Study for Integration of Multi Modal Biometric Personal Identification Using Heart Rate Variability (HRV) Parameter

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Abstract. Authentication and Identification is primary part of biometric technology. Currently, electrocardiogram (ECG) is not only being used as a diagnostic tool for clinical purposes, but also as a new biometric tool for high level security system because of its liveliness and uniqueness that is hard to imitate and manipulate. There are many fiducial (signal mark) that is classified from ECG morphology (QRS Complex, P, T waves) has already been researched for this purpose. For non fiducial, many researches are focus on dynamic character from heartbeat (ECG Signal). Heart Rate Variability (HRV) analysis is part of non fiducial classifier. This paper reviews Heart Rate Variability analysis (time and frequency domain) as part of multi matches, one of scenario from multimodal biometric. Sample of person’s heartbeat signal is taken from ECG Database MIT-BIH (MIT and Harvard) and the result of every parameter will be analyzed by Biometric Performance Standards Tools (ISO/IEC IS 19795-1) such as: False Non-Match Rate (FNMR), False Match Rate (FMR) and Thresholds EER (Equal Error Rate). Analysis should show accuracy of multi matches Heart Rate Variability (HRV). As integrator tool, LabView is used to collect offline ECG, process the data and generate HRV Analysis.

1. Introduction

This paper have purpose to review literature and tools to expand possibility of biometric technology that has already been used. Many biometrics type have already been researched. Such as fingerprint, palm geometry, face recognition, iris recognition, voice recognition, heartbeat until DNA. Every type has its own uniqueness, accuracy and difficulties. This paper is focus on one biometric scenario which is multimodal biometric. Multimodal biometric is combination or fusion of multiple sensors, biometric, unit, snapshots and matches [7][11]. Multimodal take different classifier from the same person. Multimodal do have possibility to get more accurate and reliable authentication. This paper also covers tools to be applied, in purpose to get multimodal biometrics parameter.

2. Literature Review and Development

Usually generic biometric system have modules : (a) sensor module which capture trait as raw biometric data property. (b) feature extraction/model and transformation module which process the data to representation of individual/person trait or classifier. (c) matching module which compare stored classifier and new data classifier. (d) decision module which generate matching score to validate pass and identity of classifier[8]
As common criteria biometric system should have properties as follows [19]:

• Universality: Every individual have biometric trait. For biometric purpose, person’s trait used as property data.
• Exclusivity: Every individual have unique biometry property data.
• Permanence: The biometric trait should stable and long time permanence as individual property.
• Collectability: Biometric trait of individual should be easy, quick to be collected.
• Performance: Performance of biometric method should be measured.
• Acceptability: Selected biometric must be compatible and acceptable on society.

Multimodal biometric can increase accuracy and security [7][11] comparing with unimodal biometric [7]. There are several strategies for multimodal biometric [8][10] as described on figure 1 below. Multiple matches is the suitable strategy, because one set of individual physiological can be identified with two kinds of method or algorithm [1].

![Figure 1. Strategy for Multimodal Biometrics](image1.png)

Figure 1. Strategy for Multimodal Biometrics

ECG has unique character, which can be employed as a biometric attribute. As a classifier for biometric, ECG can be categorized to two approach, fiducial (biomarker) approach and non fiducial approach [19] Fiducial techniques or feature extraction use composite waves of heartbeat: P, QRS and T as biomarker. But non fiducial techniques more focus on modelling and derive of ECG waves. Fiducial Techniques need complex calculation to point ECG biomarkers (P, QRS, T waves). Non fiducial techniques more easy, because this algorithm using established mathematical transform or statistical tools.

![Figure 2. ECG Morphology](image2.png)

Figure 2. ECG Morphology
Several techniques and model from ECG Signal already developed and can be used as a classifier for biometric application[16][17][18][19][20][21][22][32]

Figure 3. Classifier for ECG Based Biometrics

One model of ECG Signal is Heart Rate Variability, that developed intensively by The European Sociaty of Cardiology and The North American Society of Pacing and Electrophysiology in 1996[26]. In beginning HRV created to find relationship between autonomous neuron system (relate with ECG signal as indicator) and fitness or nervous level of human.[26]

For biometric application, many researchers already released their papers[37], but less or only few of them using all HRV parameters as multimodal biometric and embeeded in one integrated software and hardware. Every parameter result comes from R-R interval peaks of ECG. So to put all parameters as multimodal biometrics also involves computer based complex calculation[2][3][31].

For integration purpose, biometric technology needs flexible tools to integrate input data computing, analysis and decision making [9]. Multi modal biometric have more difficulties and complex calculation that should be accommodated [2]. Matlab and [7] LabView [13] could be explored as powerful tool to all job tasks for this purpose. But Matlab has restriction in hardware integration. And LabView is chosen to this kind of task.

In the future, authentication and identification will be used on massive scale. Biometry will be used with huge numbers of database. Biometry technology will follow that. Faster, bigger, more accurate and secure are big challenge for development. Area of hardware, software, algorithm will increase on efficiency deployment.

3. Methods
Study and review cover possibility to use HRV parameter as a candidate of multimodal biometrics. There has been a study that already use HRV time domain for biometric [35] and HRV time and frequency domain for medical tools [36]. So the possibility to use HRV time and frequency domain as multimodal biometric is open.

The next step is to explore LabView capability to take offline and online ECG data. LabView can accommodate online or offline ECG’s input data [13]. There is biomedical toolkit that can used for this purpose. There are two ways to take data from a person’s heart beat (ECG). Firstly, data can be taken online with one lead probe and integrated with data acquisition [21]. Secondly, data also can be taken from extracted file that has already been published on public repository, such as MIT-BIH [33][34].
HRV Analysis is the most important step to get parameter as multimodal biometric. LabView is used for this purpose with outstanding capabilities. Coding, recording, result and decision making can be applied by features of LabView. HRV Parameter have time domain (mean R, mean HR , RMS Standard Deviation, NN50, pNN50) and frequency domain (Power Spectral Density , VLF, LF, HF, LF Normal, HF Normal, Ratio of LF/HF) . All parameters already embedded on Biomedical Tool kit of Labview

To analyze the performance of every HRV Parameter, biometrics technology have standard (ISO/IEC IS 19795-1). Performance analysis of multimodal biometric can use this standard [4] [11]. Accuracy and error of every parameter can be calculated. False Non Match Rate (FNMR), False Match Rate (FMR), Equal Error Rate (EER), Fail to Enroll (FTE) used as indicator for biometrics performance.
Table 1. HRV Parameter for Time domain

| No | Measure   | Unit | Formula                                                                 |
|----|-----------|------|-------------------------------------------------------------------------|
| 1  | mRR       | ms   | $\frac{1}{N} \sum_{i=1}^{N} (RR_i) - mRR$                           |
| 2  | mHR       | bpm  | $\frac{1}{N} \sum_{i=1}^{N} (RR_i - mRR)^2$                          |
| 3  | SDNN      | ms   | $\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (RR_i - mRR)^2}$                |
| 4  | SDANN     | bpm  | $\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (RR_i - mRR)^2}$                |
| 5  | CVNN      | bpm  | $\text{mHR} \times 100$                                             |
| 6  | RMSSD     | ms   | $\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (RR_i - mRR)^2}$                |
| 7  | pRR20     | %    | $\text{Cum}\left[RR_i \geq 1 + RR_i - 20 \text{ms} \times 100\right]$ |
| 8  | pRR50     | %    | $\text{Cum}\left[RR_i \geq 1 + RR_i - 50 \text{ms} \times 100\right]$ |

Table 2. HRV Parameter for Frequency domain

| No | Measure | Unit | Description                                                                 |
|----|---------|------|-----------------------------------------------------------------------------|
| 1  | VLF     | mV   | Power spectrum from 0.003 to 0.04 Hz                                        |
| 2  | LF      | mV   | Power spectrum from 0.04 to 0.15 Hz                                         |
| 3  | HF      | mV   | Power spectrum from 0.15 to 0.4 Hz                                          |
| 4  | vVLF    | %    | $VLF \times 100 \times (VLF+LF+HF)$                                        |
| 5  | vLF     | %    | $LF \times 100 \times (VLF+LF+HF)$                                         |
| 6  | vHF     | %    | $HF \times 100 \times (VLF+LF+HF)$                                         |
| 7  | dLFHF   | %    | $|\text{vLF} - \text{vHF}|$                                                |
| 8  | SMI     | mV   | $LF/(LF+HF)$                                                               |
| 9  | VMI     | mV   | $(HF/(LF+HF))$                                                             |
| 10 | SYI     | mV   | $LF/HF$                                                                    |

Figure 7. Result of HRV Analysis by LabView

4. Conclusion

After reviewing all references and study capability of LabView to integrate all subject requirement, it is possible to make comprehensive integration from sample, processing-computing to get HRV parameter until decision making to biometric authentication. The big challenge after analysis of every parameter of HRV is to get the most suitable parameter to be used. After that, multimodal biometric for personal identification using HRV parameter can be more accurate. The other challenge is to put optimum weight factor to every parameter in time and frequency domain. Weight factor is important to make easier to next algorithm’s decision.

For Hardware, the big issue is to get the fastest time for database search processing. This kind of biometric is very useful when applied to Mobile-Health and Public Health Server. Biometric Technology to handle huge database is different area to be studied. Sensor (lead probe) to take ECG Bio signal from an individual, is also another subject to be developed. For practical application, one lead probe should be used rather than 3 or 12 lead probe.

After reviewing all references and tools, the possibility to use and integrate HRV analysis as multimodal biometrics is possible and can be applied. The next step of this paper is to analyze HRV parameters and their effects on biometric authentication.
parameter to get good result in accuracy. LabView also can be explored to do data acquisition, processing, analyzing until decision making.

References

[1] S. Chaudhary and R. Nath, “A Hybrid Multibiometric Approach for Fusion of Iris and Face.”
[2] R. Giot, M. El-abed, and C. Rosenberger, “Fast computation of the performance evaluation of biometric systems: application to multibiometric,” 2012.
[3] U. Uludag et al., “Biometric cryptosystems: Issues and challenges Biometric Cryptosystems: Issues and Challenges,” vol. 92, no. July, 2004.
[4] F. Saavedra, S. Reillo, A. Moreno, M. Hurtado, and others, “Environmental Testing Methodology in Biometrics,” Technology, 2010.
[5] Shobha. D, “Biometric Cryptosystems: for User Authentication,” Int. J. Innov. Res. Comput. Commun.Eng., vol. 3, no. 5, pp. 4322–4326, 2015.
[6] C. Y. Poon, Y. T. Zhang, and S. Di Bao, “A novel biometrics method to secure wireless body area sensor networks for telemedicine and M-health,” IEEE Commun. Mag., vol. 44, no. 4, pp. 73–81, 2006.
[7] M.K. Dhir, T. Bansal, “Analysis of Uni-Modal & Multimodal Biometric System using Iris & Fingerprint,” vol. 6, no. 7, pp. 2–6, 2015.
[8] A. K. Jain, S. Pankanti, S. Prabhakar, H. Lin, and A. Ross, “Biometrics: A grand challenge,” Proc. - Int. Conf. Pattern Recognit., vol. 2, pp. 935–942, 2004.
[9] N. Akhter, S. Tharewal, V. Kale, A. Bhalerao, and K. V Kale, “Advanced Computing and Systems for Security,” vol. 396, pp. 15–30, 2016.
[10] A. K. Jain, A. Ross, and U. Uludag, “Biometric Template Security: Challenges and Solutions,” Secur. Watermarking Multimed., vol. 4675, no. IV, pp. 629–640, 2002.
[11] W. Almayyan, “Performance analysis of multimodal biometric fusion,” J. Comput.Sci., vol. 9, no. 3, pp. 290–296, 2012.
[12] J. M. Irvine, S. A. Israel, M. D. Wiederhold, and B. K. Wiederhold, “A new biometric: human identification from circulatory function,” Jt. Stat. Meet. Am. Stat. Assoc. San Fr., no. March 2017, pp. 1957–1963, 2003.
[13] N. Belgacem, A. Amine Naït, and R. Fethi, “Person Identification System Based on Electrocardiogram Signal Using LabView,” Int. ..., vol. 4, no. 6, pp. 974–981, 2012.
[14] K. A. Sidek, V. Mai, and I. Khalil, “Data mining in mobile ECG based biometric identification,” J. Netw. Comput.Appl., vol. 44, pp. 83–91, 2014.
[15] X. Wang, S. S. Reisman, W. N. Tapp, and B. H. Natelson, “Spectrum analysis of heart rate variability,” Images Twenty First Century Proc. Annu. Int. Eng. Med. Biol. Soc., pp. 0–3, 1989.
[16] C. Carreiras, A. Lourenço, A. Fred, and R. Ferreira, “ECG Signals for Biometric Applications: Are we there yet?,” Proc. 11th Int. Conf. Informatics Control. Autom.Robot., pp. 765–772, 2014.
[17] A. Lourenço, C. Carreiras, H. Silva, and A. Fred, “ECG biometrics: A template selection approach,” IEEE MeMeA 2014 - IEEE Int. Symp. Med. Meas. Appl. Proc., 2014.
[18] A. Fratini, M. Sansone, P. Bifulco, and M. Cesarelli, “Individual identification via electrocardiogram analysis,” Biomed.Eng. Online, vol. 14, no. 1, pp. 1–23, 2015.
[19] Z. Hassan, S. O. Gilani, and M. Jamil, “Review of fiducial and non-fiducial techniques of feature extraction in ECG based biometric systems,” Indian J. Sci. Technol., vol. 9, no. 21, 2016.
[20] P. Sasikala and R. S. D. Wahidabamu, “Identification of Individuals using Electrocardiogram,” vol. 10, no. 12, pp. 147–153, 2010.
[21] T. W. Shen, W. J. Tompkins, and Y. H. Hu, “One Lead ECG for identity Verification to Joint Conference of the IEEE Engineering in Medicine and Biology Society and the Biomedical Engineering Society,” pp. 62–63, 2002.

[22] H. P. da Silva, A. Lourenço, A. Fred, N. Raposo, and M. Aires-de-Sousa, “Check Your Biosignals Here: A new dataset for off-the-person ECG biometrics,” Comput. Methods Programs Biomed., vol. 113, no. 2, pp. 503–514, 2014.

[23] M. Merone, P. Soda, M. Sansone, and C. Sansone, “ECG databases for biometric systems: A systematic review,” Expert Syst. Appl., vol. 67, pp. 189–202, 2017.

[24] Guidelines, “Guidelines Heart rate variability,” Eur. Heart J., vol. 17, pp. 354–381, 1996.

[25] R. N. Kirtana and Y. V. Lokeswari, “An IoT based remote HRV monitoring system for hypertensive patients,” Int. Conf. Comput. Commun. Signal Process. Spec. Focus IoT, ICCCSP 2017, 2017.

[26] M. 31], “Guidelines Heart rate variability,” Eur. Heart J., vol. 17, no.June, pp. 354–381, 1996.

[27] Z. Germán-Salló, A. Gligor, and H. S. Grif, “Wavelet based HRV analysis,” IFMBE Proc., vol. 44, pp. 229–232, 2014.

[28] T. Cui, “Spectrum Analysis of Heart Rate Variability (HRV),” 2013.

[29] H. ChuDuc, K. Nguyen Phan, and D. Nguyen Viet, “A Review of Heart Rate Variability and its Applications,” APCBEE Procedia, vol. 7, pp. 80–85, 2013.

[30] J. Wayman, A. Jain, D. Maltoni, and D. Maio, “An Introduction to Biometric Authentication Systems,” Biometric Syst., pp. 1–20.

[31] J. S. Paiva, D. Dias, and J. P. S. Cunha, Beat-ID: Towards a computationally low-cost single heartbeat biometric identity check system based on electrocardiogram wave morphology, vol. 12, no. 7. 2017.

[32] A. B. Amiruddin, O. O. Khalifa, and F. A. F. Rabih, “Performance evaluation of human identification based on ECG signal,” 2015 Int. Conf. Comput. Control. Networking. Electron. Embed. Syst. Eng., no. 2011, pp. 479–484, 2015.

[33] M. M. Tantawi, K. Revett, M. F. Tolba, and A. Salem, “An evaluation of the generalisability and applicability of the {PhysioNet} electrocardiogram (ECG) repository as test cases for ECG–based biometrics,” Int. J. Cogn. Biometrics, vol. 1, no. 1, pp. 66–97, 2012.

[34] K. K. Patro and P. R. Kumar, “Machine learning classification approaches for biometric recognition system using ECG signals,” J. Eng. Sci. Technol. Rev., vol. 10, no. 6, pp. 1–8, 2017.

[35] N. Akhter, V. Gaike, and K. V Kale, “Classification of Heart Rate Variability Features for Person Identification,” no.March, pp. 371–380, 2016.

[36] P. K. Dabas and D. Shaw, “Reliability of frequency domain HRV analysis,” IFMBE Proc., vol. 31 IFMBE, pp. 1615–1618, 2010.

[37] N. Akhter, S. Tharewal, V. Kale, A. Bhalerao, and K. V Kale, “Heart-Based Biometrics and Possible Use of Heart Rate Variability in Biometric Recognition Systems, “Advanced Computing and Systems for Security,” vol. 396, pp. 15–30, 2016.