BSIP seminar 1 report: Implementation and evaluation of Chen's QRS detector

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***Abstract*—In this work, we implemented H.C. Chen and S.W. Chen's QRS detector, based on their work from 2003. The algorithm performance was validated on LTST and MIT-BIH Arrhythmia database. We proposed two potential improvements to the original algorithm, which ended up giving us more accurate detection of QRS complexes. Results of the final implementation yielded more than 92% sensitivity, and more than 95% positive predictivity.**

I. Introduction

QRS complex detection is a problem that has been tackled by many scientists, and for which many different detectors have been proposed. Some examples include popular detectors by Pan and Tompkins [1], Moraes [2], Ligtenberg and Kunt [3], and so on. In this work, we implemented and tested another popular QRS detector from H.C. Chen and S.W. Chen [4], which we will simply call "Chen's detector". The authors state that the algorithm is simple yet reliable enough for very accurate detection of QRS complexes, achieving over 99.7% sensitivity and positive predictivity on the MIT-BIH database [5] in their original work.

Chen's detector does indeed consist of three simple stages: (1) a linear, high pass filtering stage, (2) a non linear, low pass filtering stage, and (3) a decision making stage with a simple adaptive threshold. We do not believe explaining the algorithm in more detail here is necessary, as the authors did a great job of doing so in their original paper. We will test our implementation of Chen's detector against popular ECG databases, LTST [6] and MIT-BIH [5].

A. Informal note for professor

As you may remember, I originally wanted to implement Moraes' QRS detector. I thought I understood the algorithm entirely, however when I got to actually coding it, I found out there were many other ambiguities and unclear parts, and just too many areas where I needed to make assumptions and predictions on what the authors wanted to say. I gave it a shot anyway, but I couldn't get it to work, or better yet, I couldn't get it to work as good as I made Chen's detector work in the end. Hence, to save my time and nerves, I went with Chen's detector.

II. Methods

We implemented the original Chen's detector, as described in the paper. Furthermore, when searching for QRS complexes, we scanned for them in a window of certain size - we chose 130 samples. In other words, we scan for a QRS complex in the first 130 samples, then in the next 130 samples, then in the next 130, and so on. This was done for two reasons. Firstly, the original paper's title is "A moving average based filtering system with its application to **real-time** QRS detection" - this approach with a moving window exactly achieves the real time aspect. Secondly, while a QRS complex is of width only maybe 200ms (which would equal to 50 samples for LTST and 72 samples for MIT-BIH database), it may not be a good idea to check for it in a window of size 200ms, or even 250ms, because the window could easily position itself so that we detect two QRS' instead of just one. For that reason, a larger window seems more appropriate.

Chosen parameters for the detector were M = 5, $\alpha = 0.055$, $\gamma = 0.15$. The paper did not say what to initialize the threshold to, but there are multiple valid ideas. The one we chose initializes the threshold to 60% of the maximum value from the first 5 seconds of the signal.

However, as we will see in the Results and Discussion sections, there was room for improvement. One crucial thing the authors did not consider is the proximity of the next QRS complex to the previous one. Namely, after a QRS complex is detected, some small amount of time (200ms) should pass before another QRS complex can physiologically occur. This idea was taken from Pan and Tompkins' algorithm [1]. While intuitively, this should yield better results, we will see by how much exactly in the Results section.

Another "oversight" by authors of Chen's detector was that the records from LTST and MIT-BIH databases contain multiple channels. The authors did not explicitly state which channel signal to use. While the one from the first channel is generally used, there is no reason not to consider all of them. Hence, another potential improvement was to take the average signal from all channels. We will see how if (and how) this affected our results.

III. Results

Implementation of original Chen's detector gave rather poor results - 92.58% sensitivity, and 76.79% positive predictivity on the LTST database, and 99.79% sensitivity and 66.11% positive predictivity on the MIT-BIH database.

To (try to) improve the results, we took into account that the next QRS complex should occur only after 200ms from the previous one, as described in the Methods section. With that implemented, we decided to test the performance with or without taking the average signal, which is the second potential improvement. Obtained results are presented in Table I.

.	Channel 1 signal	Average signal
LTST	92.56 Se / 98.84 +P	93.39 Se / 99.57 +P
MIT-BIH	99.66 Se / 98.16 +P	99.28 Se / 95.65 +P

TABLE I
SENSITIVITY AND POSITIVE PREDICTIVITY RESULTS, ON LTST AND MIT-BIH DATABASES, WHERE WE TOOK INTO ACCOUNT MINIMUM DISTANCE OF NEXT QRS COMPLEX FROM PREVIOUS. WE TESTED IF TAKING JUST THE CHANNEL 1 SIGNAL, OR THE AVERAGE SIGNAL FROM ALL CHANNELS, MAKES ANY DIFFERENCE.

Before moving to the discussion, we wanted to state that we tried a lot of variations of the parameters (M, α, γ), but sensitivity and positive predictivity varied around 1-3% from results presented in Table I. Likewise, the choice of parameters which worked best for MIT-BIH database for example, were among the worst for the LTST database, and vice versa. For those reasons, we decided to stay with the ones we originally used (M = 5, $\alpha = 0.055$, $\gamma = 0.15$), which empirically proved as the "best of both worlds" case.

IV. DISCUSSION

The results of our implementation of original Chen's detector were quite poor. We did account for over 92%, i.e. for over 99% of all QRS complexes on the LTST and MIT-BIH databases respectively. However, there was definitely room for improvement, as our positive predictivity in both cases was quite low (number of false positives was really high) - 76.79% on LTST and 66.11% on MIT-BIH. This is probably due to the original implementation not being able to distinguish between a QRS complex and "high amplitude" T waves. This most likely happens due to the simplicity of the adaptive threshold, i.e. the T waves are just high enough to be above the threshold.

However, as we can see in Table I, taking into account that the next QRS complex can occur only after 200ms from the previous one helped our algorithm tremendously. Sensitivity remained pretty much the same, while our positive predictivity jumped to above 95% in all cases, which means our number of false positives dropped by a lot. On the other hand, we can see that taking the average signal slightly favours the LTST database, while it somewhat degrades the performance of the detector on MIT-BIH database, especially regarding positive predictivity.

V. CONCLUSION

In this work, we implemented a popular QRS detector, from H.C. Chen and S.W. Chen, and validated its performance on popular ECG databases, LTST and MIT-BIH. We saw that our implementation of the original algorithm proposed in [4] failed to distinguish between QRS complexes and high amplitude T waves, resulting in a really high number of false positives. We proposed an improvement, where we said that the next QRS complex can only occur 200ms after the last one, which helped drastically reduce the number of false positives. The other proposed improvement, where we tried taking the average of signals from all channels, didn't really come out as a success, but it wasn't a total failure either.

The presented results in Table I leave something to be desired - while the results are in our opinion really good, more can definitely be done to bump up the sensitivity/positive predictivity in cases where it seems like it could be improved. This could most likely be accomplished with a more robust way to detect high amplitude T waves, and/or with a more complex adaptive threshold technique.

REFERENCES

[1] Pan, Jiapu and Tompkins, Willis J., "A Real-Time QRS Detection Algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.

[2] Moraes, José and Freitas, M.M. and Vilani, F.N. and Costa, E.V., "A QRS complex detection algorithm using electrocardiogram leads," vol. 29, 10 2002, pp. 205 – 208.

[3] Ligtenberg, Adriaan and Kunt, Murat, "A robust-digital QRS-detection algorithm for arrhythmia monitoring," *Computers and biomedical research, an international journal*, vol. 16, pp. 273–86, 07 1983.

[4] Chen, H.C. and Chen, S.W., "A moving average based filtering system with its application to real-time QRS detection," in *Computers in Cardiology, 2003*, 2003, pp. 585–588.

[5] Moody, G.B. and Mark, R.G., "The impact of the MIT-BIH Arrhythmia Database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.

[6] Jager, Franc and Taddei, Alessandro and Moody, G and Emdin, Michele and Antolic, G and Dorn, R and Smrdel, Ales and Marchesi, C and Mark, R, "Long-term ST database: A reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia," *Medical and biological engineering and computing*, vol. 41, pp. 172–82, 04 2003.