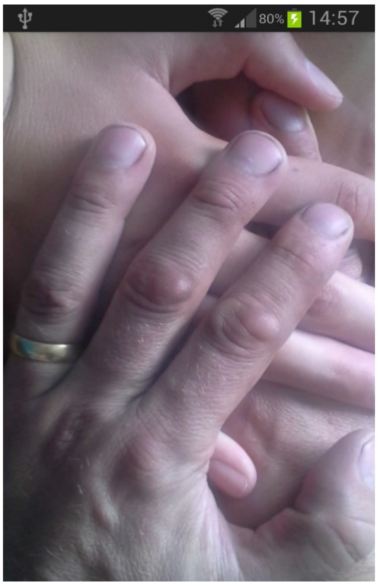


Fig 46. Palm2Palm splash screen

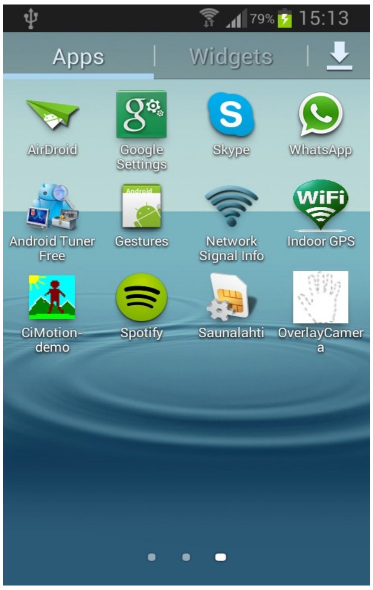


Fig 47. Palm2Palm launch icon from desktop

Hand and personal image

The Main Activity is launched after the splash-screen. This has a small state machine which controls whether the overlay shows a left hand, right hand, or personal image that needs to be captured. The researcher knows what image is required at each stage. Tapping in the circled area in the center of the screen captures the image. Fig 48, 49 and 50 show the three images that need to be obtained. The first left hand message also shows the pop-up message that appears after the image was acquired. The others are waiting for the image to be captured.

Fig 48. Palm2Palm left hand palmprint captured

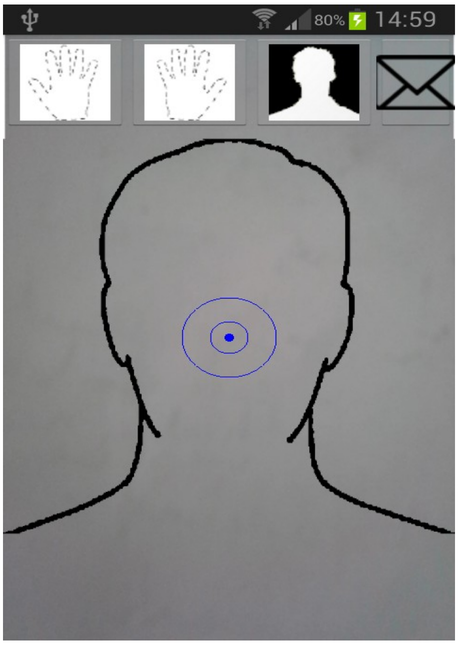


Fig 49. Palm2Palm ready to capture a person's image

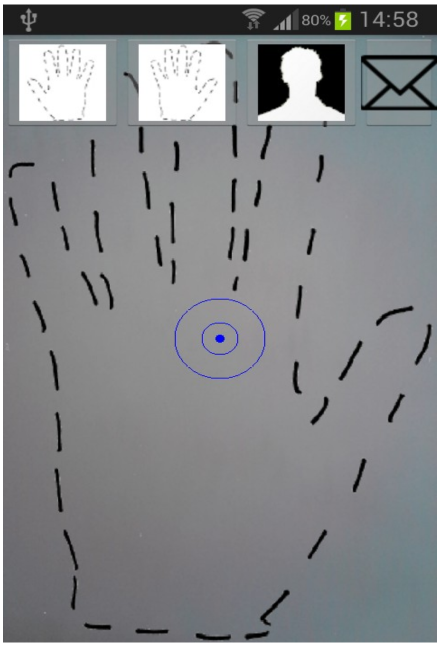


Fig 50. Palm2Palm ready to capture right hand palmprint

At the top of the screen is a button tool-bar. The button icons have similar pictures of the overlays displayed on the screen. Pressing any one of these allows navigation to the next state and overlay of the image that is required next. If at any time a mistake is made then the tool-bar allows navigation to retake another image if necessary.

Posting data

The final tool-bar button on the right indicates posting of data. This brings up the Palm Post Activity which is only tasked with entering the name of the person, asking for consent to use the data. Once consent is given the images and data are posted to the Palm2Palm server.

It cannot be stressed enough that the person owning the data is responsible for reading, accepting and posting it.

Once posted a pop-up notification will indicate the data has been received in the palmprint database.

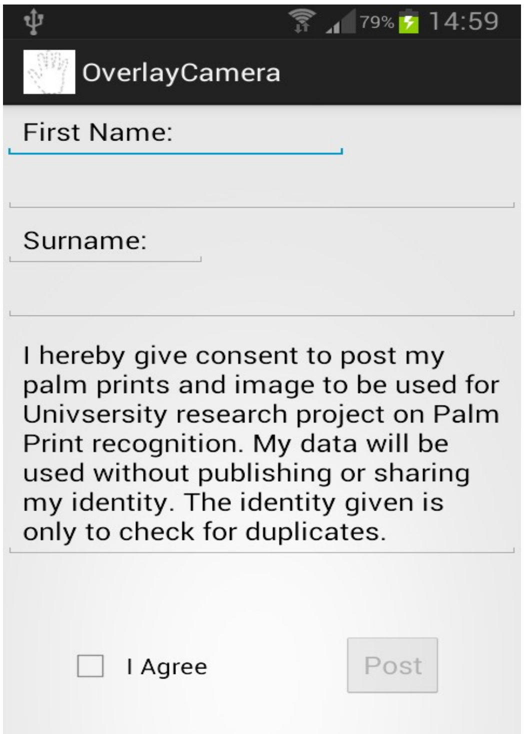


Fig 51. Palm2Palm consent form

6.1.3 Conclusions

It has been demonstrated that palmprint data acquisition using an Android device along with an open source database could be secure, keep the legal and moral frameworks for personal security, and gather the needed information. The database shown allows researchers to distribute data gathering to trusted sources like Universities anywhere in the world. It was also discussed and demonstrated that data collection in this way does enable researchers to increase the amount of useful data, research ethnic/cultural and cross border palmprints using this tool. So providing a tool for palmprint acquisition was considered successful for the Bachelor's thesis.

The short coming at the time of the development was the fact that the data could not be measured and validated to be trusted. In other words that the researchers could not trust the palmprint images to be taken in such a way that results would be repeatable and they would not have to verify the quality of the images. So although fulfilling the data gathering requirement further research on checks and validation at the time of the images being taken would be needed.

In that respect this was proposed to be the next step in the Masters thesis, to investigate how to validate the images allowing the researcher to concentrate on the field of research rather than verifying the data to enable the research.

6.2 Appendix 2–Selection of sample palmprints using session deviation.

There are a total of 356 people, each having two sessions consisting of ten images in each. Session deviation is used to extract the best two sets of fifty people is described using the following pseudo code:

Iterate through each of the 356 people

For each person test the first session, then the second session calculating the session deviation.

Once a list of person name, First session and second deviation are known sort ALL output by the first session deviation, ascending order.

Session deviation is calculated by

Calculate the average feature vector for the session

Measure the Canberra distance for each image feature vector in relation to the average session feature vector, finding the max and min deviation.

The session deviation is the max – min deviations calculated.

The first few are shown as follows:

Name='001', Sav='1.5388677568234506', Fav='1.2589889745836311', av-av='6.665426007679765'
Name='002', Sav='2.118499253818143', Fav='1.779660161162675', av-av='5.553244069152411'
Name='003', Sav='3.8445033083411575', Fav='5.127549416039851', av-av='4.628006864663201'
Name='004', Sav='2.0675508173993964', Fav='3.3184513125152186', av-av='6.342463605348033'
Name='005', Sav='1.9295751954064313', Fav='2.2745325897963795', av-av='2.9367259440148956'
Name='007', Sav='1.5055435283707665', Fav='1.8771611551444662', av-av='2.802901176405463'

The last few are shown as follows:

Name='382', Sav='1.376983890066294', Fav='1.9173427851936309', av-av='2.26256813287452'
Name='383', Sav='1.7495733800964113', Fav='2.3415068008397912', av-av='2.7983545170492614'
Name='384', Sav='1.7358801173250071', Fav='1.5972557547448523', av-av='2.0713153544054483'
Name='385', Sav='3.562462368383739', Fav='2.751394582945022', av-av='5.628549263300593'
Name='386', Sav='2.1408409312460837', Fav='3.024018968497109', av-av='6.512321221905607'

After sorting a list gives the first session deviations starting from 0.8 ending up until 5.12. So the session deviation can be huge. This is why the first and second 50 are chosen for the tests.

The first few sorted people can be seen as follows to demonstrate the kinds of values given:

Name='100', Fav='0.8065497069040822"
Name='266', Fav='0.8346931290134"
Name='062', Fav='0.8583335699003984"
Name='088', Fav='0.8717347041958845"
Name='145', Fav='0.9252620606573725"
Name='308', Fav='0.949543609450418"
Name='242', Fav='0.9567719286595706"
Name='307', Fav='0.9875701002537263"
Name='059', Fav='1.025279890897203"
Name='319', Fav='1.0370258536259216"
Name='099', Fav='1.0567318696084114"
Name='060', Fav='1.063134241032311"

A full list of all the sorted data can be given upon request. The selected sets of people are summarized in the following table:

Description	**Lowest Session Deviation**	**Largest Session Deviation**
First top fifty people	0.8065497069040822	1.3133057083371673
Second top fifty people	1.3150134625733652	1.4816849460605483

Table 7: People test set selection using Session Deviation Results