

# A FRAMEWORK FOR BIOMETRIC RECOGNITION USING NON-IDEAL IRIS AND FACE

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A thesis submitted in fulfilment of the  
requirement for the award of the degree of  
Doctor of Philosophy (Computer Science)

Faculty of Computing  
Universiti Teknologi Malaysia

JULY 2014

To my beloved supervisors, and family

## ACKNOWLEDGEMENT

First and foremost, I would like to express my gratitude to all my supervisors, Dr. Hishammuddin Asmuni, Dr. Rohayanti Hassan, and Dr. Muhamad Razib Othman for their patience, guidance, encouragement, invaluable comments, and advices that have made this research possible and can be completed in due time. My gratitude is also extended to my funder - MyPhD Scholarship of the Malaysian Ministry of Higher Education for continuously sponsoring this research. Of course, the invaluable cooperation given by Gates IT Solution Sdn. Bhd. cannot be forgotten as well. Their staff have been very helpful in providing the needed guidance, resources, space, and assistance in collecting the UTMIFM datasets. In addition, portions of the research have used the West Virginia University Iris datasets and UBIRIS version 2.0 iris datasets. I thus hereby would like to officially express my gratitude to both universities for sharing their datasets. My deepest appreciation goes to my family for their moral support. Special thanks to Mr. Teo and his family for encouraging me through the hardships and gave me the strength to continue this journey. Lastly, I would like to express my appreciation to God for simplifying this path and prepare all the resources I needed.

## ABSTRACT

Off-angle iris images are often captured in a non-cooperative environment. The distortion of the iris or pupil can decrease the segmentation quality as well as the data extracted thereafter. Moreover, iris with an off-angle of more than  $30^\circ$  can have non-recoverable features since the boundary cannot be properly localized. This usually becomes a factor of limited discriminant ability of the biometric features. Limitations also come from the noisy data arisen due to image burst, background error, or inappropriate camera pixel noise. To address the issues above, the aim of this study is to develop a framework which: (1) to improve the non-circular boundary localization, (2) to overcome the lost features, and (3) to detect and minimize the error caused by noisy data. Non-circular boundary issue is addressed through a combination of geometric calibration and direct least square ellipse that can geometrically restore, adjust, and scale up the distortion of circular shape to ellipse fitting. Further improvement comes in the form of an extraction method that combines Haar Wavelet and Neural Network to transform the iris features into wavelet coefficient representative of the relevant iris data. The non-recoverable features problem is resolved by proposing Weighted Score Level Fusion which integrates face and iris biometrics. This enhancement is done to give extra distinctive information to increase authentication accuracy rate. As for the noisy data issues, a modified Reed Solomon codes with error correction capability is proposed to decrease intra-class variations by eliminating the differences between enrollment and verification templates. The key contribution of this research is a new unified framework for high performance multimodal biometric recognition system. The framework has been tested with WVU, UBIRIS v.2, UTMIFM, ORL datasets, and achieved more than 99.8% accuracy compared to other existing methods.

## ABSTRAK

Imej iris sudut terpesong terjadi apabila gambar diambil dalam keadaan tidak kooperatif. Herotan pada iris atau pupil boleh menjejaskan kualiti segmentasi dan imej yang diekstrakkan. Sudut pesong iris yang lebih daripada  $30^\circ$  boleh mempunyai ciri iris yang tidak dapat dipulihkan akibat daripada ketidakupayaan pengenalan sempadan ciri iris. Ini kerap menjadi punca kepada keupayaan diskriminan terhad. Data hingar juga disebabkan oleh letusan imej, ralat latar belakang imej, dan kebingaran isyarat piksel kamera. Untuk menyelesaikan masalah yang dinyatakan seperti di atas, kajian ini telah dijalankan untuk membangunkan satu rangka kerja yang: (1) menambahbaikkan penyetempatan sempadan bukan bulat, (2) mengatasi masalah kehilangan ciri-ciri, dan (3) mengesan dan mengurangkan ralat yang disebabkan oleh data hingar. Masalah sempadan bukan bulat diselesaikan dengan menyatukan penentuan geometri dengan *direct least square ellipse* di mana herotan bentuk bulat dipulihkan, disesuaikan dan diskalakan secara geometri. Untuk penambahbaikan rangka kerja ini, kaedah pengekstrakan yang menggabungkan *Haar Wavelet* dan rangkaian neural telah dicadangkan untuk mentransformasikan ciri-ciri iris kepada pekali *wavelet* yang boleh mewakili data iris yang berkaitan. Masalah ketidakupayaan untuk memulihkan ciri-ciri diselesaikan dengan cara gabungan aras markah berdasarkan berat yang mengintegrasikan biometrik muka dengan biometrik iris. Kaedah ini membekalkan maklumat tambahan untuk meningkatkan kadar ketepatan pengesanan. Isu ralat data pula boleh ditangani dengan pengubahsuaian kod Reed Solomon untuk merangkumi keupayaan pembetulan ralat supaya variasi intra-kelas boleh dikurangkan melalui pengenalanpastian dan penghapusan perbezaan antara templat-templat enrolmen dan pengesanan. Sumbangan utama penyelidikan ini adalah rangka kerja yang baru bagi prestasi tinggi sistem pengiktirafan biometrik multi modal. Kajian ini telah diuji dengan menggunakan pangkalan data WVU, UBIRIS.v2, UTMIFM, dan ORL dan mencapai ketepatan lebih daripada 99.8% berbanding dengan kaedah-kaedah lain yang sedia ada.

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## LIST OF ABBREVIATIONS

ACC	-	Accuracy
ATM	-	Automated Teller Machine
AUC	-	Area Under Curve
BAT	-	Biometric Automated Toolset
BATH	-	University of Bath
BCH	-	Bose-Chaudhuri-Hocquenghem
CASIA	-	Institute of Automation, Chinese Academy of Science
CCD	-	Charged Couple Device
CMC	-	Cumulative Matching Curve
CPU	-	Central Processing Unit
DI	-	Decidability Index
DLSE	-	Direct Least Square Ellipse
DoD	-	U.S. Department of Defense
DNA	-	Deoxyribonucleic acid
ECC	-	Error Correction Codes
EER	-	Equal Error Rate
FAR	-	False Acceptance Rate
FRR	-	False Rejection Rate
GAR	-	Genuine Acceptance Rate
GC	-	Geometric Calibration
HD	-	Hamming Distance
HT	-	Hough Transform
HW	-	Haar Wavelet
ICA	-	Independent Component Analysis
ICE	-	Iris Challenge Evaluation
IOM	-	Iris On the Move
LSEFGC	-	Direct Least Square Ellipse Fitting Geometric Calibration

MMU	-	Multimedia University
NICE I	-	Noisy Iris Challenge Evaluation Part I
NN	-	Neural Network
PCA	-	Principle Component Analysis
PIN	-	Personal Identification Number
ROC	-	Receiver Operating Characteristic
RS	-	Reed Solomon
TSR	-	Total Success Rate
UBIRIS v.1	-	University of Beira Interior version One
UBIRIS v.2	-	University of Beira Interior version Two
UIDAI	-	Unique Identification Authority of India
UPOL	-	University of Olomuc
UTMIFM	-	Universiti Teknologi Malaysia Iris Face Multimodal Dataset
WED	-	Weighted Euclidean Distance
WSLF	-	Weighted Score Level Fusion
WVU:IBIDC	-	West Virginia University Iris Biometric Image Dataset Collection/Off-Axis/Angle



## CHAPTER 1

### INTRODUCTION

#### 1.1 Background

For years, our securities are safe-kept based on what we know or have such as password, token, Personal Identification Number (PIN), or answer to a security question such as mother's maiden name. Though 'safe' as they may sound, these security features can also create problems because they can be easily forgotten, stolen, shared, or cracked by other individuals. As such, a robust and reliable recognition system is needed, and a good example to this is the biometric authentication system, an automated use of behavioral or physiological characteristics to determine or verify identity. Unlike password or keys, biometrics cannot be given to another person, and this has encouraged its evolution to become one of the most important security measurements to answer the question: "Who are you?". Reasons to its rapid advancement are due to its high security, speed, reliability, ease of use, and difficulty in duplication (Szewczyk *et al.*, 2011; Tan *et al.*, 2010). Generally, a biometric system can be categorized as physiological or behavioral. The physiological biometric system detects a physical feature of the user such as face (Caifeng *et al.*, 2009), hand geometry or veins patterns (Honarpisheh and Faez, 2013), fingerprints (Akbari and Sadr, 2012), iris patterns (Chen *et al.*, 2010; Li and Savvides, 2013); , retina patterns (Fuhrmann *et al.*, 2009), and Deoxyribonucleic acid (DNA) pattern (Biedermann *et al.*, 2012). On the other hand, behavioral features are extracted from day-to-day sociological behaviours of a person

such as voice (Charlet and Lecha, 2007), keystroke (Karnan *et al.*, 2010), and gait (Hadid *et al.*, 2013).

Unimodal biometrics systems is a system which perform an authentication based on a single source of biometric information (Nandakumar *et al.*, 2006). The main process in a unimodal biometric recognition includes enrollment acquisition, image pre-processing, feature extraction, and template matching. Every unimodal biometric system has its own strength and weaknesses. The three most popular unimodal biometric are the fingerprint, face, and iris. The advantages of fingerprint is its availability in the huge legacy dataset that is capable of performing 1: $N$  (millions) search, relatively low cost, and small size. Fingerprint biometrics is commonly deployed for law enforcement and forensic application, banking, and some physical access. The strength of face biometric, on the other hand, lies on its huge legacy dataset and ability to covertly capture images of the user. Face biometrics is often use in surveillance applications, e.g., government or casino, identification system, and access control (Nieto *et al.*, 2002). Iris biometrics is also capable of performing 1: $N$  search and has the highest accuracy and persistency compared to other available biometric traits. This biometrics is mostly used for applications that need stronger security such as border crossing control and military access control. An example of this is the U.S. Department of Defense (DoD) Iris Recognition (Al-Raisi and Al-Khoury, 2008). However, according to Jain *et al.* (2004), no single biometric is both sufficiently accurate and robust to hindrance. In today's implementation, unimodal biometric systems are still unable to provide consistently good quality samples, have missing biometric traits, and may even be rejected due to religious or cultural concerns (Modi, 2011).

Another strategy to build a biometric authentication system is by incorporating multiple sources of information to establish a single identity. It fuses information from multiple biometric traits, algorithms, sensors, and other components to make a recognition decision (Modi, 2011). Multi biometrics has received much attention in recent years, and its researches as well as commercialization have grown considerably since it has lower error rate and can accommodate larger population. Multiple sources of information can increase inter-

class variability and reduce intra-class variability. Multimodal approach is one of the categories of multi-biometrics which integrates two or more types of biometric traits. The most prominent implications of multimodal biometrics are the increase in accuracy, decrease in enrollment problems, and enhancement in security. Moreover, it reduces the unacceptable rates occurred in unimodal biometrics, failure to enroll rate, and makes it difficult to employ fake biometric. However, the weaknesses of multimodal biometric system is that it is more expensive compared to other multibiometric systems. Well known application of multimodal system includes the Unique Identification Authority of India (UIDAI: Nagar *et al.*, 2012) which assign all Indian residents a unique number with 10 fingerprint images, two iris images, and a face images. Another example is the Biometric Automated toolset (BAT: Modi, 2011) that is consisted of fingerprints and iris biometrics of the U.S. military in Iraq and Afghanistan. To design a high performance multimodal biometrics system, the choice and number of biometrics, level of fusion, fusion methodology, assignments of weight to biometrics, and the acquisition of multimodal dataset are the main aspects to configure.

## 1.2 Challenges of Multimodal Biometrics

Ideal iris images are hard to acquire in a non-cooperative environment. More often than not, non-ideal images such as off-angle iris images, motion-blurred images, images with reflection, and occlusion are captured. The uniqueness of off-angle compared to other non-ideal images is in the existence of non-circular boundaries due to off-axis iris. Off-angle iris recognition is challenging because the non-circular iris boundary may lead to faulty segmentation (localization of iris and pupil boundary) and can affect the quality of features extracted from the iris biometric templates. Faulty segmentations can result in lost of important discriminant features and wrong segmentation of unwanted features such as pupil, sclera, or eyelashes. Simply to say, non-circular boundaries degrades the data quality, making it more challenging to segment and extract iris features for recognition purposes. In this research, this issue is taken as the first challenge to the off-angle iris recognition.

Although some new segmentation methods have already been recommended for unimodal iris recognition using either calibration/active contour approaches or artificial intelligence feature extraction techniques to recover off-axis angle iris features, the high possibility of losing important features is still present. This is especially true when the iris off-axis angle is more than  $30^\circ$ , making it even more challenging to segment and extract iris features and some may even be lost completely. All in all, this hampers the quality of the authentication since discriminant features cannot be identified. Such condition with lack of discriminant features stimulates highly unacceptable False Rejection Rate (FRR) and False Acceptance Rate (FAR). Hence, the second challenge lies in integrating more features to overcome and increase the existing authentication methods' limited ability to segment and extract discriminant iris features due to non-recoverable features caused by the unconstrained biometric recognition environment.

The third challenge in this study is regarding the intra-class variations in biometric templates. Intra-class variations are the differences in bits between two biometric samples taken from the same subject. Aside from off-angle iris recognition or biometric authentication done in unconstrained environment (such as multi face expression), intra class variation may happen due to uncontrollable factors during sample acquisition. These include image bursting error, background error, and Charged Couple Device (CCD) camera pixel noise. These factors exist by nature and are unavoidable, but they cause deviations on the similarities between two biometric templates taken from the same subject. Such situation is technically coined as the "unreliability bits" in biometric templates. According to Hao *et al.* (2006), the hardest problem with biometrics is these "unreliability bits" in the biometric templates because it is the main cause to fuzzy biometric data that creates discrepancies in the acquired and stored biometric data. Most existing biometric recognition systems do not take this factor of variation into much consideration as well, but prefer to pay more attention to inter-class variation. This eventually decreases the recognition performance in terms of FRR, overall accuracy, and Decidability Index (DI).

### 1.3 Current Methods of Multimodal Biometrics

In many research studies, multimodal biometrics are proposed to resolve the problems of unimodal biometrics. In general, there are five types of multibiometric system which include: (1) Multi-sample - collect and process multiple images of same biometric; (2) multi-instance - collect and process images of several distinct instances such as multiple fingerprints or both of the irises for recognition; (3) multisensor - collect the same biometric trait using more than one sensor; (4) multi algorithm - use more than one matching algorithm of the same biometric and fuse the results; and (5) multi-modal approach - a fusion of different biometric traits that can be further categorized into three main level, i.e., score level fusion, feature level fusion, and decision level fusion:

- (i) Score level fusion method calculates the match score based on the degree of similarity between two biometric samples. Score fusion can be generally done using the classification and combination approach. Zhang *et al.* (2007), Chen and Chu (2005) and Eskandari *et al.* (2013) have presented score level fusion based on face and iris biometrics using the classification approach. For example, in Chen and Chu (2005) the authors used an unweighted average of outputs based on neural network. Classification methods requires large amount of training data to determine its optimal decision boundary. The combination approach, on the other hand, is a technique which combines multiple scores to calculate a single match scores (Connaughton *et al.*, 2012; Nandakumar *et al.*, 2006; Ulery *et al.*, 2006). It uses simple sum, min score, max score, and weighting rules to consolidate the matching score. Another more recent combination approach that fuses face and iris biometrics using Iris on the Move (IOM) sensor have been presented by Connaughton *et al.* (2012). This sensor is designed for high throughput stand-off iris recognition which features a portal of subjects walk through at normal walking pace.
- (ii) Feature level fusion method extracts the different features from biometric modalities and combines the feature set to create single template. Feature level fusion using face and iris biometrics are presented in Rattani and Tistarelli (2009), and Son *et al.* (2006). A new feature vector has also been

constructed using concatenation rule (Ross and Govindarajan, 2005), and parallel rule (Yang *et al.*, 2003). Challenges in this feature level fusion are in the incompatibility of various feature sets as well as high dependencies between each other.

- (iii) Decision level fusion is the easiest among the others. It applies a Boolean response to indicate the matching degree of two biometrics templates. A simple logic rule of “AND” and “OR” are used to decide the fusion. As the fusion level progresses from feature level to decision level, the amount of information decreases. Therefore, decision level fusion is the fusion with the least information available. Kapale *et al.* (2011), in particular, has recommended the usage of iris and face verification using decision level fusion.

#### 1.4 Problem Statement

“Given the dataset of off-angle iris images captured in a non-cooperative environment, the first challenge is to improve non-circular iris boundary localization with better segmentation and accuracy rates. As such, the proposed method should introduce a better segmentation and feature extraction to correctly localize the boundary of the unconstrained off-angle iris images. In order to overcome non-recoverable or lost features caused by off-angle and leads to limited discrimination ability, the method should incorporate the fusion of more biometrics traits information instead of unimodal iris to provide extra distinctive features which can enhance the decidability index and the results of the Receiver Operating Characteristic (ROC) curve. Finally, to tackle with the intra-class variation caused by image burst error, background error, and camera pixel noise, the proposed method has to be able to detect and minimize the errors to improve the FRR and overall accuracy by providing a larger gap between the intra-variability values and the inter-variability values”

The first challenge is to enhance the performance of the off-angle iris image segmentation and to obtain highly distinctive iris patterns. Off-angle iris images are

caused by variations in user height, gaze direction, and tilting of the head. These cause the pupil and iris boundaries to be non-circular and become difficult to segmentate. Fault segmentation leads to lost of significant features that can be non-recoverable or even segmentation of unwanted features. Many existing methods are able to localize the iris boundaries in good quality data, which means the images have been taken in ideal situations. However, due to unconstrained off-angle, these methods become incompetent in properly localizing the limbic and pupillary boundaries of the iris. Thus, regard this problem, this study intend to address this by proposing a segmentation and feature extraction method to significantly localize the iris boundaries and extract the most useful and deterministic feature from the data.

The second cause is referring to the non-recoverable iris features. If off-axis iris gaze is more than  $30^\circ$ , some of the iris features becomes difficult to be segmented correctly and this limits the discriminant ability to recognize biometric traits. In this case, the iris biometric traits have to be supported by additional traits to provide extra significant features. Therefore, this study aims to develop a method which integrates the complementary information comes primarily from different modalities with the iris biometrics to provide more distinctive features for the enhancement of the recognition accuracy.

The third factors are related to the intra-class variations. Besides those that are caused by the off-angle or unconstrained environment issues, intra-class variations may arise from image burst, background error or camera pixel noise. These are unavoidable errors which come by nature in every authentication. Therefore, for the same subject, each newly generated biometric templates from the same subjects are always different, though they are still interrelated. Many existing methods have only focused on the solution to increase the dissimilarity for the inter-variance rather than increase the similarity of the intra-variance. In the desire to minimize the intra-variance of the biometrics, this study proposes a method to detect and eliminates the differences between enrollment templates and verification templates caused by the aforementioned errors to significantly reduce the FRR and increase the DI of the recognition performance.

## 1.5 Objective of the Study

The main goal of this study is to develop a unified framework which: (1) correctly localizes iris boundaries of the off-angle iris images; (2) integrates more features to increase the limited discriminant ability of unimodal biometrics; and (3) detects and corrects the uncontrollable errors of biometrics. This goal was achieved through the objectives outlined below:

- (i) To develop an improved segmentation and feature extraction techniques by combining Geometric Calibration (GC) and Direct Least Square Ellipse (DLSE) as well as fusing Haar Wavelet (HW) and Neural Network (NN) to effectively localize the non-circular boundaries from off-angle iris images.
- (ii) To develop a Weighted Score Level Fusion (WSLF) method for the multimodal biometrics which integrates iris biometric traits with face biometric traits to increase the recognition's discriminant ability.
- (iii) To develop a modified error correction codes by modifying the Reed Solomon codes to detect and correct the biometric image nature unavoidable errors and ultimately increase the similarity of biometric intra-variance.

## 1.6 Scope of the Study

In this study, UBIRIS v.2, WVU:IBIDC (Iris Biometric Image Dataset Collection/Off-Axis/Angle) datasets and self-acquired datasets were used. For WVU-IBIDC datasets, the off axis/angle iris dataset contained 808 images collected with two cameras, a Sony Cyber Shot DSC F717 and a black and white monochrome camera. The monochrome camera had 584 iris images captured from 73 subjects and chosen for this study. The WVU-IBIDC datasets contained iris images captured from different gaze directions (angle in degrees) which were 0, 15, 30, and 0 in .bmp format. In addition, a new multimodal datasets named Universiti Teknologi Malaysia Iris Face Multimodal Dataset (UTMIFM) which had off-angle iris images and face images with varying expressions was built up in this study. The dataset had 150 face samples and iris images collected from users of different ethnics with five images taken from each individual from right to left.



The unified framework proposed had three main components that were used to correctly localize the iris boundaries of the off-angle iris images, integrate more features to increase the limited discriminant ability as well as detect and correct the uncontrollable errors of the biometric recognition. To be more specific, GC and DLSE were used to correctly localize the limbic and pupillary boundaries of the off-angle iris images. The discriminant features were then extracted through a method that fused both HW and NN algorithms from the off-angle iris. In the multimodal biometrics, WSLF was used to integrate face and iris biometrics by providing more informative features to reach a better matching value. The modified Reed Solomon codes was used to reduce large scale intra-variation by detecting and correcting the errors of two correlated features arisen from uncontrollable errors.

The segmentation and feature extraction method's performance was analyzed based on segmentation rates, ROC, and Decidability Index (DI). On the other hand, the efficiency of WSLF method was evaluated using UTMIFM datasets, UBIRIS v.2 datasets and ORL face datasets based on the ROC, Cumulative Matching Curve (CMC) analysis, FAR, and FRR. Furthermore, to evaluate the modified Reed Solomon codes' recognition performance, WVU-IBIDC, UBIRIS v.2, and UTMIFM and ORL face datasets were used and based on ROC, CMC, DI, FAR, and FRR analysis.

## **1.7 Significance of the Study**

This research study was done to contribute to the domains of biometric recognition and its practical application to the general population. The framework of biometric recognition proposed had achieved minimal intra-class variations and optimal inter-class variations. In terms of theoretical knowledge, a better segmentation method that has combined GC and DLSE has been proposed to correctly localize non-circular boundary of unconstrained off-angle iris images. Another significance of this study is that the proposed "NeuWave Network" is a fusion method of HW and NN to extract features of unconstrained off-angle iris

images. Both proposed methods had demonstrated high segmentation and iris recognition accuracy. This study had also proposed WSLF for the multimodal biometrics that had integrated features of iris biometrics with information from face biometrics. From a technical perspective, this increases the performance by resolving the limited discrimination capability and insufficient accuracy of unimodal biometrics, and thus lowers FRR and FAR. Furthermore, the proposed improved Reed Solomon codes had minimized intra-class variations of the biometric templates for errors arisen from image burst, background errors, and CCD camera noise. It can therefore provide lower FRR and better DI for recognition.

In terms of practical real life applications, with the capability of recognizing errors caused by unconstrained environments, user can save time and minimize the annoyance from repeatedly being asked for their biometric images. Moreover, multimodal recognition approach makes it harder to falsify biometric templates, and thus enhances the user's confidence and sense of security from unwanted offenses. According to Modi (2011), multimodal biometric system is best suit for large scale identity management system in real life such as national identification, border control, and military control. Examples of multimodal recognition that have been successfully deployed in this area include the UIDAI used to address large scale identity exercise for India residents and the BAT used by U.S. military to create records of residents, wanted individuals, detainees shared across multiple military bases in Iraq.

## **1.8 Organization of the Thesis**

This thesis has been organized into seven chapters. A general description on the content of each chapter is given as follows:

- (i) Chapter 1 describes the key concepts of the research with the challenges, problems, current methods, objectives, scope, and significance of the study outlined.

- (ii) Chapter 2 reviews the main issues of interest, which are non-cooperative iris images, iris segmentation, feature extraction techniques, multimodal recognition techniques, and error correction techniques.
- (iii) Chapter 3 presents the design of the proposed unified framework that supports the objectives of the study. This includes data sources instrumentation and analyses.
- (iv) Chapter 4 presents the improved GC and DLSE in localizing boundaries of iris for eye images captured in non-cooperative environment and fusion of NeuWave Network to extract features of off-angle iris images.
- (v) Chapter 5 presents the proposed WSLF used to integrate the iris and face images to facilitate biometric authentication.
- (vi) Chapter 6 presents the modified Reed Solomon codes used to minimize the intra-variance of biometric authentication.
- (vii) Chapter 7 draws out the overall findings and the contributions of the research together with suggestions on future works. This chapter also concludes this study.

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