Fingerprint Recognition System Performance in the Maritime Environment

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Abstract

This study assesses the effects of prolonged exposure of fingers to water on the performance of existing fingerprint recognition systems. The dataset used in this research is collected using a high-end, multispectral fingerprint scanner. To perform a data acquisition, we recruited volunteers to contribute their fingerprint samples to the dataset in multiple sessions. Once the dataset is filled with both fingerprints under normal and wrinkled conditions, we use a minutiae-based fingerprint verification system to retrieve the match scores between all combinations of prints. Finally, we use receiver operating characteristic (ROC) curve to measure the behavior of such systems under maritime environment. Using the equal error rate (EER), we successfully quantify the degradation in performance due to water-induced skin pruning, which is approximately 1% reduction in EER.

1. Introduction

A biometric identification system is defined as any system using an individual's physiological and behavioral characteristics to automatically verify their identity [1]. Fingerprint authentication system is among the most commonly used biometric technologies [2]. An important question that has received insufficient attention has to do with how well a sophisticated, commercially available fingerprint recognition system will perform in a maritime environment. This paper explores the impacts of water-induced finger pruning on a typical fingerprint recognition system.

Pruning is a temporary skin condition caused by prolonged exposure to water. A wrinkled finger affected by pruning is often referred to as a pruney or water aged finger [3]. Figure 1 is an example of a water aged finger of a baby after a warm bath [4].

In most practical scenarios, a person will not be identified in the same environment or on the same day as they first enrolled their fingerprint; hence, more research is required to evaluate system performance under different circumstances. Since understanding the impacts of the maritime environment on the performance of fingerprint ecognition systems would be significant to large scale

implementations of this technology, in this paper, we present our findings and evaluations of the performance of fingerprint systems for water-induced skin pruning.

Figure 1: Example of a water aged finger after a warm bath [4].

1.1. Methodology

The purpose of this research is to perform a comparative analysis for ROC curves of dry and wrinkled fingerprint to evaluate the changes in the error rates. The dataset used in this research is collected from a multispectral sensor that is commercially available [5]. Figure 2 presents an overview of the project's design flow.

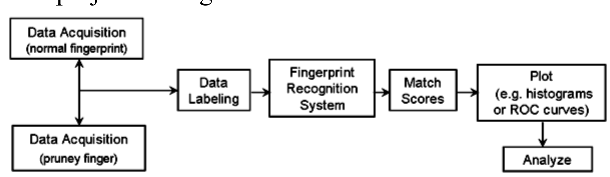

Figure 2. Block diagram illustrating the project flow.

Fingerprints were collected from 18 subjects, 10 females and 8 males with an age range from 18 to 26. Each subject provided a template print, two or more dry and wrinkled fingerprint samples of their right index finger where the resultant images were used in their raw format for all analyses. The "template" print refers to the original print collected during the enrollment process. Table I illustrates the specific overview of the data statistics.

participants	Male	Female	Dry	Wet
18	8	10	65	87

Table I. Overview of data statistics.

2. Experimental Procedure

For the purpose of this research, the authors propose an innovative method of exposing fingers to water. This procedure provides sufficient amount of wrinkling in the designated time while it allows the volunteers to continue their work as they are waiting for wrinkling to occur.

Instead of having maritime subjects immersing their fingers in a cup of warm water for 20-30 minutes, we provided them with non-latex surgical gloves that contains small amount of water in its index finger. The subjects wore the glove for approximately 30 minutes while continuing their errands. We repeated this procedure for multiple sessions every week until we were able to acquire at least two dry and two or more wet wrinkled samples from every participant.

2.1. Data Organization

In order to establish a control experiment, we first assess the performance of a commercially used minutiae-based fingerprint recognition system under normal (or dry) condition. Then we compare the ROC curve acquired under maritime environment against the ROC curve obtained from the control study. For each analysis, we discriminated between genuine and impostor scores to generate a meaningful ROC curve.

dry genuine	dry impostor	wet genuine	wet impostor
65	556	105	914

Table II. Distribution of match scores.

For normal samples, genuine scores are recognized as the scores between the template and dry samples of the same individual. This gives us 65 dry genuine scores—same as the total number of dry samples. On the other hand, the impostor scores contain the genuine scores in addition to all the scores between the template print of one individual and template samples of other subjects, as well as all the match scores between template prints and dry prints of all participants (e.g. template.A, template.B, dry.B1, dry.B2 …). After acquiring the dry impostor scores, we ended up with a total of 556 impostor scores.

After collecting the dry samples, we collected a series of wrinkled fingerprint samples from each subject in multiple sessions. Like the normal dataset, we distinguished between the impostor and genuine scores of samples collected under maritime environment. For water-induced samples, the

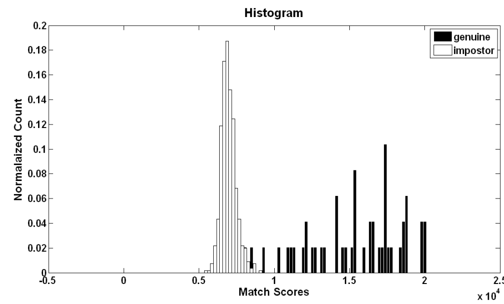

Figure 3. A match score histogram obtained by the minutiae-based fingerprint recognition system under normal (dry) conditions. The black bars represent the genuine distribution (the range and frequency of genuine scores) and the white bars represent the impostor distribution (the range and frequency of impostor scores).

genuine scores are recognized by the match scores between a reference template and series of pruney fingerprint samples of the same individual. Since we have 18 template prints and 87 wet prints, the wet genuine match scores will add up to be 105. Furthermore, the impostor scores are the match scores between the template of a person, and the template and pruney samples of all other participants. In which case, it adds up to be 914 impostor match scores.

3. Fingerprint Reader

To acquire fingerprint samples, we obtained a fingerprint reader equipped with high-end multispectral imaging technology. The configuration of the multispectral sensor is particularly designed to avoid the Total Internal Reflection (TIR) phenomena by orienting the light source such that the relevant angles do not exceed any critical-angle conditions. This is certainly a valuable characteristic for the purpose of our project since it adds more to the image quality and the robustness of the data acquisition process. The designated fingerprint reader includes a user friendly Software Development Kit (SDK) that allows us to store the samples as bitmap files on our computer. This is highly valuable,

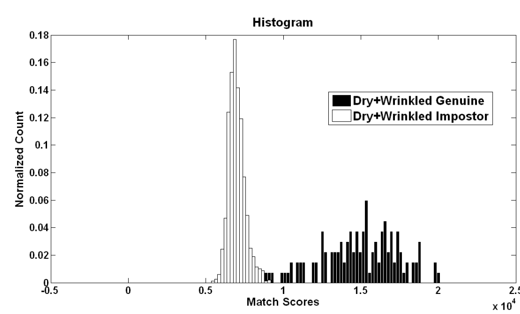

Figure 4. A match score histogram for dry scores as well as wrinkled. The black bars represent the range and frequency of genuine scores acquired under dry and wet conditions, and the white bars represent the combination of the impostor scores collected under both dry and wet conditions.

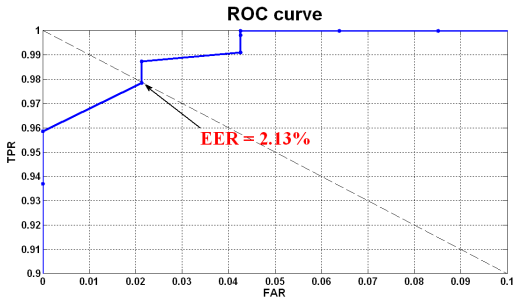

Figure 5. The ROC curve is depicting the relative trade offs between true positive and false acceptance rate of the dry match scores. The dashed, diagonal is a reference line. FAR and TPR are x and y axes respectively. Blue line sweeps over different threshold values. EER is where ROC curve intersects with the line:(0,1), and (1,0), which is roughly 2.13%.

since we can then directly input these images into a minutiae-based fingerprint recognition system and seamlessly acquire the match scores. The acquired match scores will be automatically stored in a text file and will be read by a MATLAB algorithm that plots the histogram plots and ROC curves.

4. Fingerprint Authentication Algorithm

We used a commercially available minutiae-based fingerprint matching SDK[1]. Like many other fingerprint recognition processes, this algorithm is made of two steps: (1) Fingerprint model extraction, and (2) Model matching.

The first part processes a raw fingerprint image and extracts fingerprint features from that image. These distinctive "minutiae" features form a unique fingerprint model. Once the fingerprint model is extracted, the fingerprint image is not used anymore. For additional identity verification, only the extracted fingerprint model is, in fact, used. During model matching, two models are compared and resulting similarity score is returned.

Because of translation, deformations, random noise, finger humidity and sensor conditions, it is impossible that two images of the same finger, acquired in different sessions to have an exact match. Therefore, the matching is performed by an algorithm which computes a *similarity*. This similarity have to be compared with acceptance *threshold t*: in case that similarity is greater than t, the system claims that two samples match [5].

5. Experimental Results

We first plotted the histogram diagram between the dry genuine and dry impostor match scores. To outline the changes in the overall performance of the designated fingerprint recognition system, we then compared this against the histogram diagram obtained from the match scores between dry and wet fingerprints. As expected, the distributions of scores are very similar; however, there is more overlap between genuine and impostor scores of the data collected under maritime environment. This overlap is an indication of slight degradation in the performance of the system due to the effects of maritime environment.

After the comparative analysis between two histogram diagrams we plotted the ROC curves of both situations. To summarize the quality of the ROC curve, we used the equal error rate (EER) which corresponds to the point where the line FPR = 1 – TPR intersects the ROC curve [6].

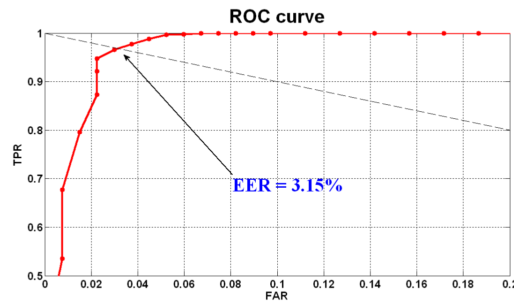

Figure 6. The ROC curve is depicting the relative trade offs between true positive and false acceptance rate of the dry+wet genuine scores versus dry+wet impostor scores. The dashed, diagonal is a reference line. FAR and TPR are x and y axes respectively. Red line sweeps over different cut-off points. EER value as ROC curve intersects with the diagonal line (reference line) is 3.15%.

5.1. Histogram

Figure 3 shows the match score histogram obtained by the minutiae-based fingerprint recognition system under dry conditions. In an ideal situation, one expect no overlap between genuine and impostor scores; however, in reality, there are always some imperfection impacting the system. Hence, the overlap between impostor and genuine scores can be caused by several reasons such as different positioning, deformations, random noise, finger humidity and sensor conditions as a result of collecting the prints in multiple sessions.

Figure 4 represents the match score histogram obtained by the same system for the match scores of the wet and dry prints. From the two histogram plots, we can see the shift in scores and the overlap between the genuine and impostor scores. However, it is hard to determine the amount of overlap. So in order to assess the behavior of the system under maritime environment, we need to also look at the ROC curve corresponding to these histogram plots.

[1] For future details on the choice of sensor and algorithm, please contact the authors.

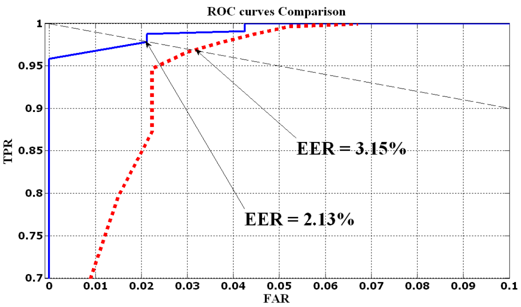

Figure 7. This is the combination of the two ROC curves on one plot. The red dashed line is the ROC curve for wrinkled vs. dry, and the solid blue curve is the curve corresponding to dry vs. dry distribution. The solid blue curve is closer to the left corner; hence a smaller value of EER.

5.2. ROC curves

The interpretation from the histogram plots is valuable, but not enough to draw a strong conclusion. In order to evaluate the performance of the system, one needs to analyze the ROC curve of both situations. For an ideal result, there is no overlap between the two distributions; hence, the ROC curve passes through the upper left corner (100% TPR and 100% FAR). To summarize the quality of the ROC curve, we use the equal error rate (EER) which corresponds to the point where the line FPR = 1 – TPR intersects the ROC curve [6]. Ideally, the EER value is expected to be low. The lowest value is 0. Therefore, the closer the ROC plot to the upper left corner, the lower the EER, and the higher the overall accuracy of the system [7].

The ROC curve in Figure 6 illustrates the relative trade offs between true positive rate (TPR) and false acceptance rate (FAR) of the match scores for dry dataset. Since there is a minor overlap between the distributions of genuine and impostor scores, we have a low EER value of ~ 2.13%.

As expected, the similarity between a pruney finger and a dry finger is lower. So we expect to see a decrease in the performance quality of the fingerprint recognition system. The ROC curve in Figure 6 illustrates the impact of wrinkling on the performance of the fingerprint authentication system. Figure 7 compares the dry genuine versus dry impostor score distribution against the ROC representation of wrinkled vs. dry curve. This comparison illustrates how the ROC curve of wrinkled vs. dry is more distanced from the left corner and its EER value increases by a factor of 1.02% from 2.13% to 3.15%. Table III is a brief statistical analysis of this comparison.

	EER	TPR @ FAR = 1%	TPR @ FAR = 5%
Dry	2.13%	96.7%	100%
Wrinkled	3.15%	72.4%	98%

Table III. Numerical comparison between the performances of the fingerprint matcher under dry vs. martime environment.

5.3. Variability of Inter Finger Pruning

In this paper, we evaluated the performance of a fingerprint recognition system using prints collected from the right index finger. We chose index finger mainly because it is frequently used in practice. Also, since 70-95% of adult population is right-handed, we preferred right index finger over left index finger [8].

We have noted an interesting phenomenon during data acquisition process. Since we only poured a small amount of water for the index finger in the glove, we expected to see the maximum pruning to occur on the right index finger. However, as the participants took off their gloves, we have noticed for the majority of their ring finger wrinkled more than other fingers, and the index finger wrinkled less.

Figure 8. The image on the left views the right hand of subject A. The image on the right views the right hand of subject B. Subject A's 4 fingers has roughly even pruning. Subject B has the most pruning in his ring finger and the least in his index finger.

Figure 8 is a side-by-side image showing four fingers of one subject on the left and the same four fingers of a different subject on the right. The fingers of the subject on the left evenly wrinkled, while the ring finger of subject on the right has the most wrinkling.

To sensibly use this phenomenon to our advantage, we will conduct an experiment in which we compare the behavior of the system using ring finger—a finger that had the largest amount of pruning—with the result obtained from the index finger. This will give us insight about the behavior of the system when there is more wrinkling occurring on index finger. In other words, we do not use ring finger because it is commonly used, but to evaluate the behavior of the system in the presence of more pruning.

6. Conclusion and Future Work

The purpose of this study was to quantitatively assess the effect of water-induced finger pruning on the performance of a commonly used, minutiae-based fingerprint recognition system. We were able to show the degradation in the performance of the system by a comparative analysis between the ROC curves of dry and wrinkled fingerprint match scores. Furthermore, to acquire a quantitatively approximation, we computed the EER values of both curves. Since the EER value of dry vs. wrinkled fingerprint match scores was 1% higher, we were able to successfully measure the system's degradation.

As feature work, we would like to:

- Expand our dataset by recruiting more volunteers
- Explore other commercially available sensors
- Examine the variablity of inter finger pruning
- Utilize different fingerprint matching algorithms

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