

BeatGAN: Anomalous Rhythm Detection using Adversarially Generated Time Series

Bin Zhou¹, Shenghua Liu¹, Bryan Hooi², Xueqi Cheng¹ and Jing Ye³

¹Institute of Computing Technology ICT, CAS ²School of Computer Science, NUS ³Department of Anesthesiology, Nanfang Hospital

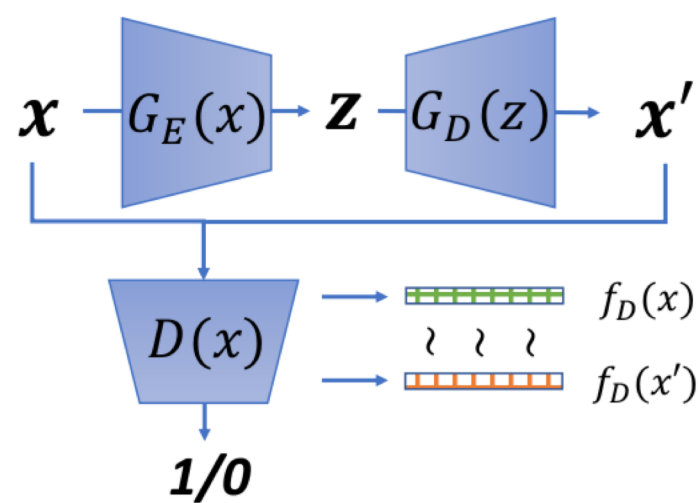
Introduction

Given a large-scale rhythmic time series containing mostly normal data segments (or ‘beats’), how can we automatically detect anomalous beats in an effective yet efficient way? Can we pinpoint the anomalous time ticks that led to our decision?

Anomaly detection on monitoring time series is a challenging task because:

- 1) Massive time series can contain few anomalies
- 2) Anomalous segments can be very different from one another
- 3) Heartbeat characteristics vary from one beat to another

Approach



Adversarial Regularization

Learn the data distribution of the normal time series using the adversarial training framework by minimizing the reconstruct error and adversarial error.

Take the CNN based architecture to capture different characteristics and use the pairwise feature matching error as the adversarial error for a stable training process.

Time Warping Augmentation

Learn the robustness against variations in speed (i.e. ‘time warping’), by augmenting training data with a modified time warping approach.

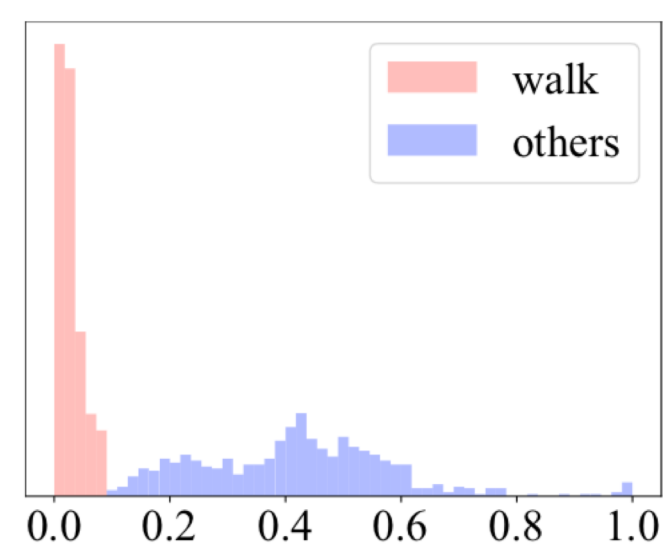
Randomly select a small number of time ticks to “speed up” or “slow down”. (like heartbeats naturally and slightly speed up or slow down.)

Result

Method	AUC	AP
PCA	0.8164 ± 0.0037	0.6522 ± 0.0061
OCSVM	0.7917 ± 0.0018	0.7588 ± 0.0027
AE	0.8944 ± 0.0128	0.8415 ± 0.0163
VAE	0.8316 ± 0.0025	0.7882 ± 0.0024
AnoGAN	0.8642 ± 0.0100	0.8035 ± 0.0069
Ganomaly	0.9083 ± 0.0122	0.8701 ± 0.0141
BeatGAN	0.9447 ± 0.0053	0.9108 ± 0.0049
BeatGAN _{aug}	0.9475 ± 0.0037	0.9143 ± 0.0047
BeatGAN ^{0.1%} _{aug}	0.9425 ± 0.0022	0.8973 ± 0.0042

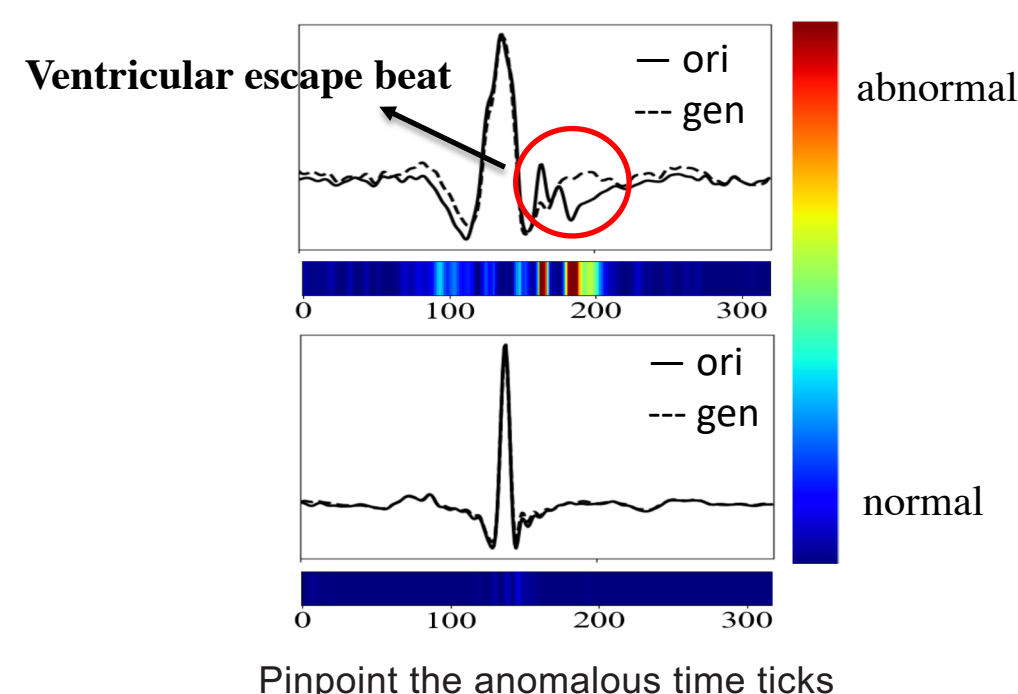
Result on ECG

BeatGAN achieves the best performance with time warping augmentation compared to baselines. The result is robust even we add the 0.1% anomalous time series to the training data.

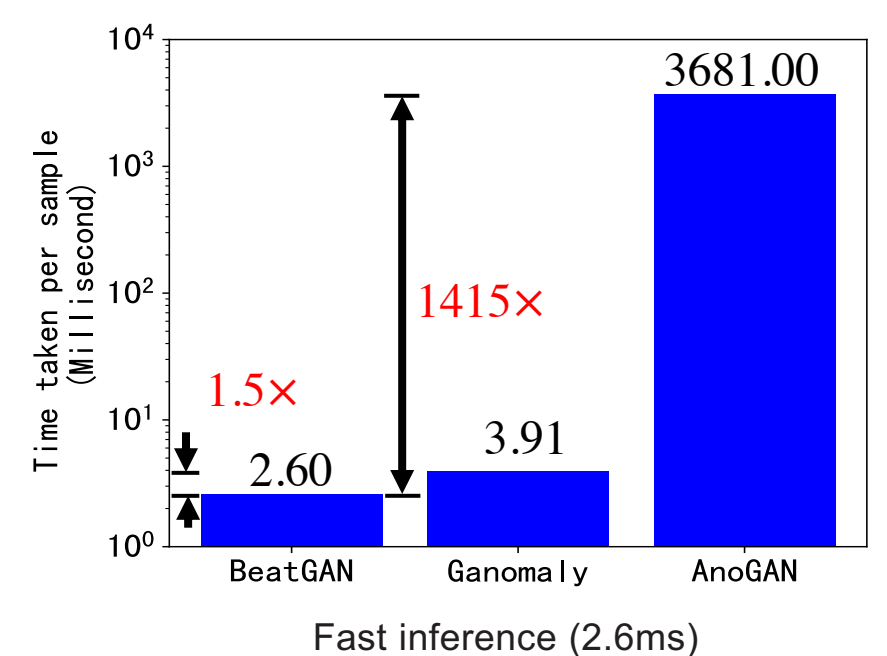
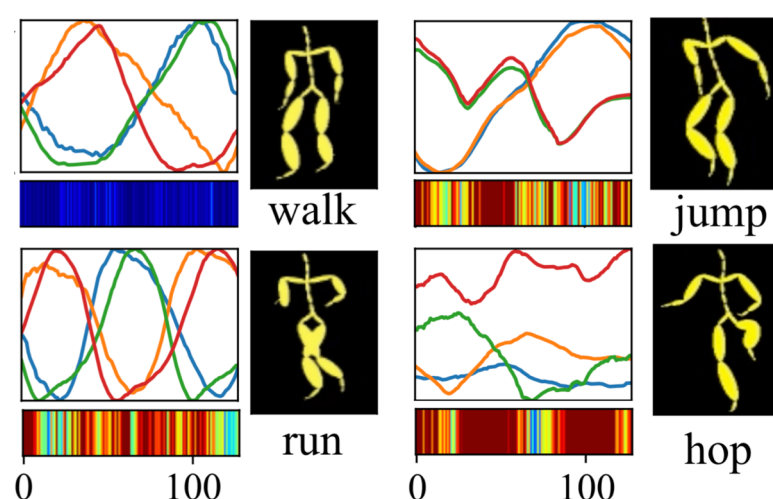


Result on motions

BeatGAN can perfectly separate unusual motions (jogging/jumping/running) from usual motion (walking) by only using time series of walking for training.



Performance



Acknowledgment

This material is based upon work supported by the Strategic Priority Research Program of CAS (XDA19020400), NSF of China (61425016, 61772498, 91746301), and the Beijing NSF (4172059).

References

- 1Hyun Ah Song, et al, PowerCast: Mining and forecasting power grid sequences, PKDD'2017
- 2M. Jereminov, et al, Linear load model for robust power system analysis, ISGT-Europe'2017
- 3Yasuko Matsubara, Yasushi Sakurai, and Christos Faloutsos. AutoPlait: automatic mining of co-evolving time sequences, SIGMOD'2014.

Contact

zhoubin17g@ict.ac.cn
liushenghua@ict.ac.cn
bryan.hooi.ky@gmail.com
cxq@ict.ac.cn
w1605@163.com