Master project

Synthesis of realistic electrocardiogram signals during cardiac magnetic resonance imaging acquisition using deep learning

Context and tasks

Recording electrocardiograms (ECG) during cardiac magnetic resonance imaging (CMR) acquisition is a key function in the synchronizing process of image acquisition [1]. During CMR, the quality of the acquired images depends considerably on the heartbeat estimation, and more specifically on the R-peak detection. The faster and more reliable the R-peak detection is, the better the quality of the acquired images. However, detecting R-peaks in ECG recorded in magnetic resonance imaging (MRI) scanners is tricky due to the superposition of several effects: magnetohydrodynamic (MHD), gradient switching and radio frequency emission [2,3]. Recently, considerable attention has been paid to the use of deep learning (DL) architectures to analyze ECG signals. It has been shown that the DL architectures continue to outperform human experts [4-6]. Analyzing and tracing ECG recorded in MRI scanners (MRI-ECG) using DL require large, annotated datasets. However, publicly available large-scale datasets with the MRI-specific artefacts, do not exist currently [7]. Hence, to handle the scarcity of annotated MRI-ECG , the objective of this project consists in exploring DL architectures, such as variational autoencoder (VAE), generative adversarial networks (GAN), conditional GAN (CGAN), Wasserstein GAN (WGAN) and Wasserstein conditional GAN (WCGAN), to generate high-quality synthetic ECG representative of MRI-ECG . For example, GAN which are a set of deep neural network models, are used to generate synthetic data by learning patterns from input datasets and then creating new examples which are similar to the training data. GAN have the advantage to generate synthetic data that do not require input from domain experts [8-10].

The main project tasks are:

- conduct a thorough survey of the main recent state-of-the-art architectures dedicated to synthetic data generation;
- implement few DL architectures for both MRI-ECG data generation and analysis;
- carry out a comparative study of the different investigated DL architectures in terms of their performance and execution time (before and after data generation).

Profile

You are in your final year of a master degree's program motivated by artificial intelligence / machine learning with a particular interest in DL. You demonstrated curiosity, rigor and autonomy during your education curriculum. You enjoy discovering new programming languages and are not afraid of tackling complex problems.

Having a knowledge of programming language, such as Python and basic of classical machine learning algorithms are essential. A background in biomedical applications would be a plus.

Practical details

This 6-month project, starting between January and March 2023, will take place at LATIS premises (LATIS-Laboratory of Advanced Technology and Intelligent Systems, ENISo-National Engineering School of Sousse, Sousse University, 4023 Sousse, Tunisia).

Applications should be sent to maroua.mehri@eniso.u-sousse.tn with 1-page CV, ½ page motivation letter, latest grade transcripts and optionally recommendation letters, referencing 2023-INT-AI.

Bibliographic references

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[6] S. W. Chen, S. L. Wang, X. Z. Qi, S. M. Samuri and C. Yang, « Review of ECG detection and classification based on deep learning: coherent taxonomy, motivation, open challenges and recommendations », Biomedical Signal Processing and Control, vol. 74, no. 103493, 2022.

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