

# Thesis Literature Review

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February 2, 2021

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# Chapter 1

## Good Sources

### 1.1 e

e

#### Summary

Well written paper

- signal processing and data analysis are widely used methods
- detecting cardiovascular abnormalities with an ECG is possible
- a fuzzy-based multi-objective algorithm using a fast fourier transform is used to extract rough features like PQRS amplitude
- then apply an algorithm to classify the abnormality
- ECG behavior depends on many different factors
- accuracy is achieved by taking into account these factors
- maintaining a database of previous results makes prediction better
- this provides 98.7% efficiency in abnormality detection
- accurate ECGs are necessary to classify cardiac abnormalities
- ECGs are noisy and thus an algorithm needs to de-noise the signal
- after noise removal, ECG signals must be extracted – FFT
- fuzzy-based scheme should classify how sick a patient is
- de-noising can be done using a wavelet transform
- contour wavelet transform CTW – Daubechies algorithm for de-nosing
- goal is to remove all noise
- discrete wavelet transform is not accurate enough, adaptive wavelet decomposition is proposed
- then FFT is used to extract the features
- ANN for classification
- FFT to discretize the signal
- radix-2 FFT, is the simplest way to evaluate the DFT
- heartbeat is calculated as the interval between two R peaks – heartbeat is the number of

R peaks in a particular minute

- RR interval can be useful for finding symptoms that include heart-rate variation
- QRS is the main thing that a heart's conditions is measured by
- QRS duration is the time interval between the two peak Q and S signals
- multi-objective genetic algorithm is exactly what it sounds like
- uses MIT-BIH arrhythmia database
- finds good results for their approach
- methods is more efficient than previous results
- IFR: analysing and modelling the sequence of heartbeats using advanced machine learning methods can be implemented to achieve better performance

## 1.2 b

b

### Summary

Really well done and researched paper

- early revascularization (stenting basically) is essential for survival
- ECGs are widely used, but not all information contained in them can be extracted, even by well-trained physicians
- make a prediction model for urgent revascularization based on 12-lead ECG
- they collected 6 years of data for their study
- about 1% to 6% of patients with ACS have "normal ECG"
- random splitting of the dataset
- an AI model that can learn time-dependent data in the right order
- 12-lead ECG data for 10 seconds at rest
- pretty efficient model for prediction
- IFR: validate the model using other datasets; no heed given to other biomarkers, drugs, age, sex, fitness; they suspect that the ECG contains important data, but they do not know where the data comes from

## 1.3 1

1

### Summary

- 2D ventricular tissue model
- model Hyperkalemia (too much potassium), acidosis (lower conductivity)
- ischemia might leave traces that can be picked up using an ECG
- because ischemia is hard to properly study in the wild, having a model is very convenient
- they use the Luo–Rudy I cellular formulation for a 2D slice
- based on guinea–pig hearts
- equation of electrical activity of a stimulated cell
- the differential equations were solved using a combination of explicit (Euler) and implicit methods
- intracellular loss of potassium ions is the main alteration of electrical activity – hyperkalemia
- electrical parameters were altered to simulate these conditions
- good description of why they tweaked which parameters for simulation
- myocardium cell model: 2D
- cells are connected by gap junctions (low resistance "bridges")
- even a simple square–grid can be used to study complex phenomena
- simple impedance is enough to model the cell–to–cell interactions
- no–flux boundary conditions – no current is leaving the system at the edges
- it needs to be sufficiently big to have some area that is not affected by the disturbance at the boundaries
- you excite a layer of 5 cells, then let the model run

# Chapter 2

## Bad Sources

### 2.1 d

d

#### Summary

- using FFT to find abnormalities in ECGs
- ischemia or infarct can be seen in the ST-segment of the ECG
- ischemia can also cause low-amplitude notches and slurs in the ECG
- Holter monitors are ECGs over  $> 24$ h, you need programs to analyze that much data
- major problem is the feature extraction
- mentions a bunch of other peoples attempts at feature extraction
- FFT breaks down a signal into its sinusoidal components
- nothing that interesting

## 2.2 c

c

### Summary

- digital signal filtering methods for ECGs
- remove 50Hz network and breathing muscle artifacts
- 3 heart rate detection algorithms
- main problems with ECGs are interfering 50Hz supply signals and muscle artifacts
- for real-time applications, these things should be very efficient
- heart rate is important and can be computed from ECGs among other things
- often, heart rate is detected by measuring the distance between QRS complexes
- neural networks, genetic algorithms, wavelet transforms, filter banks, adaptive threshold, signal spectral analysis, short-term autocorrelation can be used to find it
- the methods here are simpler and real-time suited
- Butterworth filter is used in professional ECG applications
- they remove all the noise from the signal first, using the described methods
- Butterworth filters are used to also detect the R peaks
- with the highlighted R peaks one can detect heart rate
- for heart rate detection, the autocorrelation method can be use because R peaks are quasi-periodical
- other methods find the difference between R peaks, by either using thresholds, or peak detector
- the three algorithms find completely different results



## 2.3 a

a

### Summary

- arrhythmia detection algorithm for ECGs
- uses the morphology of different diseases to make the algorithm efficient
- ECG – electric activity of the heart, generally charted on paper
- ECG features can be extracted in the time domain or in the frequency domain
- morphological information can be time intervals, voltage extremes, duration, location
- Harr Wavelet Transform for ECG feature extraction
- MIT–BIH is used here again; forward–feed neural network
- ECG analysis is carried out using a digital audio processing chip
- they put a window on the QRS complex to only look at that
- PVC can simply be classified by using a threshold
- they implement stuff in MATLAB
- it works for implementation

## 2.4 Colli-Franzone *et al.* (1985)

Colli-Franzone, P. *et al.* A mathematical procedure for solving the inverse potential problem of electrocardiography. analysis of the time-space accuracy from in vitro experimental data. *Mathematical Biosciences* **77**, 353–396. ISSN: 0025-5564. <http://www.sciencedirect.com/science/article/pii/0025556485901063> (1985)

### Summary

- Cauchy problem for elliptic operator that's strongly ill posed
- solution is regularized
- electrocardiography potential problem: body surface potential from epicardial potential, also inverse problem
- epicardial data can be estimated using surface potential data
- estimates are good because they contain information not really available purely on the surface
- high errors are common with this procedure because: (1) simplification of body inhomogeneity, (2) reconstruction of data on static heart, (3) constant (over heart beat) smoothing parameter
- computed epicardial potential maps (CEPMs) still not clear
- not having the heart centered could improve accuracy for one side of the heart
- new experiment with a dog heart in a child-sized torso (roughly appropriate location)
- detailed analysis of potential estimates
- only errors should be noise in measurements, misaligned electrodes
- finite element matrix links surface to epicardial potential, fine 3D surface grid
- optimized for CEPm accuracy
- efficiency of choosing a time-dependent smoothing parameter
- applied inverse procedure to heart beat to reconstruct ECG
- for experiment description read the paper
- tank surface is  $\Gamma_1$ , epicardial frame surface is  $\Gamma_0$ , and  $\Omega$  the volume bounded by  $\Gamma_0, \Gamma_1$
- we have electrodes on the gammas and can approximate omega
- the electric cardiac potential  $V(x, t)$  is the solution to

$$\Delta V(x, t) = V_{xx} + V_{yy} + V_{zz} = 0 \quad \text{in } \Omega,$$

$$V(x, t) = u(x, t) \quad \text{on } \Gamma_0,$$

$$\frac{\partial V(x, t)}{\partial n} = 0 \quad \text{on } \Gamma_1$$

- $u(x, t)$  is the epicardial potential distribution at  $t$ ,  $n$  is the normal vector to  $\Gamma_1$  (from the insulating layer around the whole thing, nothing gets out)
- trace of  $V$  on  $\Gamma_1$  is the thorax potential distribution, denoted by  $z(x, t)$
- we have a linear operator  $A$  transforming  $u$  to  $z$
- direct problem of electrocardiography is solving the above system of equations

- problem is discretized using finite-element methods

# Chapter 3

## Other

### 3.1 f

f

#### Summary

- propose a mathematical model of the ECG wave
- human body == cylindrical composite dielectric and conducting medium
- heart == harmonic bio-signal generator
- can use this model to predict experimental data
- ECG signal is due to heart beat and that is due to the signal of the S.A. node
- the electric field generated by this is then propagated to the surface through the dielectric medium that is the human body
- many different approaches to ECGs mentioned here, list here
- compression techniques to help with large amounts of data
- QRS complex evaluation in one paper
- the signal measured by an ECG electrode can be represented by Fourier harmonic components
- dense mathematical description of the model
- they test their model using an actual ECG – get the Fourier components from it
- all 12 ECG leads have about the same makeup of Fourier components
- they have to randomly assign some of the values to make the model fit
- this model is more accurate because it assumes a cylindrical body and not a sphere like the classical models
- good source list
- IFR: do rigorous experimentation to really test this model;

## 3.2 Unknown Presentation

### Summary

- ischemic – lacking sufficient blood flow; generally because coronary arteries are obstructed
- infarction – cell death as result of ischemia
- heart failure is number 1 cause of death in the western world
- majority of that are infarctions
- on a cellular level, oxygen is not provided anymore, waste is not removed anymore
- this fucks with the heart on a cellular level
- reduced pH leads to reduced conductivity of the tissue
- necrotic tissue is basically non-conductive
- use a cell model (Luo–Rudy I) to model ischemia
- the voltage potential drops significantly if ischemia is present
- the upstroke is delayed and amplitude reduces
- the article uses a monodomain model of cardiac tissue (slide 15)
- model propagation on an  $200 \times 200$  layer
- when ischemia is present, the wave is stunted and fucked up, parts of it might get stuck – leads to arrhythmia for example
- they may use their model to reconstruct ECGs based on the level of ischemia that they want
- they were able to reproduce qualitative characteristics using their model

# Bibliography

1. Armstrong, P. W., Gershlick, A. H., *et al.* Fibrinolysis or primary PCI in ST-segment elevation myocardial infarction. *N Engl J Med* **368**, 1379–1387 (Apr. 2013).
2. Armstrong, P. W., Watts, D. G., Hamilton, D. C., Chiong, M. A. & Parker, J. O. Quantification of myocardial infarction: template model for serial creatine kinase analysis. *Circulation* **60**, 856–865 (Oct. 1979).
3. Bera, S., Chakraborty, B. & Roy, D. J. A mathematical model for analysis of ECG waves in a normal subject. *Measurement* **38**, 53–60 (July 2005).
4. Cimponeriu, A., Starmer, C. F. & Bezerianos, A. A theoretical analysis of acute ischemia and infarction using ECG reconstruction on a 2-D model of myocardium. *IEEE Trans Biomed Eng* **48**, 41–54 (Jan. 2001).
5. Colli-Franzone, P. *et al.* A mathematical procedure for solving the inverse potential problem of electrocardiography. analysis of the time-space accuracy from in vitro experimental data. *Mathematical Biosciences* **77**, 353–396. ISSN: 0025-5564. <http://www.sciencedirect.com/science/article/pii/0025556485901063> (1985).
6. Eagle, K. A. *et al.* A validated prediction model for all forms of acute coronary syndrome: estimating the risk of 6-month postdischarge death in an international registry. *JAMA* **291**, 2727–2733 (June 2004).
7. Goto, S. *et al.* Artificial intelligence to predict needs for urgent revascularization from 12-lead electrocardiography in emergency patients. *PLOS ONE* **14**, e0210103 (Jan. 2019).
8. Hakeem, A. *et al.* Incremental Prognostic Value of Post-Intervention Pd/Pa in Patients Undergoing Ischemia-Driven Percutaneous Coronary Intervention. *JACC: Cardiovascular Interventions* **12**, 2002–2014. <http://www.sciencedirect.com/science/article/pii/S1936879819315419> (2019).
9. Ibanez, B. *et al.* 2017 ESC Guidelines for the management of acute myocardial infarction in patients presenting with ST-segment elevation: The Task Force for the management of acute myocardial infarction in patients presenting with ST-segment elevation of the European Society of Cardiology (ESC). *European Heart Journal* **39**, 119–177. <https://doi.org/10.1093/eurheartj/ehx393> (Aug. 2017).

10. Ieva, F., Paganoni, A. M., Pigoli, D. & Vitelli, V. Multivariate functional clustering for the morphological analysis of electrocardiograph curves. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* **62**. <https://www.jstor.org/stable/24771812>, 401–418 (2013).
11. Jeremias, A. *et al.* Blinded Physiological Assessment of Residual Ischemia After Successful Angiographic Percutaneous Coronary Intervention: The DEFINE PCI Study. English. *JACC Cardiovascular Interventions* **12**, 1991–2001 (Oct. 2019).
12. Knuuti, J. *et al.* 2019 ESC Guidelines for the diagnosis and management of chronic coronary syndromes: The Task Force for the diagnosis and management of chronic coronary syndromes of the European Society of Cardiology (ESC). *European Heart Journal* **41**, 407–477. <https://doi.org/10.1093/eurheartj/ehz425> (Aug. 2019).
13. Kudenchuk, P. J. *et al.* Utility of the prehospital electrocardiogram in diagnosing acute coronary syndromes: the Myocardial Infarction Triage and Intervention (MITI) Project. *J Am Coll Cardiol* **32**, 17–27 (July 1998).
14. Liu, Y. *et al.* ECG morphological variability in beat space for risk stratification after acute coronary syndrome. *J Am Heart Assoc* **3**, e000981 (June 2014).
15. Milasinovic, D. *et al.* Timing of invasive strategy in NSTEMI-ACS patients and effect on clinical outcomes: A systematic review and meta-analysis of randomized controlled trials. *Atherosclerosis* **241**, 48–54 (July 2015).
16. Morrow, D. A. *et al.* TIMI risk score for ST-elevation myocardial infarction: A convenient, bedside, clinical score for risk assessment at presentation: An intravenous nPA for treatment of infarcting myocardium early II trial substudy. *Circulation* **102**, 2031–2037 (Oct. 2000).
17. Murphy, E., Rahimtoola, S. & Grüntzig, A. Transluminal dilatation for coronary-artery stenosis. *The Lancet* **311**. Originally published as Volume 1, Issue 8073, 1093. <http://www.sciencedirect.com/science/article/pii/S0140673678909315> (1978).
18. Myers, P., Scirica, B. & Stultz, C. Machine Learning Improves Risk Stratification After Acute Coronary Syndrome. *Scientific Reports* **7** (Oct. 2017).
19. Navarese, E. P. *et al.* Optimal timing of coronary invasive strategy in non-ST-segment elevation acute coronary syndromes: a systematic review and meta-analysis. *Ann Intern Med* **158**, 261–270 (Feb. 2013).
20. Neumann, F. J. *et al.* 2018 ESC/EACTS Guidelines on myocardial revascularization. *Eur Heart J* **40**, 87–165 (Jan. 2019).
21. Pinto, D. S. *et al.* Benefit of Transferring ST-Segment–Elevation Myocardial Infarction Patients for Percutaneous Coronary Intervention Compared With Administration of Onsite Fibrinolytic Declines as Delays Increase. *Circulation* **124**, 2512–2521 (2011).
22. Prasad, B. V. P. & Parthasarathy, V. Detection and classification of cardiovascular abnormalities using FFT based multi-objective genetic algorithm. *Biotechnology & Biotechnological Equipment* **32**, 183–193. <https://doi.org/10.1080/13102818.2017.1389303> (2018).

23. Roffi, M. *et al.* 2015 ESC Guidelines for the management of acute coronary syndromes in patients presenting without persistent ST-segment elevation: Task Force for the Management of Acute Coronary Syndromes in Patients Presenting without Persistent ST-Segment Elevation of the European Society of Cardiology (ESC). *European Heart Journal* **37**, 267–315. <https://doi.org/10.1093/eurheartj/ehv320> (Jan. 2016).
24. Sigwart, U., Puel, J., Mirkovitch, V., Joffre, F. & Kappenberger, L. Intravascular stents to prevent occlusion and restenosis after transluminal angioplasty. *N Engl J Med* **316**, 701–706 (Mar. 1987).
25. Stefanini, G. G. & Holmes, D. R. Drug-eluting coronary-artery stents. *N Engl J Med* **368**, 254–265 (Jan. 2013).
26. Timmis, A. *et al.* European Society of Cardiology: Cardiovascular Disease Statistics 2019. *European Heart Journal* **41**, 12–85. <https://doi.org/10.1093/eurheartj/ehz859> (Dec. 2019).
27. Zègre Hemsey, J. K., Dracup, K., Fleischmann, K., Sommargren, C. E. & Drew, B. J. Prehospital 12-lead ST-segment monitoring improves the early diagnosis of acute coronary syndrome. *J Electrocardiol* **45**, 266–271 (2012).