Fingerprint Verification using Mutual Information

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ABSTRACT

One of the most reliable biometric identification methods is fingerprint verification, which is in use over a century all over the world. Fingerprint verification became inexpensive, more reliable and less time consuming after the introduction of Automatic Fingerprint Identification System (AWIS). Today, fingerprints are used broadly as an authentication to access a computer, bank account, building, car etc apart from identifying criminals, which was the major use of fingerprints years ago. There are several algorithms available for fingerprint verification. This project aims at verifying the reference fingerprint against target fingerprint using Mutual Information algorithm where the input images undergo translation and rotation process in the preprocessing stage and calculates the mutual information value for each step of rotation and translation. The ultimate aim is to find the best alignment of fingerprints by maximizing the mutual information value.
# TABLE OF CONTENTS

Abstract .................................................................................................................. ii

Table of Contents .................................................................................................. iii

List of Figures ......................................................................................................... v

1. Background and Rationale ................................................................................ 1
   1.1 History of Fingerprints .............................................................................. 1
   1.2 Nature of Human Fingerprints .................................................................. 3
   1.3 Fingerprint Patterns .................................................................................. 4
   1.4 Why Fingerprint Verification ..................................................................... 9
   1.5 Digital Image Registration ....................................................................... 10
      1.5.1 Area and feature based Image Registration ...................................... 13
      1.5.2 Transformation Model ...................................................................... 14
      1.5.3 Spatial and Frequency Domain Methods ......................................... 15
      1.5.4 Search based and Direct Methods ..................................................... 15
      1.5.5 Image Similarity Methods – Mutual Information ............................. 15

2. Narrative ......................................................................................................... 18
   2.1 Approach Followed ................................................................................... 18
   2.3 Implementation Language ....................................................................... 19

3. Proposed System Design ................................................................................ 20
   3.1 Data flow diagrams .................................................................................. 20
   3.2 System Overview ..................................................................................... 22
   3.3 Preprocessing ........................................................................................... 24
   3.4 Mutual Information Algorithm .................................................................. 26
      3.4.1 Entropy .............................................................................................. 26
3.4.2 Mutual Information..........................................................29

4. Evaluation and Results...............................................................31

5. Conclusion and Future Work.......................................................40

Acknowledgements........................................................................41

Bibliography and References..........................................................42
LIST OF FIGURES

Figure 1.1: Fingerprints on clay potteries .......................................................... 2
Figure 1.2: The Arch ......................................................................................... 5
Figure 1.3: The Tented Arch ............................................................................. 5
Figure 1.4: The Loop ......................................................................................... 6
Figure 1.5: The Whorl ...................................................................................... 6
Figure 1.6: The Twined Loop .......................................................................... 7
Figure 1.7: The Central Pocket Loop ............................................................... 7
Figure 1.8: The Lateral Pocket Loop ................................................................. 8
Figure 1.9: The Composite .............................................................................. 8
Figure 1.10: The Accidental .......................................................................... 9
Figure 1.11: Grayscale Image ........................................................................ 12
Figure 3.1: 0-Level Data Flow Diagram ......................................................... 21
Figure 3.2: 1-Level Data Flow Diagram ......................................................... 22
Figure 3.3 Fingerprint Verification Process .................................................... 23
Figure 3.4 Image entropy – pixel values ....................................................... 28
Figure 3.5 One pixel translation ................................................................. 28
Figure 3.6 Joint Outcome ............................................................................. 29
Figure 3.7 Joint Histogram .......................................................................... 28
Figure 4.0 Threshold graph ............................................................................ 32
Figure 4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8, 4.9, 4.10, 4.11, 4.12, 4.13 Fingerprint Images
and MI graph ........................................................................................................... 33-39
1. BACKGROUND & RATIONALE

A fingerprint is an impression of the friction ridges of all or any part of the finger. A friction ridge is a raised portion of the epidermis on the palmar (palm and fingers) or plantar (sole and toes) skin, consisting of one or more connected ridge units of friction ridge skin. These ridges are sometimes known as dermal ridges or dermal papillae [Wikipedia 2007a]. If the question is “Is fingerprint identification a science?” the answer is “yes”. For more than 100 years, fingerprint has been collected, identified and tested as a means of unique identification of persons. Many scientists have proven the validity of fingerprint identification over several years [Fingerprints 2005]. Two major ideas scientists believe about fingerprints are:

- No two fingerprints are alike. Three characteristics are identified within the ridges of all persons – bifurcations, dots, and ridge endings. These ridges appear in several combinations that are never repeated on the hands or feet of any two persons.

- Fingerprints never change. Small ridges form on a person’s hands and feet before they are born and do not change for the rest of his life.

1.1 History of fingerprints

Archeological evidence says that fingerprint is used as a form of identity by ancient Chinese since 6000 BC. Figure 1.1 shows the clay potteries from these times had fingerprint impressions to identify the potter. Some of the houses of ancient city of
Jericho have pairs of fingerprints imprinted on the bricks. Though fingerprint was found then but there is no evidence that it was used as universal basis [Gorman 2000].

In 14th century, one government official, a doctor identified that no two fingerprints are exactly alike [Moore 2007]. In 1600s Marcello Malpighi, an Italian anatomist and microscopist was the first to describe patterns on a human finger tips. He was called the first histologist. The lower epidermis “Malpighian layer” is named after him. Later In the same century, Dr. Nehemiah Grew conducted a palm survey where he described little innumerable ridges running parallel to one another. He also published detailed pictures of fingerprint patterns. Later in 1800s, Jan Purkinje, a Czechoslovakian physiologist did a detail survey on fingerprints and he came up with the following patterns namely transverse curve, central longitudinal stria, oblique stripe, oblique loop, almond whorl, spiral whorl, ellipse, circle, and double whorl. By the end of century William Herschel, first European to recognize the fingerprint value for identity, published a paper “Skin Furrows of the Hand”. The paper had results of fingerprints as sign-manuals or signatures as identity. During the same time, Dr. Henry Faulds, a Scottish physician published a paper “Scientific Identification of Criminals” where he used fingerprints to identify criminals after extensive research for many years. He has been credited the first European to publish an article about crime investigation using fingerprints. A year after, Alphonse Bertillon, clerk at the Paris police records office designed a system called Anthropometry which he used for fingerprint verification. Initially the system was rejected, after three
years, it was finally approved and was used in a case to identify a victim. He has the
credit to be the first person to practically use the fingerprint for identifying criminals. In
19th century, Sir Francis Galton published a book on fingerprints after extensive research
for several years. This led the first step in science of fingerprint identification. Sir Edward
Henry traveled all over the world researching on fingerprints and published a paper
“Fingerprints and detection of crime in India” where he used a kind of classification
system which is now called as Henry’s classification system. This system started a
modern era in fingerprint identification [Pioneers 2004].

After the introduction of computer hardware in 1960s, computer processing of
fingerprints was more efficient. This led to the raise of Automated Fingerprint
Identification System (AFIS), which has been used worldwide in law enforcement
agencies. After the introduction of optical scanners, the fingerprint capture was made
practical in non-criminal applications such as ID-card programs. Now, after 2000,
fingerprint devices have been marketed so inexpensively that it is being used as an
authentication technique to log on to computers [Gorman 2000].

1.2 Nature of Human Fingerprints

The unique nature of ridges has made fingerprint verification process possible.
The nature of human fingerprint is based on permanence and individuality.
Permanence: The ridges on the hands and feet are formed during the third to fourth
month of fetal development. As mentioned before these ridges has many unique
individual characteristics called ridge endings, bifurcations, dots and many ridge shape
variances. The ridge characteristics do not change for a person through his entire life until
his body decomposition after his death. The growth of these ridges can be compared to
drawing on a balloon. When the balloon is inflated, the drawing just expands and does
not change, it is same way in human too. There is size difference in the ridges during his
infant and adult stage but no change in it. Injuries or deep cuts penetrating all layers of
epidermis and some diseases such as leprosy cause unnatural changes to fingerprint
ridges [Fingerprints 2005].

Individuality: There is routine comparison of fingerprints worldwide from the past 150
years and it is noted that no two areas of friction skin on any two persons (including
twins) have the same ridge patterns. Experts have testified that no two fingerprints in the
hundreds of millions of individuals in the whole world would be alike [Fingerprints
2005].

1.3 Fingerprint Patterns

As explained before, each individual has unique fingerprint ridge pattern. Let us look at
some of the characteristics of these patterns based on Henry’s classification system.

1.3.1 The Arch:

In this pattern, the ridges lay one above the other like an arch. Figure 1.2
represents the arch shaped fingerprint pattern.
1.3.2 The Tented Arch:

The pattern has at least one upthrusting ridge, which bisects superior ridges at right angles. Figure 1.3 represents the tented arch shaped fingerprint pattern.

![Figure 1.3 The Tented Arch [Patterns 2007]](Image)

1.3.3 The Loop:

The pattern has one or more recurving ridges and one delta. Loops are again two kinds – ulnar or radial. Ridges flowing from little finger side – ulnar loop. Ridges flowing from the thumb side – radial loop. Figure 1.4 represents the loop shaped fingerprint pattern.
1.3.4 The Whorl

It has two points of delta surrounded by one or more free recurving edges. Figure 1.5 represents the whorl shaped fingerprint pattern.

1.3.5 The Twinned Loop

Pattern has two loop formation with recurving ridges. There are two points of delta that originate from the same side of the pattern. Figure 1.6 represents the twinned loop shaped fingerprint pattern.
1.3.6 The Central Pocket Loop

The pattern has two delta points with one or more free recurving edges. The line between two points of detail will fail to bisect any of the ridges of the core group which is opposite of the whorl. Figure 1.7 represents the central pocket loop shaped fingerprint pattern.

Figure 1.7 The Central Pocket Loop [Patterns 2007]

1.3.7 The Lateral Pocket Loop

The pattern has two delta points and the recurving ridges present two separate loop. The flow for the delta originates from the same side of the pattern. Figure 1.8 represents the lateral pocket loop shaped fingerprint pattern.
1.3.8 The Composite

It consists of two or more patterns, which might be separate and exclusive of arch. Figure 1.9 represents the composite shaped fingerprint pattern.

1.3.9 The Accidental

Pattern has two points of delta. One delta is related to a recurve and the other will be related to an up thrust. Figure 1.10 represents the accidental shaped fingerprint pattern.
1.4 Why Fingerprint Verification?

Fingerprints offer a trustworthy means of personal identification. Fingerprint verification is chosen as best compared to other biometric verification systems because of the following reasons:

- No two fingerprints are alike among billions of human beings and it has provided accurate results in identifying criminals for the past 100 years. Every police agency has adapted fingerprints as a foundation for criminals and their history.
- It led to establishment of International Association of Identification (IAI) in 1915 and first professional certification program for forensic scientists.
- Remains the most commonly used forensic evidence worldwide and continues to expand as a premier method for identifying persons.
- Outperforms DNA and all other human identification systems to identify more criminals.
1.5 Digital Image Registration

Digital Image Registration is the process where two or more images of the same scene taken at different times are overlaid for comparison. It geometrically aligns two images [Zitova 2003]. Before going through image registration in depth, let’s understand the characteristics of a digital gray scale image so that it better helps to understand the image registration.

Images are produced by a variety of physical devices, including still and video cameras, x-ray devices, electron microscopes, scanners, radar, and ultrasound, and used for a variety of purposes, including entertainment, medical, business, industrial, military, civil security, and scientific. The goal in each case is for an observer, human or machine, to extract useful information about the scene being imaged. A raw image is not directly suitable for this purpose, and must be processed in some way. Such processing is called image enhancement; processing by an observer to extract information is called image analysis. Image enhancement has been done by chemical, optical, and electronic means, while analysis has been done mostly by humans and electronically [Silver 2000].

Digital image processing is a subset of the electronic domain wherein the image is converted to an array of small integers representing a physical quantity such as scene radiance, stored in a digital memory, and processed by computer or other digital hardware. Digital image processing, either as enhancement for human observers or performing autonomous analysis, offers advantages in cost, speed, and flexibility, and with the rapidly falling price and rising performance of personal computers it has become the dominant method in use [Silver 2000].
A digital image is simply a matrix where each number represents the brightness at regularly placed points or very small regions in the image. These points are called pixels (picture elements), they are arranged in rows and columns, and the brightness value of a pixel is called its gray level. Scanners are commonly available to convert photographs to digital images. In video cameras, the brightness of the pixel is represented by a time varying voltage as the scene is scanned, and the digitalized version of the image is obtained by sampling the voltage using an analog-to-digital converter or frame grabber [Gose 1996].

In a (8-bit) grayscale image, each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey [Spacetelescope 1999]. This means that each pixel image is stored as a number between 0 to 255, where 0 represents a black pixel, 255 represents a white pixel and values in-between represent shades of grey [Hanbury 2000]. Figure 1.11 shows the grey scale image.

A normal grey scale image has 8-bit color depth, which is equal to 256 grayscales. A “true color” image has 24-bit color depth i.e. $8 \times 8 \times 8 = 256 \times 256 \times 256$ colors, which is appropriately 16 million, colors [Spacetelescope 1999].
There are two groups of images. Namely vector graphics (or line art) and bitmaps (pixel-based). Images can be represented in different file formats [Spacetelescope 1999]. Some of them are:

GIF – an 8 bit compressed bitmap format mostly used for websites. It has several sub-standards, one of them is animated GIF

JPEG – 24 bit compressed bitmap widely used for web and internet

TIFF – 24 bit publication bitmap format

PS – standard vector format

PSD – a dedicated Photoshop format that keeps all information including layers

Image Registration is one of the many processing operations of image processing. It is the process of finding an optimal geometric transformation between the corresponding image data. It has applications in many fields like remote sensing, (environmental monitoring, weather forecasting, multispectral classification, integrating information into geographical information systems etc) in medicine (medical image registration – CT scan, MRI, monitoring tumor growth etc) and in computer vision (fingerprint, iris etc). To see how image processing is related to fingerprint verification,
the following steps are done. The first step is to get the fingerprint image from a scanner. Once, the image is scanned, the second step is to process it. Next, normalize it and finally, feed it to the algorithm.

A detailed survey of image registration techniques was first published by Brown in 1992, but the methods published before 1992 are considered as classic ones and form the basis of today’s image registration techniques. Since last ten years, the image registration has been in the top stack mainly because of the rapid development in the image acquisition devices. Image registration applications can be divided into four groups in the manner of image acquisition [Zitova 2003]

1. Multiview Analysis – same image scene captured at different viewpoints. The purpose is to get a larger two dimensional representation of the scanned image.

2. Multitemporal Analysis – same image scene captured at different time intervals. The purpose to find the changes in the scene and evaluate it.

3. Model Registration – creating a model of an image and registering it. The model may be a computer generated image. The purpose is to localize the image and compare with the model.

4. Multimodal Analysis – image of a scene captured by different sensors. The purpose is to represent a detailed image by integrating the image captured from different sources.

There are many techniques available for image registration and they are classified based on feature and area, transformation, spatial and frequency domain, image similarity etc.
1.5.1 Area and Featured based image registration:

Area based method, the algorithms are written based on image area and none of the other features are considered in this approach. Feature based methods are based on image structure, which includes boundaries, points, lines, line intersection, curves etc. It is also based on correlation metrics, fourier properties and other image structure analysis. Feature based methods are also needed when images do not contain enough texture for the area based method to work well. Feature based includes region based and edge based features. Images where the features are distinct and spread all over can be used under feature based method. The comparability feature is mainly based on overlap criteria and the high percentage of common elements found in the images. Registration methods using area and feature a based method has gained importance nowadays [Eikvil 2005].

1.5.2 Transformation Model:

In this method, properties like linear transformations, (translation, rotation, scaling etc) global mapping models, local mapping models, elastic transformations (polynomial wrapping, smooth basis interpolation etc) are applied for the image registration. This method can remove deformations in image geometry and adapts to correct the errors induced by inaccuracy location of control points [Peng 2006].

Global mapping models use bivariate polynomials of low degrees with other transformations like translation, rotation and scaling. Local mapping models use local geometric distortion registering local areas of the image. When a group of global mapping methods is applied on images, the method is called radial based image registration. In some cases the image has to be stretched for alignment, such a method is
called elastic based image registration. In this method, the image is viewed as a rubber sheet where the external force is used to stretch the image and internal force is used for smoothing the constraints [Zitova 2003].

### 1.5.3 Spatial and Frequency domain methods:

Spatial algorithms are combination of area and feature based methods where they are based on spatial domain, which uses all the characteristics of feature and area based methods. It forms a spatial domain representation of each of the images that is invariant to the translation of images. If the users want to directly determine the shifts between two images, then they use the frequency domain method. This is done by applying the phase correlation over a pair of overlapping images, which produces a third image that contains a single peak constituting the relative translation between the two images. This method has a large performance gain as it computes the cross-correlation between the images using fast fourier transform [Wikipedia 2007b].

### 1.5.4 Search based and direct methods

In search based method, image deformations effects are evaluated and compared. When the deformation is computed from the local image statistics and compared, it is said to be direct method of image registration.

### 1.5.5 Image Similarity based methods:

This method consists of a transformation model, image similarity metric and an optimization algorithm. The transformation model when applied to a reference image
locates the similar co-ordinates in the target image space. The image similarity metric quantifies the degree of correspondence between both the image spaces. Finally the optimization algorithm maximizes the image similarity by changing the transformation parameters.

Algorithms that come under this category include cross co-relation, mutual information, ratio image and mean square difference. Cross co-relation uses a method to evaluate the degree to which two series correlate. Mutual information also belongs to area based image registration method. It gives mutual dependency between two variables.

All the above methods discussed above should give an estimate of image registration accuracy irrespective of the image, the registration method and the application area [Zitova 2003].

1.5.5.1 Mutual Information

Mutual information is the measure of the amount of information that one random variable contains about another random variable. Imagine two random variables, just by seeing those two variables one cannot say or predict the mutual dependency among them; Mutual information gives the mutual dependencies between those two random variables. The two variables may be signals, waves, images (fingerprint, iris, signature etc). Mutual information is the reduction in the uncertainty of one random variable due to the knowledge of the other [Bachman 2005]

So, how is mutual information related to image processing? The answer is; the two random variables mentioned above may be two images of fingerprints/iris/signature. The mutual information theory when applied on digital images gives the detailed
comparison between the two images and thus helps the user to know whether the image in question is genuine or not. For two identical images, the mutual information value is maximum and on the other hand, you get a minimum mutual information value if the images are dissimilar. [Pluim 2003].
2. NARRATIVE

The main aim of the project is to verify any two fingerprints using mutual information algorithm. Usually a number of sample fingerprint from the user is taken and good (impression with clear ridges) fingerprints are considered for the comparison process against the fingerprint in question. As mentioned above, the comparison process involves mutual information, which compares the fingerprint at pixel level.

2.1 Approach Followed

Whenever there is a need for fingerprint verification, first the fingerprint in question is scanned as a grayscale image using a scanner at 300 dpi with a fixed length and width. Later, fingerprint images, selected from the list of samples available are scanned as a grayscale image at 300 dpi with the same length and width as of the fingerprint in comparison.

Once grayscale images are available, then the next task is to make the images compatible for the algorithm. Since the images are scanned as grayscale images, the intensity value of every pixel would be in the range 0 to 255 (0 – black and 255 – white. Other intensity values represent different shades of gray). Now, next step is filtering where the intensity values of the image pixels are altered so that fingerprint can be clearly distinguished from the background. This is done by converting all the pixel values of the fingerprint impressions to 0 (black) and the background pixel values to 255 (white).

Next, is the normalization process, the sample image has be normalized in order to compare with the image in question. It can also to be done vice versa i.e. normalize the image in question with the sample image.
After the filtration and normalization process, the images are now ready for comparison process done using mutual information.

### 2.2 Implementation Language

The code for filtration, normalization and mutual information algorithm is written in MATLAB. In other words, entire project is coded in MATLAB, a numerical computing environment and programming language.
3. PROPOSED SYSTEM DESIGN OR RESEARCH

Fingerprint verification has a significant use mainly in identifying criminals, establishing the authenticity of any system and other uses. In most of the law enforcing agencies hundreds of fingerprints are being processed everyday; hence, there is a great need of automation of this process. The design process involves developing several models of the system at different levels of abstraction.

The following section depicts the data flow representation of the proposed fingerprint verification, which includes 0-level and 1-level data flow diagrams.

3.1 Data Flow Diagrams:

Data flow models are an intuitive way of showing how data is processed by a system or how data flows through a sequence of processing steps. The data is transformed at each step before moving on to the next stage. 0-level data flow diagram is shown in figure 3.1 and 1-level data flow diagram is shown in figure 3.2
Figure 3.1: 0-Level Data Flow Diagram
3.2 System Overview

Figure 3.3 depicts the overall process of offline signature verification. User supplies a number of reference fingerprint samples that are scanned. One fingerprint at a time from the available sample fingerprint is compared with the fingerprint in question or the best fingerprint is chosen from the available fingerprints for comparison.
The verification engine is used to verify the fingerprints using mutual information algorithm. Comparison results in a matching or non-matching fingerprint depending upon the authenticity of the fingerprint. In addition, a certain range of variation in the values is allowed because there might be cases where the fingerprints cannot be aligned exactly even after normalization process. If the values obtained by the fingerprint verification algorithm lie between a specified range, then the fingerprint is said to be genuine.

Figure 3.3: Fingerprint Verification Process
3.3 Preprocessing

An ordinary scanner with enough resolution can be used as an image acquisition device. Scanning hardware may introduce noise to a fingerprint image. Another source of noise may be speckled paper background on which the fingerprint is present. Noise on a fingerprint image may thwart feature extraction process; hence, it needs to be removed. However, preprocessing methods should be selected carefully as they remove fingerprint properties [Kholmatov 2003].

Image size is one of the most important characteristic. If the image size is large, then the algorithm takes a bit more time to throw the outputs and more time is consumed during preprocessing stage too. Therefore, a standard size of 2 inch by 2 inch at 300 dpi scanned as a grayscale image serves as input. The preprocessing stage has two levels. One is filtration and the other is normalization.

The filtration process is done to distinguish the fingerprint from the background. This is done by analyzing the image. The image is read for the intensity value of each pixel and later, the intensity value is change to either 1 (black – fingerprint) or 255 (white – background). In this way, the fingerprint can be easily distinguished from the background.

The next step after filtration is normalization. One of the images should be normalized with respect to the other image in comparison so that the fingerprints can be aligned each other exactly. Normalization plays a very important role because this phase helps in maximizing the mutual information value. If an image is normalized perfectly and both the fingerprints are genuine, then the mutual information value is maximized. Normalization is done in two steps:
3.3.1 Translation:

Image translation is a process of geometric transformation of an image to a new position with respect to its current position based on the translation value (x, y) i.e. an image at original position (x1, y1) is shifted to a position (x2, y2) in the output image by a displacement of the translation value (x, y). The size of both images remains the same. The translation works as follows:

\[ x_2 = x_1 \pm x \] ……………………………..(3.1)
\[ y_2 = y_1 \pm y \] ……………………………..(3.2)

The area of the image (x, y) moved from the original image is lost in the new image and it is by default filled by black color.

3.3.2 Rotation:

Rotation is a process of geometric transformation of an image to a new position with respect to its current position based on the rotation angle \( \theta \) i.e. an image at original position (x1, y1) is rotated to a position (x2, y2) in the output image by an angle of \( \theta \) with respect to the co-ordinates (x0, y0) as the center of rotation. Usually the size of the output image changes after rotation is performed. Rotation works as follows:

\[ x_2 = \cos \theta \times (x_1 - x_0) - \sin \theta \times (y_1 - y_0) + x_0 \] ………………. (3.3)
\[ y_2 = \sin \theta \times (x_1 - x_0) + \cos \theta \times (y_1 - y_0) + y_0 \] ………………. (3.4)

In rotation, the entire image is rotated by an angle \( \theta \) and the additional image area is by default filled by black color [Liu 2006].
3.4 Mutual Information Algorithm

As stated before, Mutual information gives the mutual dependencies between two random variables. The two variables may be signals, waves, images etc. Mutual information is the measure of the amount of information that one random variable contains about another random variable. It is the reduction in the uncertainty of one random variable due to the knowledge of the other [Bachman 2005]

3.4.1 Entropy:

Generally, entropy is the measure of information. In 1928, Hartley defined a measure of information of a message, which is the basis of present day measures. He saw message as a string of symbols where each symbol has s different possibilities. Therefore, if the message consists of n symbols, then there are s to the power n different messages possible where s being different possibilities for each symbol. The problem with this was the amount of information would increase exponentially with the length of the message, which was not realistic. Hartley wanted a measure that increases linearly with the message i.e. \( H = Kn \) where K is the constant depending on the number of symbol s. He assumed that the number of possible messages is equal and the amount of information per message is equal. This led him to define the following measure of information [Pluim 2003].

\[
H = n \log s \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 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The above measure depends on the number of possible outcomes i.e. if the number of possible messages is larger, then the amount of information sent is also larger and if there is a single message then no information is gained because \( \log 1 = 0 \). A major drawback to Hartley’s measure is that it assumes all symbols are equally likely to occur.
In 1948, Shannon introduced an adapted measure, defined as:

\[ H = p \log p \] 

where \( p \) is the probability of an event \( e \).

Shannon’s entropy not only depends on the number of possible messages, but also on the occurrence of each message. The value of entropy is maximum when all the messages are equally likely to occur.

Shannon Entropy is the measure of image information content [DIP 2000]. Given a random variable \( A \), entropy is defined as an expectation of the information.

\[ H(A) = -\sum p(A = a) \log p(A = a) \]

where \( p(A=a) \) denotes the probability that a random variable \( A \) turns out to be an outcome \( a \) [Pluim 2003].

So, how Shannon entropy is applied on an image? The answer is; it is applied considering the distribution of grey values of the image. The probability distribution can be calculated by counting the number of times each grey value occurs in the image divided by total number of occurrences. Low entropy value is the result of an image of single intensity. High entropy is the result of an image, which contains a lot of information, or image with different intensity values. Shannon entropy also yields high value for dispersed probability distribution than a distribution of single sharp peak. Thus, Shannon entropy depends on amount of information, uncertainty of an event, and probability dispersion.

The formula 3.7 represents the entropy of a single random variable. The below formulae gives the entropy of two random variables. The joint entropy and the conditional entropy are defined below
\[ H(A, B) = -\sum_a \sum_b p(A = a, B = b) \log p(A = a, B = b) \] ........................................(3.8)

\[ H(A | B) = \sum_b p(B = b)H(A | B = b) \] .........................................................(3.9)

\[ H(A | B) = -\sum_b p(B = b)\sum_a p(A = a | B = b) \log p(A = a | B = b) \] ..................................(3.10)

\[ H(A | B) = -\sum_a \sum_b p(A = a, B = b) \log p(A = a | B = b) \] ........................................(3.11)

and the above concepts are related by

\[ H(A, B) = H(A) + H(B | A) \] .................................................................(3.12)

Joint entropy of two images can be calculated in the following way:

Figure 3.4 Image with pixel values from 0 to 4 [Ahn 2001]

Figure 3.5 Translation of figure 3.4 by one pixel [Ahn 2001]
3.3 4.3 4.4 5.4 5.5  
3.2 3.3 4.3 4.4 5.4  
2.2 3.2 3.3 4.3 4.4  
2.1 2.2 3.2 3.3 4.3  
1.1 2.1 2.2 3.2 3.3  

Figure 3.6 Joint outcomes of 1-pixel misalignment and exact alignment respectively  
[Ahn 2001]

3.3 4.4 4.4 5.5 5.5  
3.3 3.3 4.4 4.4 5.5  
2.2 3.3 3.3 4.4 4.4  
2.2 2.2 3.3 3.3 4.4  
1.1 2.2 2.2 3.3 3.3  

Figure 3.7 Joint histogram of 1-pixel mis-alignment and exact alignment respectively  
[Ahn 2001]

Figure 3.4 represents an image and its pixel values. Figure 3.5 is the same image  
where the pixel is shifted by one column. Figure 3.6 explains the joint outcome of 1-pixel  
mis-alignment and exact alignment respectively.

3.4.2 Mutual Information:  

Mutual Information was first introduced in 1990’s by Woods in the field of  
medical image registration. He assumed that the regions of similar tissue in one image  
would correspond to the regions in the other similar image. His assumption was true
because the grey values of the tissues in one image were similar to the grey values in the other image. Woods assumption was practically proved by Hill and he observed that alignment plays an important role in maximizing the mutual information value. If the image is mis-aligned by 10 pixels then it results in a low mutual information value [Pluim 2003]

Mutual Information can be defined in two ways. One definition is using the conditional entropy, where the mutual information of two random variables is defined as

\[
I(A, B) = H(B) - H(B | A)
\]

where \(H(B)\) is the Shannon entropy of image B and \(H(B|A)\) is the conditional entropy.

The other definition of mutual information is using the joint entropy, which is defined as:

\[
I(A, B) = H(A) + H(B) - H(A, B)
\]

Where \(H(A)\) and \(H(B)\) is the Shannon entropy of image A and image B respectively and \(H(A,B)\) is the joint entropy of image A and B. Since the joint entropy has negative value, it can be said that maximization of mutual information occurs only when the joint entropy is less. The condition where the joint entropy is zero is considered as ideal means that both the images are same and the mutual information value got from this condition is the maximum [Ahn 2001]
4. EVALUATION AND RESULTS

The project was tested by collecting several fingerprint samples from different users. For every set of fingerprints compared, the algorithm gives the value of the mutual information, translation value, angle, a graph of mutual information with the columns on x axis and mutual information values on the y axis. After conducting several experiments, a threshold value of mutual information (0.15) was selected. Fingerprints are said to be matched if the mutual information value is above 0.15 else unmatched. Results were very impressive. The algorithm is smart enough to identify genuine and fake fingerprints in most of the cases. The False Acceptance Ratio (FAR) was found to be 1 in 20. The value of mutual information of same user was found to be high compared to the value of different users’s fingerprint and with a random image. Following is table 4.1 with maximum MI value for each experiment.

<table>
<thead>
<tr>
<th>Genuine Fingerprints</th>
<th>Different Fingerprints</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2814</td>
<td>0.1335</td>
</tr>
<tr>
<td>0.2028</td>
<td>0.1319</td>
</tr>
<tr>
<td>0.2334</td>
<td>0.1322</td>
</tr>
<tr>
<td>0.2485</td>
<td>0.1297</td>
</tr>
<tr>
<td>0.1678</td>
<td>0.1259</td>
</tr>
<tr>
<td>0.1920</td>
<td>0.1379</td>
</tr>
<tr>
<td>0.2459</td>
<td>0.004</td>
</tr>
<tr>
<td>0.2641</td>
<td>0.1169</td>
</tr>
<tr>
<td>0.2428</td>
<td>0.0981</td>
</tr>
<tr>
<td>0.2805</td>
<td>0.1431</td>
</tr>
<tr>
<td>0.1730</td>
<td>0.0352</td>
</tr>
<tr>
<td></td>
<td>0.1087</td>
</tr>
<tr>
<td></td>
<td>0.1132</td>
</tr>
<tr>
<td></td>
<td>0.1328</td>
</tr>
</tbody>
</table>

Table 4.1 MI values of different experiments
The figure 4.0 gives a clear explanation for calculating the threshold value. The threshold value was selected as 0.15.

Figure 4.0 Threshold graph with x-axis being number of experiments and y-axis being the mutual information value.

Following are the selected results of the experiment.
1. Fingerprints of the same user – right thumb. Figure 4.2 shows the MI graph.

![Fingerprints](image)

Figure 4.1 MI - 0.2814 at a translation value (-1,2) and at rotation angle of 1 degree.

![MI Graph](image)

Figure 4.2 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value.
2. Fingerprints of same user – right left of middle finger. Figure 4.4 shows MI graph

Figure 4.3 MI – 0.2028 at translation value (17,2) at a rotation angle of 358 degree.

Figure 4.4 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value.
3. Fingerprint of same user – right middle finger. Figure 4.6 shows MI graph

Figure 4.5 MI – 0.2334 at translation value (-8, -8) at a rotation angle of 10 degree

Figure 4.6 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value
4. Fingerprint from different user – left thumb. Figure 4.8 shows MI graph.

Figure 4.7 MI – 0.1379 at translation value (18,-7) at a rotation angle of 2 degree

Figure 4.8 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value
5. Fingerprint from different user – left middle finger. Figure 4.10 shows MI graph.

Figure 4.9 MI – 0.1169 at translation value (-1,-13) at a rotation angle of 1 degree

Figure 4.10 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value
6. Same fingerprint of a single user (same image). Figure 4.12 shows MI graph.

Figure 4.11 MI – 0.2485 at translation value (0,0) at a rotation angle of 360 degree

Figure 4.12 MI Graph where x-axis is the maximum value of MI in each column of the joint outcome matrix and y-axis is the MI value
7. Fingerprint and a random image

Figure 4.13 MI – 0.004 at translation value (0, 0) at a rotation angle of 360 degree
5. CONCLUSION AND FUTURE WORK

In this project, we propose mutual information algorithm for fingerprint verification. Grayscale fingerprint images are the input to the algorithm. The target image is preprocessed (translation and rotation) with reference to the reference image and then the mutual information algorithm is applied to the images. The value of mutual information depends on the image quality. Better values are obtained for high quality images but again running time of the program increases exponentially. The project aims at maximizing the mutual information value by aligning the fingerprints.

Future work for this research can be listed as follows:

• Graphical User Interface can be built to make it user friendly
• Additional algorithms can be added to make the verification process more efficient
• Filtration process can be improved by retaining all the pixel values rather than changing them to a different value as some of the image data is being lost during the process.
• Application can be used in real world with some modifications towards performance to verify fingerprints
ACKNOWLEDGEMENTS

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BIBLIOGRAPHY AND REFERENCES


