# ADAPTIVE MATCHED FILTERING FOR QRS DETECTION

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## ABSTRACT

Matched filters maximize the signal-to-noise ratio for a known signal in noise with known statistics. In QRS detection both the shape of the QRS complex and the statistics of the noise change with time. Matched filters that have previously been applied to QRS detection have generally had impulse responses shaped like a simplified QRS complex inherently assuming a white noise environment. We have investigated using an adaptive filter to whiten the noise in the ECG signal and adjust the matched filter response accordingly. We applied a simple QRS detection strategy to the filtered signal and evaluated the QRS detector with ECG data containing severe motion artifact and muscle noise. Preliminary results indicate that in the presence of severe motion artifact adaptive matched filtering for QRS detection represents a significant improvement over application of a matched filter with a white noise assumption.

## INTRODUCTION

QRS detection is the first step in any ECG analysis system. A number of QRS detectors which work well in the presence of moderate noise have been based on matched filtering of the ECG signal [1][2]. Because neither the signal to be detected nor the noise in an ECG can be specified *a priori*, suboptimal matched filters have been used which approximate the QRS complex and assume that any noise present is white. We have investigated an adaptive matched filter for QRS detection which adjusts its coefficients to compensate for local noise conditions.

## ADAPTIVE MATCHED FILTERING

A matched filter maximizes the signal-to-noise ratio (SNR) of a signal. If a known signal occurs in a given period the maximum likelihood estimate of the signal arrival time will be the time of maximum output from the matched filter [3]. The impulse response of a matched filter for discrete time processes may be found by solving the vector equation:

$$\mathbf{h} = \mathbf{R}^{-1}\mathbf{s}$$

where $\mathbf{h}$ is the vector representing the impulse response of the matched filter, $\mathbf{R}^{-1}$ is the inverse of the covariance matrix of the noise, and $\mathbf{s}$ is the signal. In the case where the noise is white $\mathbf{R}^{-1}$ will be the identity matrix and the impulse response of the filter will be equal to the signal vector.

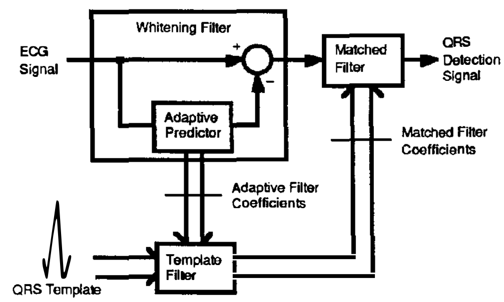


**Fig. 1:** Adaptive matched filter block diagram.

In the case of correlated noise, matched filtering is equivalent to passing the original signal through two filters. The first filter whitens the noise. The second filter is a matched filter with an impulse response equal to the signal to be detected passed through the same whitening filter. We have investigated using an adaptive filter to whiten the ECG signal. The coefficients of the whitening filter are then used to periodically update the the coefficients of the matched filter. Figure 1 shows a block diagram of our adaptive matched filter.

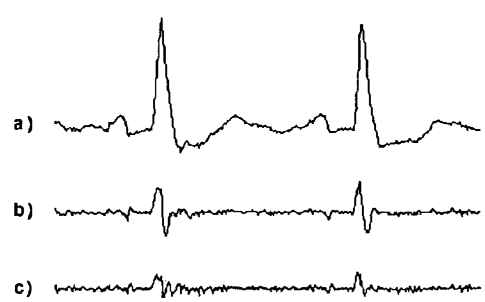


**Fig 2:** Relative effect of LMS and modified LMS whitening algorithms on the ECG. a) The original ECG. b) The ECG filtered with the modified LMS algorithm. c) The ECG filtered with the standard LMS algorithm.

We whiten the ECG noise by subtracting the output of an adaptive predictor from the original signal. We use the so called sign adaptive algorithm to update filter coefficients according to the equation [4]:

$$w_i[t+1] = w_i[t] + \Delta\ \mathrm{sign}(e[t]\ x[t-i])$$

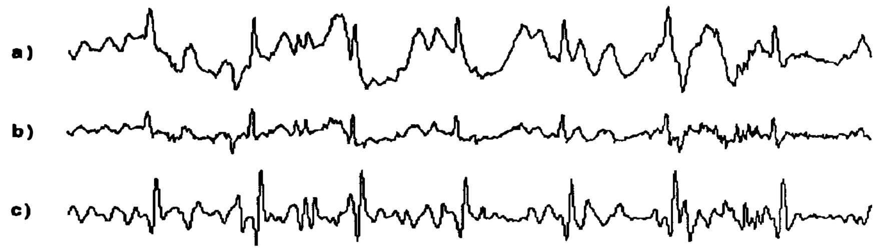


Fig. 3: a) ECG with motion artifact. b) ECG after adaptive filtering. c) ECG after adaptive matched filtering.

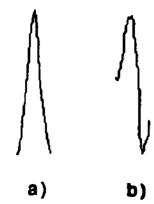


Fig 4: Matched filter impulse responses. a) The *a priori* matched filter impulse response. b) Impulse response after whitening.

where $\Delta$ is a constant equivalent to $\beta$ for the LMS algorithm. This algorithm converges more slowly than the LMS algorithm but is computationally more efficient. More important in our application, convergence is not affected by the variance of the signal. Adaptation of the standard LMS algorithm is strongly influenced by signal variance and adapts preferentially to the QRS complex. In contrast, this algorithm adapts preferentially to signal portions with longer relative durations. Because the QRS complex is typically only a small portion of the ECG signal it should not significantly affect the whitening filter.

Figure 2 shows an ECG signal and the signals resulting from whitening with an LMS adaptive algorithm and a sign adaptive algorithm. The QRS complex is not as significantly reduced in amplitude with the sign algorithm as it is with the LMS algorithm.

## RESULTS

We have obtained preliminary results on three ECG records. The records were all approximately 60 seconds in length. Two of the records contained severe motion artifact and the third contained a low-level ECG corrupted with muscle noise.

All results presented here were produced with a third order adaptive filter and a 200 samples-per-second sampling rate. The *a priori* matched filter template was obtained by averaging the first eight QRS complexes in each data record.

Figure 3 shows a section of ECG containing motion artifact and the signals resulting from adaptive whitening and matched filtering. The regular peaks corresponding to the QRS complexes are prominent in the signal produced by adaptive matched filtering. Figure 4 compares the *a priori* matched filter template with the matched template processed by the whitening filter.

We compared the effect of three filtering approaches on a simple QRS detector. The simplest filtering strategy applied the *a priori* matched filter to the ECG signal. The second filtering method prefiltered the ECG with the adaptive whitening filter and then applied the *a priori* matched filter. The third filtering scheme implemented our adaptive matched filter as described earlier.

As mentioned previously the maximum value produced by a matched filter in a given interval will be the maximum likelihood estimate of the signal location. The trick in applying this to QRS detection is defining an interval where at least one, but no more than one QRS complex occurs. Our QRS detector searches the filtered signal in an interval from 150 ms following the last detected QRS complex to 1.5 times the average R-to-R interval. The maximum value in this interval is taken to be the next QRS complex and the next search interval is defined from that point.

**TABLE I**
**QRS Detection Results**

| Filtering Scheme | False Pos. | False Neg. | Std. Dev. (Sample Periods) |
|---|---|---|---|
| No adaptation | 34 | 27 | 2.72 |
| Adaptive whitening | 15 | 16 | 2.04 |
| Adaptive matched filter | 6 | 6 | 1.31 |

Table I show the false positives and false negative detections produced by the three filtering approaches and the standard deviations of the detection errors for the valid QRS detections. A QRS complex was considered to be detected if the QRS detector estimated the QRS location within 100 ms of the actual QRS location. It is evident that for an ECG with severe noise the adaptive matched filter constitutes an improvement over the other two schemes, and application of adaptive whitening alone produces an improvement over the matched filter with a white noise assumption.

There was no significant difference between any of the filtering schemes on the ECG record containing muscle noise. This is understandable when one considers that muscle noise may be modeled as white over the bandwidth imposed by our sampling rate.

## REFERENCES

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