UNIVERSITI PUTRA MALAYSIA

NON-FIDUCIAL BASED ELECTROCARDIOGRAM BIOMETRICS WITH KERNEL METHODS

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By

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June 2017

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Electrocardiogram (ECG) biometrics is a relatively novel trend in the field of biometric recognition. ECG is a new generation of biometric modality which presents a number of notable problems in signal processing, extraction of significant features from the ECG signals and construction of an accurate subject recognition system. These notable problems are due to time-varying nature of ECG signals implying cardiac conditions and the type of ECG signal acquisition. This thesis considers all the inherent processes to an ECG biometric system involving pre-processing, feature extraction and classification. The thesis proposes a novel ECG verification technique based on non-fiducial approach which explores waveform itself using kernel methods for feature extraction and classification after preprocessing (denoising ECG signals) one lead ECG signals of 52 subjects. For ECG signal processing, Coiflet3 wavelet and Rigrsure rule of hard threshold is proposed after evaluating different discrete wavelets based on statistical measuring criteria which include cross-correlation, signal-to-noise ratio, reconstruction error, root-mean-square error, and others. A new non-fiducial approach is proposed for feature extraction. This approach constructs an algorithm by combining autocorrelation (AC) and Kernel Principal Component Analysis (KPCA) techniques. The effectiveness of this algorithm is investigated by comparing with other AC based feature extraction algorithms involving AC/LDA (Linear Discriminant Analysis) and AC/PCA (Principal Component Analysis). At classification level, Gaussian multi-class Support Vector Machine (SVM) with the One-Against-All (OAA) approach is proposed to evaluate verification performance rates of the feature extraction algorithms. The results of analysis demonstrate that the AC/KPCA has a maximum effect on achieving high subject and window recognition rates in different operational conditions. The highest window and subject predictive accuracies achieved are approximately 92% and 77% on KPCA data set with the lowest biometric error and overfitting. The lowest biometric errors of false non-match rate and false match rate are decreased to about 6.19% and 1.79%, respectively on the KPCA data set.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

BIOMETRIK ELEKTROKARDIOGRAM BERASASKAN BUKAN FIDUSIAL DENGAN KAEDAH KERNEL

Oleh

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Elektrokardiogram (ECG) biometrik adalah satu arah aliran yang agak baru dalam bidang pengiktirafan biometrik. ECG adalah generasi baru modaliti biometrik yang membentangkan beberapa masalah yang ketara dalam pemprosesan isyarat, pengekstrakan ciri-ciri penting dari isyarat ECG dan pembinaan sistem pengiktirafan subjek yang tepat. Masalah-masalah ketara ini adalah disebabkan oleh masa yang berbeza-beza sifat isyarat ECG membayangkan keadaan jantung dan jenis pemerolehan isyarat ECG. Tesis ini mengambilkira semua proses bawaan yang wujud dalam sistem biometrik ECG yang melibatkan pra-pemprosesan, pengekstrakan ciri dan klasifikasi. Tesis ini mencadangkan satu teknik novel pengesahan ECG berdasarkan pendekatan bukan fidusial yang meneroka gelombang itu sendiri menggunakan kaedah kernel untuk pengekstrakan ciri dan klasifikasi selepas pra-pemprosesan (membuang hingar isyarat ECG) isyarat ECG satu led daripada 52 orang. Untuk pemprosesan isyarat ECG, gelombang Coiflet3 dan peraturan Rigrsure ambang keras adalah dicadangkan selepas menilai riak diskret yang berbeza berdasarkan kriteria pengukur statistik termasuk silang korelasi, nisbah isyarat-kepada-hingar, pembinaan semula ralat, punca min kuasa dua ralat, dan lain-lain. Pendekatan bukan fidusial baru adalah dicadangkan untuk pengekstrakan ciri. Pendekatan ini membina algoritma dengan menggabungkan autokolerasi (AC) dan teknik analisis komponen utama kernel (KPCA). Keberkesanan algoritma ini disiasat dengan membandingkan dengan algoritma ciri pengekstrakan lain AC yang melibatkan AC/LDA (analisis beza layan linear) dan AC/PCA (analisis komponen utama). Pada peringkat klasifikasi, mesin vektor sokongan (SVM) pelbagai kelas dengan pendekatan Satu-Terhadap-Semua (OAA) dicadangkan untuk menilai kadar prestasi pengesahan algoritma ciri pengekstrakan. Keputusan analisis menunjukkan bahawa AC/KPCA mempunyai kesan maksimum kepada pencapaian kadar pengiktirafan subjek dan tetingkap yang tinggi dalam keadaan operasi yang berbeza. Tetingkap tertinggi dan ketepatan ramalan subjek mencapai kira-kira 92% dan 77% ke atas data KPCA dengan ralat biometrik yang paling rendah dan berlebihan.

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I certify that a Thesis Examination Committee has met on 19 June 2017 to conduct the final examination of Maryamsadat Hejazi on her thesis entitled “Non-fiducial based Electrocardiogram Biometrics with Kernel Methods”in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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LIST OF ABBREVIATIONS

AC	Autocorrelation
AD	Automated Delineation
AEL	Across Electrode Location
ANN	Artificial Neural Network
AST	Across Stress Task
ASWF	Across Session With Fusion
AT	Adaptive Threshold
Avg	Average
BBF	Butterworth Bandpass Filter
BF	Bandpass Filter
BsF	Bazett's Formula
BN	Bayesian Network
C	Clinical Source Data
CAD	Cardiac Arrhythmia Dataset
CC	Correlation Coefficient/ Cross-Correlation
CHR	Christov
CNN	Convolutional Neural Network
CRF	Conditional Random Field
C-SVC	C-Support Vector Classification
CWT	Continuous Wavelet Transform
BAN	Body Area Network
DB	Database
DBNN	Decision-Based Neural Network
DBSCAN	Density-based Spatial Clustering of Applications with Noise
DCT	Discrete Cosine Transform
DNF	Digital Notch Filter
DR	Dimension Reduction
DT	Decision Tree
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EEG	Electroencephalogram
EEMD	Ensemble Empirical Mode Decomposition
EG	Engelse and Zeelenberg
IDE	Identification Error
EMD	Empirical Mode Decomposition
ERM	Empirical Risk Minimization
ERR	Equal Error Rate
EZA	Englese and Zeelenberg Algorithm
F	Fiducial
FE	Feature Extraction
FEA	Feature Extraction Approach
FFT	Fast Fourier Transform
FIRF	Finite Impulse Response Filter
FMR	False Match Rate

FNMR	False Non-match Rate
FSC	Feature Selection Context
FSE	Feature Subspace Ensemble
FT	Fourier Transform
GM	Generative Model
GMC	Generative Model Classifier
GMM	Gaussian Mixture Model
GS	Grid-search process
H	Hybrid
HBS	Heartbeat Shape
HM	Heuristic Method
HMM	Hidden Markov Model
HPE	Hermite Polynomial Expansion
ICA	Independent Component Analysis
ICM	Inspection of Correlation Matrix
IIR	Infinite Impulse Response
ILR	Implantable Loop Recorders
KKT	Karush-Kuhn-Tucker
k-NN	*k*-Nearest Neighbour
KPCA	Kernel Principal Component Analysis
KST	Kolmogorov-Smirnov Test
L	Lead
LDA	Linear Discriminant Analysis
LLE	Local Linear Embedding
LFCC	Linear Frequency Cepstral Coefficients
LPC	Linear Predictive Coding
LT	Local/Personalized Thresholds
M	Modality/Number of Modalities
MANRHB	Mean of Amplitude-Normalised Resampled Heartbeats
MCP	Marking Characteristic Point
MDL	Minimum Description Length
MDI	Median Imputation
MSFS	Multisession Feature Selection
MI	Mean Imputation
MITDB	MIT-BIH Arrhythmia Database
MW	Mean Waves
NC	Non-Clinical Source Data
ND	Not Defined
NF	Non-fiducial
NN	Neural Network
1DMRLBP	One Dimensional Multi-Resolution Local Binary Patterns
OAA	One-Against-All
OCSC	One-class SVM Classifier
P	Person/Number of Persons

PAR	Pulse Active Ratio
PCA	Principal Component Analysis
PD	Peak Detectors
PF	Pre-emphasis Filter
PMD	Polynomial Distance Measurement
PNN	Perceptron Neural Network
PPG	Phonocardiogram
PRD	Percent Residual Difference
Pre	Preprocessing
PSD	Power Spectral Density
PT	Periodicity Transform
PTA	Pan and Thompkins Algorithm
RBFNN	Radial Basis Function Neural Network
REnergy	Retained Energy
RError	Reconstruction Error
RF	Random Forest
RKHS	Reproducing Kernel Hilbert Space
RMSE	Root Mean Square Error
RR	Recognition Rate
S	Number of Session(s)
SAECG	Signal-Averaged ECG
SGM	Single Gaussian Model
SIMCA	Soft Independent Modeling of Class Analogy
SL	Signal Length
SNR	Signal-to-Noise Ratio
SOD	Second Order Derivative
SR	Subject Rate
SRM	Structural Risk Minimization
SRR	Subject Recognition Rate
SS	Signal Segment
SSMW	Subsampled Mean Wave
STFT	Short Time Fourier Transform
SV	Support Vector
SVM	Support Vector Machine
TD	Time Domain
TMR	True Match Rate
TNEDB	Toronto Normal ECG Database
TS	Taylor Series
WDISIT	Wavelet distance measure
WLFS	Wilks' Lambda Feature Selection
WR	Window Rate
WRR	Window Recognition Rate
WS	Within Session
WSA	Welch Spectral Analysis

WT	Wavelet Transform
ν-SVC	ν-Support Vector Classification

CHAPTER 1

INTRODUCTION

1.1 Overview on Biometrics

Automatic and reliable personal identity recognition is becoming considerably important in many aspects of daily life including financial transactions, traveling and healthcare monitoring systems and many other applications. Traditional techniques of token-based (e.g. passport, ID card) and knowledge-based (e.g. password) have been extensively utilized to automatic identity recognition. However, despite of their wide use, these approaches are not able to differentiate between an authorized person and imposters, lost card, forgotten password, and others (Agrafioti et al., 2011, Jain et al., 2004).

Biometric recognition technology provides a reliable security system through identity recognition of individuals based on their inherent characteristics to resolve the security gaps of traditional techniques. These inherent features include physiological or behavioral traits associated with the person. Physiological features include face, iris, and fingerprints whereas keystroke dynamics, gait, and voice/speech are behavioral features. Each biometric trait has unique properties with its own weakness and strengths which are applied based on the characteristics of applicant environments (Jain et al., 2004).

Circumvention is an important issue to determine whether a practical biometric system is robust to falsification using fraudulent techniques. Some instances of attacks in the biometrics security system involve the use of latex for recreation of a fingerprint, voice imitation and the application of contact lenses copied from original iris features. So, these biometric modalities are not robust enough against falsification (Wang et al., 2008). In addition, obfuscation is another important biometric attack that a person attempts to evade true subject's recognition through the use of different ways such as use of glasses or plastic surgery in face recognition, cutting or burning fingerprints, and iris transplants (Jain et al., 2011).

A new generation of biometric identity recognition modalities has been introduced extensively during the last decades, which is inherently robust to the circumvention and obfuscation attacks of the traditional biometrics. It includes bio-signals which are typically utilized for clinical diagnostic purposes such as Electrocardiogram (ECG), Phonocardiogram (PCG), Electroencephalogram (EEG), and many others. Since the medical modalities are one-dimensional physiological signals, their processing needs a low computational and storage resources. Additionally, the continuous authentication is a unique property for medical based biometrics, which enables to use in real-time platforms (Agrafioti et al., 2011; Biel et al., 2001). This thesis focuses on the ECG

signal based techniques for identity recognition; however, these techniques and concepts can be extended to other medical biometric traits.
ECG is a non-invasive diagnostic method which is effective, simple and involves a low-cost procedure to gather information on structural and functional heart muscle activity and other body tissues over time. A normal heartbeat of ECG waveform consists of a series of positive and negative waves: P wave, QRS complex wave, and T wave. The P wave corresponds to atrial contraction, and the QRS complex wave is generated when contraction of the ventricles occurs. Finally, the T wave reflects relaxation of the ventricles that depends on heart rate. Any conditions including physical and psychological changes increase cardiac function and make different deflections in each heartbeat of ECG signal. ECG biometric systems were first proposed in 2001 by Biel et al. and Kyoso and Uchiyama. The ECG signal has highly discriminative attributes which enables developing identity recognition applications for a population based on the following characteristics (Agrafioti et al., 2011, Carreiras et al. 2014; Jain et al., 2011; Odinaka et al., 2012; Silva et al., 2013a):

a) *Universality*: since the ECG is a vital signal, the biometric samples can be collected from only general living population.

b) *Uniqueness*: there is large inter-subject variability (the variability between feature sets originating from two different individuals) in ECG signals of a population because of the different electrophysiological factors which controls this waveform generation. However, Carreiras et al. (2014) has proposed a preliminary study on the uniqueness property (inter-subject variability) with different number of subjects. They showed that it is necessary to study further on uniqueness characteristics before ECG-based biometric system can be utilized in practice.

c) *Liveness detection*: while ECG signal is independent of any other process to present liveness detection, other modalities such as face, iris, signature and fingerprint need additional traits to address it.

d) *Robustness to attacks*: due to the ECG waveform's inherent properties, it is extremely difficult to manipulate its features. So, the best of our knowledge, there are no fraudulent techniques to falsify ECG-based biometric systems.

e) *Usability*: it refers to the concept that a biometric identifier can be used conveniently in people daily lives. Most studies in ECG biometric field have used signals captured traditionally from the chest area and limbs using stationary and clinical grade devices (clinical setups). Recently, some research has been done to design the ECG biometric systems involving on on-the-person and off-the-person sensing techniques (non-clinical setups), which can make the ECG acceptability comparable with other traditional biometric traits such as iris, face, fingerprint. Indeed, usability level of an ECG device must be similar to other traditional biometric modalities, which could be simply integrated into daily use equipment without any effect on the users' usual activities and potentiating its use in a continuous biometric recognition system. For instance, sensors are embedded in wearable form factors including t-shirt, necklace, mobile phones, and others to acquire ECG signals continuously (Carreiras et al. 2014; Silva et al., 2013a).

However, despite many advantages, the ECG biometric technique faces a number of notable difficulties as given below (Agrafioti et al., 2011, Carreiras et al. 2014; Jain et al., 2011; Odinaka et al., 2012; Silva et al., 2013b):

a) *Permanence over time*: intra-subject variability (the variability observed in the feature set of an individual) is a universal challenge in the biometric modalities due to appearance of physiological, psychological, and environmental changes. Time-varying (time dependency) nature of the ECG signal can cause difficulties in biometric security. The physical and mental activities and diseases can greatly impact change of the ECG waveform or even its morphology. So, the central consideration of the ECG biometric systems is often minimizing the effect of intra-subject variability on the recognition processor investigation of the sources of the changes. A useful feature set exhibits small intra-subject variation and large inter-subject variation.

b) *Heartbeat collection*: while the biometric samples in other modalities such as face and fingerprint can be captured at any moment in time, along waiting period is required for a second acquisition of each heartbeat. This challenge can affect adversely in processing time and recognition when many samples are needed.

c) *Heart conditions*: irregular conditions of cardiac disorders are another limiting factor in ECG biometric systems. However, these disorders do not occur frequently as it happens with injuries in other conventional biometric systems (face, fingerprint and many others).

1.2 Research Problem Statements

Performance and accuracy is the most important and significant criteria to evaluate a biometric recognition system (Jain et al., 2004; Sufi et al., 2010a). As the ECG is not periodic and highly repetitive dynamic signal (Wang et al., 2008), the ECG biometric systems encounter a number of challenges in building an accurate identity recognition system. The main research problems addressed in this thesis are:

a) The ECG recordings acquired from hands and/or fingers based on off-the-person approach (non-clinical source data) are nosier than the standard ECG signals captured from on the chest area with clinical grade equipment (clinical source data). So, it becomes more difficult to do subsequence processing including signal processing. A few research has been dealt with the efficiency of signal processing on recognition performance of ECG biometrics (Carreiras et al., 2013a), and hence a further investigation is needed to select proper denoising technique with several statistical measures which could significantly impact identity verification efficacy.

b) Overall, two types of feature extraction approaches have been applied which are based on fiducial points' detection (P, QRS complex, T waves) and without these points (Non-fiducial). Feature extraction based on non-fiducial approach is still open problem in ECG-based biometric system. Generally, the non-fiducial based approaches are able to independentlyextract discriminative features within ECG trace without having any information about locations of fiducial points in heartbeat cycles. The non-fiducial approaches involve the challenge of high-dimensionality and so analysis or processing in this case is a computationally demanding task (Agrafioti et al., 2011; Sufi et al., 2010a). Autocorrelation (AC) based feature extraction is among the earliest research in non-fiducial approach (Plataniotis et al., 2006). At present, in order to generate a significant ECG feature set, a combination of AC and linear dimension reduction methods has been applied earlier. However, the linear dimension reduction methods are unable to find adequate structures (feature set) in nonlinear real-world dataset. Kernel-based dimensionality reduction techniques have been developed to handle nonlinear dimension reduction problem by mapping implicitly input observations into higher dimensional feature space. Although kernel-based feature extraction has been extensively evaluated in other modalities like face, voice, and speech, it was almost unheard of in ECG-based biometric system. Therefore, an investigation is carried out to evaluate the effects of linear and non-linear based feature extraction on system performance in non-fiducial approach along with autocorrelation method.

c) Training optimal recognition (classification) model can be effective on the highest match between the ECG test signals and a collection of training feature vectors. The proper selection of robust classification methods can increase generalization property and enhance ECG biometric recognition accuracy (Odone et al., 2009); however, this issue has been almost ignored in ECG-based biometrics. General recognition algorithms have been frequently in the use of the ECG biometrics including supervised classifiers such as Linear Discriminant Analysis (LDA) (Israel et al., 2005), k-Nearest Neighbours (k-NN) (Agrafioti et al., 2008a; Agrafioti et al., 200c), and a few researches on Support Vector Machines (SVMs) (Gutta et al., 2016; Lin et al., 2014). SVM is a kernel-based classifier that can attain predictive accuracy with reduced generalization errors in object detection and classification problems. Additionally, a few researches have recently shown where SVM for classification outperforms Nearest Neighbour and Neural Networks for ECG biometrics (Gutta et al., 2016; Lourenço et al., 2012a, Silva et al., 2013b). Despite of many advantages of SVM techniques, a few non-fiducial based studies have been done with SVM classifier involving only a limited number of subjects and operational condition settings for identity recognition, and their recognition performance have not been achieved any significant results for its practical applications (Lin et al., 2014). The operational condition settings are related to short- and long term recordings, different session recordings, postures, and lead configurations. Recently, Lin et al. at (2014) has proposed a non-fiducial based methodology with the use of SVM method on a population of 26 healthy subjects in rest and exercise conditions. The system respectively achieved 71.79 and 81.73% accuracies in resting and exercise conditions for one session recordings. Therefore, this thesis proposes to study further the effects of influential factors, such as feature extraction and denoising techniques, model-parameters, window lengths, and others on SVM's accuracies which can determine whether the learning algorithm is robust and reliable for identity verification in the different operational settings.

d) The most of researches have been commonly evaluated on number of subjects less than 50 in only normal rest condition from one lead configuration undergoing short-term changes (Odinaka et al., 2012). For instance, the studies of Agrafioti et al. (2008b), Chen et al. (2014), Coutinho et al. (2013), Gutta et al. (2016), Loong et al. (2010), and Plataniotis et al. (2006) have conducted experiments on one lead ECG signals over a different number of healthy subjects ranging from 26, 19, 26, 18, 15, and 14, respectively. The recognition performances of these systems were obtained as 96.6, ≥ 90, >99, >80, >91, and >92. The performance results achieved by these studies seem to be significant. However, several factors have to be considered in order to control intra-subject variability and inter-subject variability problems for achieving robust and reliable biometric system for practical applications (Carreiras et al. 2014; Odinaka et al., 2012). Indeed, the permanence (time-varying) and uniqueness characteristics of ECG signal are still open issues in the biometric systems. The different parameters (including posture, session, recording length, lead configuration, and number of subjects) and also changing ECG morphology (heart diseases or cardiac irregular conditions) can affect significantly system performance (Agrafioti et al., 2008a; Ye et al., 2010). Therefore, it is necessary to evaluate each methodology in different operational settings to determine whether it is robust and reliable for identity recognition for practical applications.

1.3 Objectives

The main aim of this thesis is to develop a methodology for designing ECG-based biometric system based on non-fiducial approach through kernel-based methods. The basic concept in kernel-based learning is to apply the so-called kernel trick to formulate nonlinear extensions of classical linear methods by implicitly mapping the data to a high-dimensional kernel induced feature space. This leads to forming a framework where nonlinearities are easily introduced as long as the data only appear as inner products in the model formulation. To achieve this aim, the solutions related to four problems in Section 1.2 are described respectively as follows:

a) ***Developing preprocessing technique for ECG denoising*:** as the ECG is a non-stationary signal, time-frequency representation methods are typically suited for its signal processing. Wavelet transform is a non-stationary signal processing technique that can be applied to denoising a signal without appreciable degradation. Based on advantages of wavelet transform, this thesis proposes wavelet-based signal processing technique for ECG denoising after evaluating different discrete wavelet functions involving statistical measuring criteria which include cross-correlation, signal-to-noise ratio, reconstruction error, root-mean-square error, and others. The effect of wavelet transforms is also evaluated on the identity recognition performance rates.

b) ***Developing non-fiducial based feature extraction algorithm:*** To avoid fiducial point detection**,** this thesis proposes a new non-fiducial based approach involving an autocorrelation (AC) method in conjunction with Kernel Principal Component Analysis (KPCA) as nonlinear dimension reduction technique. Also, the effectiveness of this algorithm is evaluated by comparing with other AC based feature extraction algorithms involving AC/LDA (Linear Discriminant Analysis) and AC/PCA (Principal Component Analysis).

c) ***eveloping pattern classification method for subject recognition*:** Gaussian multi-class SVM classification with One-Against-All (OAA) on random unknown population is proposed for biometric recognition (classification) problem. The robustness of the learning algorithm is evaluated by a set of influential parameters such as denoising, windowing length, feature extractors, data set size, model-selection techniques, model-parameters, operational setting conditions, and others.

d) ***Validating proposed framework under different ECG variability conditions*:** the robustness of proposed methodology is validated and on one-lead ECG recordings captured at different sessions (one-session, two-session recordings), and different posture conditions (rest and exercise). Also, different feature level fusion models have been proposed on long- and short-term two-lead ECGs of a combination set of arrhythmia and normal signals to evaluate intra-subject variability problem by designing various recording and window lengths.

1.4 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 2 presents an overview of the basic fundamental concepts of ECG signal along with signal processing and also considers comprehensive schemes and lack of studies in the ECG biometric literature for data acquisition, operational setting conditions, signal processing methods, feature extraction approaches, and classification techniques. Additionally, a general comparative analysis of most of ECG-based biometric systems is also summarized according to the effective parameters on recognition performance.
Chapter 3 describes the proposed models for ECG-based biometric system with more details in three main levels of processing: denoising, feature extraction, and recognition (classification). Additionally, the design of all experiments corresponding to proposed methods are described in details.

Chapter 4 provides simulation results and discussion on the proposed models which are designed in Chapter 3. In this chapter, the different kind of analysis and their results related to each processing level such as effects of different mother wavelets and non-fiducial feature extraction algorithms on performance recognition rates are evaluated for the proposed framework. Then the results of validation of different ECG recordings under different setting are discussed. Finally, the proposed framework is compared with other available studies and published results.

The thesis concludes with Chapter 5 providing main findings presented in the thesis, and suggests for future works.

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