Genetic-algorithm cancellation of sinusoidal powerline interference in electrocardiograms

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Abstract—*The paper describes a method, based on a genetic algorithm, to remove sinusoidal powerline interference in electrocardiograms. There is a report on the use of the genetic algorithm to remove powerline interference for two different types of interference, powerline interference with frequency drift, and interference with frequency drift as well as third- harmonic distortion. The studies are conducted on electrocardiograms with simulated interference and also on actual noisy electrocardiogram records. The results obtained using the genetic algorithm in these cases of interference are presented.*

Keywords—*Electrocardiogram, Powerline interference, Genetic algorithm*

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1 Introduction

THE ELIMINATION of powerline interference from electrocardiograms (ECGs) has been the focus of research for some time. Although proper grounding and electrical shielding are important in analogue recordings to reduce powerline interference, computers have facilitated the use of digital methods to eliminate powerline interference in ECGs. The elimination of sinusoidal powerline interference corrupting an ECG signal is typically accomplished with a fixed-notch filter tuned to the interference frequency. A very narrow notch is useful to filter out the interference with negligible signal distortion. In the case of frequency-drifted powerful sinusoidal interference in ECGs, the centre of the notch filter may not coincide exactly with the interference. Such a fixed-notch frequency filter will be totally ineffective unless it is designed to be wide enough to cover the range of the frequency drift. Unfortunately, such a wide notch will result in distortion of the ECG signal.

Digital filtering of ECGs, while suppressing powerline interference, affects some of the frequency components of the signal (VAN ALSTE and SCHILDER, 1985). Some methods have been developed involving subtraction of the interference from the interference-corrupted signal, which seems to offer better preservation of the signal shape (FURNU and TOMPKINS, 1983; LEVKOV *et al.*, 1984; AHLSTROM and TOMPKINS, 1985).

The Levkov method involves the determination of the interference amplitudes in a linear segment of the ECG signal and subtraction of these amplitudes from the corrupted signal. This requires a sampling rate that is an odd multiple of the interference frequency. If the sampling rate is an even multiple of the interference frequency, a modified approach is necessary (CHRISTOV and DOTSINSKY, 1988).

Digital adaptive filters are better than fixed-notch filters in the elimination of noise (FEINTUCH, 1976; DENTINO *et al.*, 1978; KUMARAVEL *et al.*, 1995; HAMILTON, 1996). Adaptive second-order FIR notch filters operate with a sufficiently wide bandwidth to track and reduce the noise frequency, but in the process they also attenuate the frequency components of the ECG signal lying in this band (FARDJALLAH and BARR, 1990).

In Widrow's LMS adaptive noise cancellation, the primary input is taken from the ECG amplifier, and the 50 Hz powerline interference is taken from a wall outlet (WIDROW *et al.*, 1975). The adaptive filter contains two variable weights, one applied to the direct version of the reference input, and the other applied to a version of it shifted in phase by 90°. The two weighted versions of the reference are summed up to form the filter's output, which is then subtracted from the primary input. In this method, two variable weights are required to cancel the single pure sinusoid. The common-mode signal, usually taken from the right-leg reference electrode, is truly correlated with the noise in the ECG recording and, hence, it is taken as reference input for the LMS adaptive filter (THAKUR and ZHU, 1991).

The aim of this paper is to demonstrate the application of genetic algorithms in powerline interference cancellation from ECGs. This method does not require any external reference signal, unlike that using LMS adaptive filters.

2 Genetic algorithms

Genetic algorithms (GAs) are optimisation and search procedures inspired by genetics and the process of natural selection, in which the fitter individuals of a population tend to survive and reproduce for longer than others (SRINIVAS and PATNAIK, 1994; VOLI *et al.*, 1995).

In the literature, Holland's genetic algorithm is called the simple genetic algorithm (SGA) (HOLLAND, 1975). The SGA begins by randomly creating its initial population of binary strings. Each binary string is the encoded version of a solution to the optimisation problem solved using crossover and mutation genetic operators. The algorithm generates the subsequent strings from the strings of the current population. The gen-

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erational cycle is repeated until a termination criterion, such as the number of generations, is fulfilled.

The structure of a genetic algorithm is as follows:

```
Simple genetic algorithm ( )
{
  Initialise population;
  Evaluate population;
  while termination criterion is not reached
  {
    select solutions for next population;
    perform crossover and mutation;
    evaluate the population;
  }
}
```

3 Method

Sinusoidal powerline interference noise in ECGs is removed by subtracting the 'genetised' sine wave, which is generated by the genetic algorithm, from the corrupted ECG, as shown in Fig. 1.

The method of powerline interference cancellation from ECGs involves two successive operations, namely training and subtraction. First, during training, the sine wave generated by the genetics simulator is optimised using samples of the primary signal. Secondly, the 'genetised' sine wave is subtracted from the primary signal to obtain a filtered ECG.

3.1 *Genetic design for frequency-drifted sinusoidal wave removal*

The genetic simulator generates a single sine wave with three unknown parameters, frequency, amplitude and phase. These parameters have to undergo genetic optimisation using a fitness function so that the mean square error is a minimum. As the genetic algorithm is an optimisation procedure based on maximisation, the fitness function is taken as the reciprocal of the mean square value of the error.

The initial population consists of 50 randomised binary strings. The binary codes of the three parameters (frequency, amplitude and phase of the sine wave), each of 16 bits, are concatenated to obtain a binary string. We have used the fitness function,

$$f_i = \frac{1}{\frac{1}{N}\sum_{n=0}^{N-1}(a_n - b_n)^2}$$

where f_i is the fitness value of the ith string of the current population, a_n and b_n are the samples of the signals (*a*) and (*b*), as shown in Fig. 1, and N is the number of samples used for training. The fitness of each one of the strings in the current population is evaluated using the fitness function.

In the selection or reproduction phase, the current population is used to produce the next generation of strings, which, on average, have a higher fitness value. In the SGA, a fitter string receives a higher number of offspring and thus has a higher chance of surviving in the subsequent generations.

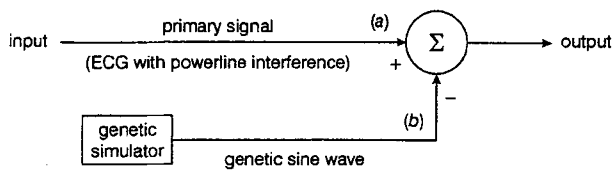

Fig. 1 *Method of powerline interference removal*

The roulette wheel selection scheme is used to implement proportionate selection. Each string is allocated a sector (slot) of a roulette wheel, with the angle subtended by the sector at the centre of the wheel equating $2\pi(f_i/f)$, where f is the total fitness value of the current population. A string is allocated an offspring if a randomly generated value in the range 0–2π falls in the sector corresponding to the string. The algorithm selects strings in this fashion until it has generated the entire population of the next generation.

After selection, pairs of strings are picked up at random from the population, and the algorithm invokes crossover only if a randomly generated value in the range 0–1 is less than the selected crossover probability of 0.9. A crossover point, representing the order number of a string bit, is selected randomly, and the positions of the two parts of strings beyond this crossover point are swapped to form two new strings. After crossover, the strings are subjected to mutation. Mutation of a bit involves flipping a 0 to 1, or *vice versa*, in a string, using a probability known as mutation probability, which is similar to the probability that controls the crossover. We have used a mutation probability of 0.1 in this case.

These processes of selection, crossover and mutation are repeated until the fitness function reaches an acceptable value, or the pre-defined number of generational cycles are completed. After this optimisation procedure, the 'genetised' parameters (frequency, amplitude and phase of the sine wave) are used to generate the sinusoidal signal, and it is subtracted from the primary signal to obtain noise-free ECGs.

3.2 *Genetic design for removal of frequency-drifted sinusoidal wave with third-harmonic distortion*

Even though the chance of distorted sine wave interference due to its harmonic generation is very rare, we have considered the third harmonic of powerline interference with its fundamental frequency. In this case, five parameters, namely frequency, amplitude and phase of the fundamental frequency, and amplitude and phase of the third harmonic are genetised according to the procedure explained in the preceding Section. The initial population consists of 50 randomised binary strings, and each string has the concatenation of binary codes of these five parameters of 16 bits each.

4 Results

In our studies, we have used ECG waveforms with a sampling rate of 600 samples per second. Three types of input datum are considered for various studies. They are: actual pure ECG with simulated sine wave interference using data translation software; actual noisy ECG with simulated sine wave interference; and actual noisy ECG with powerline frequency interference. The ECG is acquired using a data translation DT2821 data acquisition board with universal bio-amplifier.

Fig. 2 shows the performance of the genetic algorithm for a pure ECG with simulated 50 Hz sine wave interference. The time and spectral differences between the original and the filtered ECGs confirm that this method does not affect the skeletal and spectral components of ECGs. The genetic method using the three parameters described in Section 3.1 requires only 164 ms convergence time on a PC/AT 486, 66 MHz processor and less than 54 ms on a PC/Pentium, 133 MHz processor, for interference frequency detection with single decimal point precision. The simulated interference frequency is selected from the range 48.5–51.5 Hz, in steps of 0.5 Hz, and added to the ECG, and the performance of the genetic-algorithm based cancellation method is studied. The

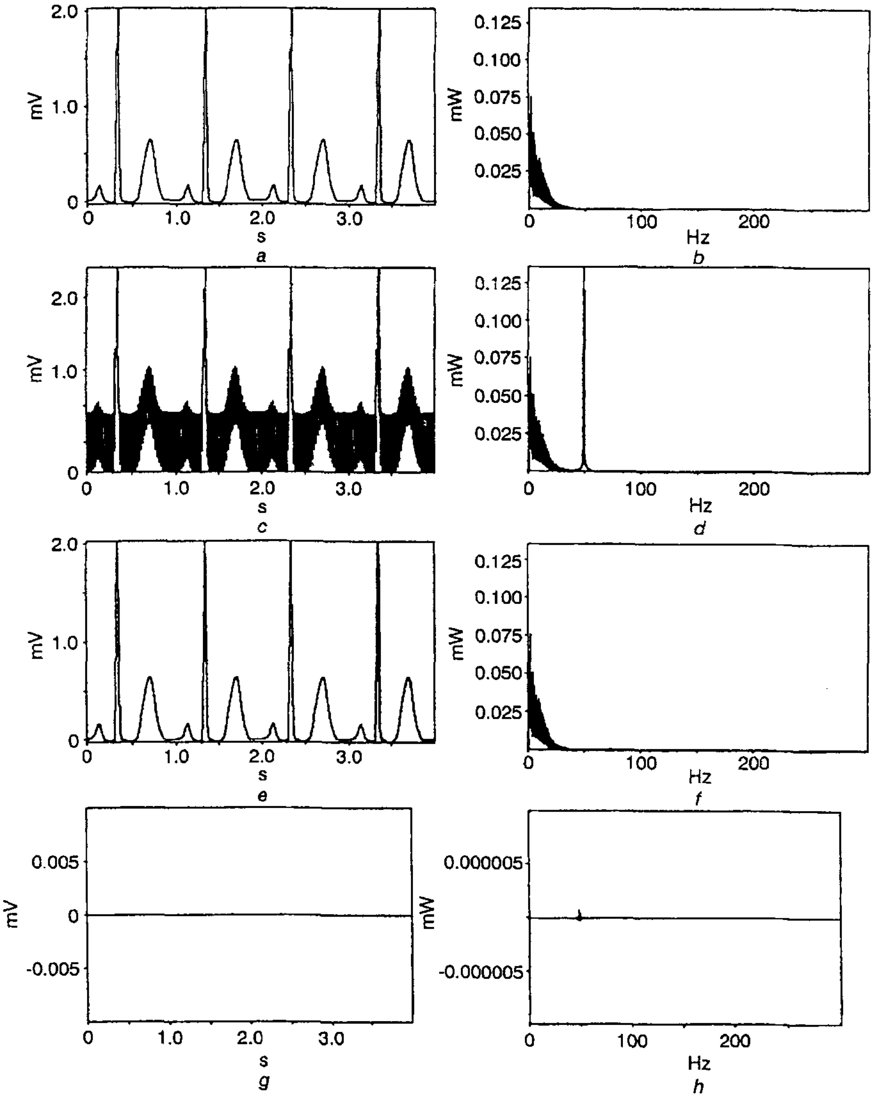

Fig. 2 *(a) and (b) Original ECG and its spectrum; (c) and (d) ECG with simulated 50 Hz sine wave, and its spectrum; (e) and (f) ECG after filtering using GA and its spectrum; (g) and (h) time and spectral differences between original and filtered ECGs*

signal-to-noise ratio (SNR) improvement obtained at the output using the GA based cancellation method, compared with that of an adaptive filter and a −120 dB, 50 Hz FIR notch filter, is given in Table 1. The results show that the SNR improvement is much better than with the other two methods.

Fig. 3 shows the input and output waveforms of the GA based cancellation method for an acquired noisy ECG with muscular activity and with a 50 Hz simulated sine wave added. Table 2 shows the performance of the GA based cancellation method compared with that of adaptive and FIR filters.

Table 1 SNR improvement for different interference frequencies

Frequency of interference, Hz	GA based cancellation, dB	Adaptive filter with $\mu=0.1$, dB	FIR filter with −120 dB at 50 Hz, dB
48.5	97.4	40.2	17.5
49.0	94.2	40.6	24.3
49.5	97.2	40.8	26.1
50.0	97.1	40.5	26.4
50.5	97.0	40.7	26.1
51.0	97.0	41.2	24.0
51.5	84.5	40.6	17.6

Fig. 4 shows the performance of the GA based cancellation method for an actuual ECG acquired with powerline interference noise.

Table 3 compares the SNR improvement and root mean square (RMS) error at the output of the GA based cancellation method with that of adaptive and FIR filters.

For different levels of interference in ECGs, the convergence time for maximum SNR improvement and SNR improvement for a fixed number of generational cycles (allowed time for convergence) are given in Table 4 for the three-parameter detection in GA based cancellation as described in Section 3.1.

In the case of third-harmonic detection, in addition to the fundamental frequency powerline interference, a simulated sine wave with third harmonic on pure ECG waveform is used and studied. The genetic design described in Section 3.2 is used. The performance of this method compared with that of adaptive and FIR filters is given in Table 5.

As the GA based cancellation method basically consists in detecting the powerline interference in the primary signal and then subtracting the 'genetised' sine wave from the primary signal, the RMS error at the output of this method, when the input is free from powerline interference, is always zero (no subtraction is done). The performance of this method with adaptive and FIR filters is given in Table 6, where the input is pure ECG free of powerline interference. It shows that the GA

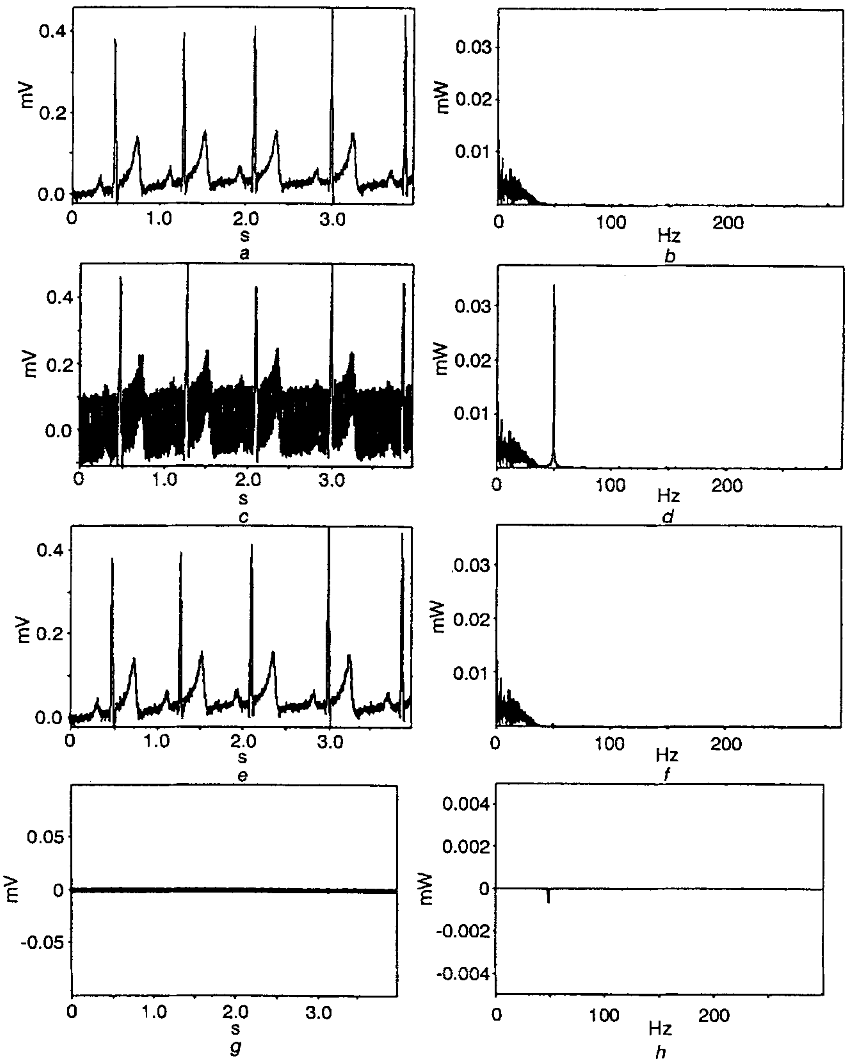

Fig. 3 *(a) and (b) Acquired (lead 12) ECG with muscular noise, and its spectrum; (c) and (d) ECG with 50 Hz simulated sine wave, and its spectrum; (e) and (f) ECG after filtering using GA and its spectrum; (g) and (h) time and spectral differences between original and filtered ECGs*

Table 2 SNR improvement and RMS error for noisy ECG with simulated sine wave interference

	GA based cancellation	Adaptive filter with $\mu = 0.1$	FIR filter with -120 dB at 50 Hz
SNR improvement at output, dB	35.0	32.0	26.7
RMS error at output, mV	0.0014	0.0020	0.0037

based cancellation method does not introduce any error, whereas the other two methods do introduce error at the output.

5 Discussion and conclusions

The GA based cancellation method is found to be very much superior to adaptive filters and FIR filters in terms of RMS error at the output and also preservation of the ECG spectrum, when the powerline frequency interference is a pure sinusoidal wave.

Examinations of Tables 1–3 and 5 show that the performance of this method is still better than adaptive-filter and FIR-filter methods, even if the sinusoidal powerline interference drifts in frequency, and with or without third-harmonic distortion. Even though the convergence time required for the removal of fixed-frequency powerline interference is less than 54 ms on a PC/Pentium 133 MHz processor, the detection of frequency with precision of third decimal place (in millihertz) resolution requires a convergence time of 2–3 s. We observed, from the studies, that the number of samples required to detect the interference frequency to a resolution of milliHerz is about 1000 times greater than the number of samples used for integer frequency detection. In the case of the input shown in Fig. 4, the frequency detected by the genetic algorithm method is 50.092 Hz. Examination of Table 4 shows that the time of convergence of solutions does not give a mathematical relationship, because the genetic algorithm method uses probabilistic rules. This does not mean that the rules perform a completely random search; they are devised to lead quickly to areas of the search space where improvement is likely.

It is observed that, if optimum convergence is obtained within the completion of the predefined number of generational cycles, the RMS error at the output of the GA based cancellation method is as low as 0.000004 mV, which is far better than for an LMS adaptive filter. In real-time processing, the algorithm can be invoked as and when powerline interference is sensed on the iso-electric potential line. The time taken for sensing powerline frequency interference is much less, and hence, it will not affect the real-time processing.

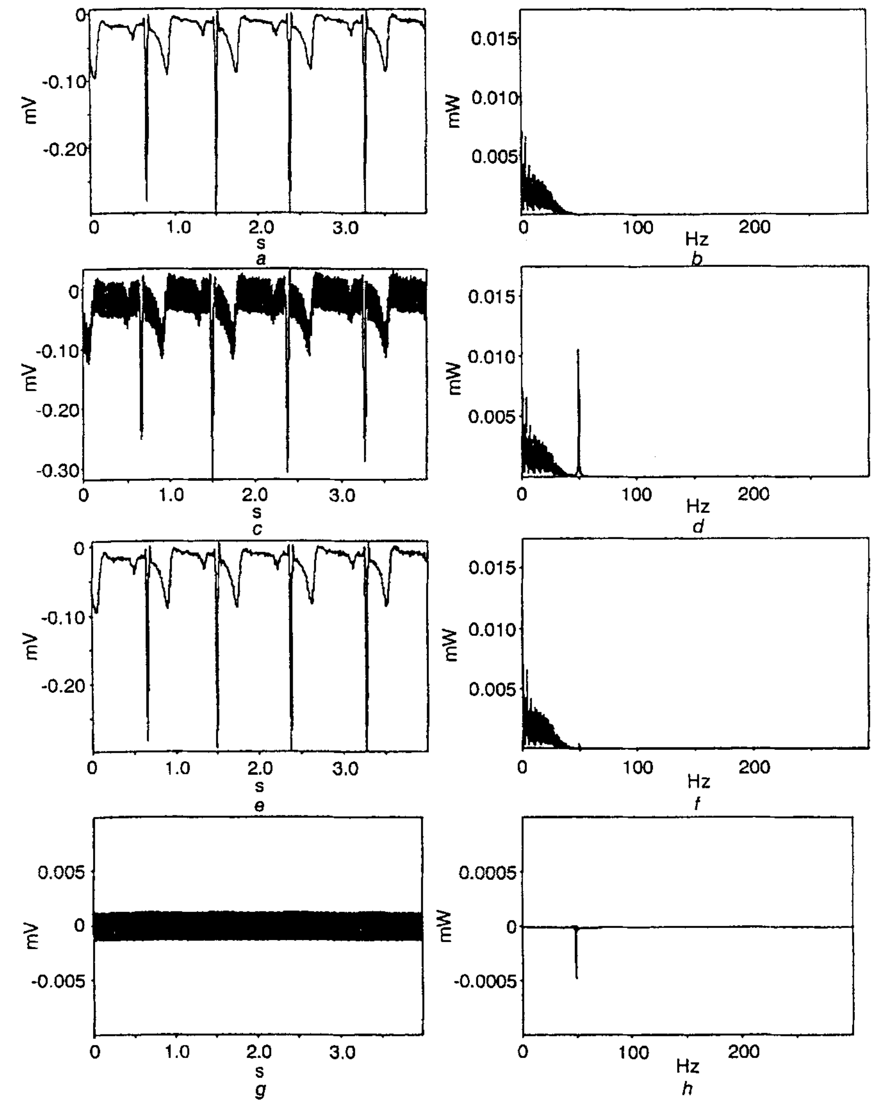

Fig. 4 *(a) and (b) Acquired (lead aVR) ECG, and its spectrum; (c) and (d) acquired ECG with sine wave interference and its spectrum; (e) and (f)ECG filtered using GA and its spectrum; (g) and (h) time and spectral differences between original and filtered ECGs*

Table 3 SNR improvement and RMS error for actual ECG acquired with sine wave interference

	GA based cancellation	Adaptive filter with $\mu = 0.1$	FIR filter with -120 dB at 50 Hz
SNR improvement at output, dB	33.8	28.7	29.5
RMS error at output, mV	0.0096	0.00172	0.00157

Hence, the training of the sine wave parameters for optimisation using the genetic algorithm has to be done as and when required, but not continuously. It is observed that, even if the optimum solution (global convergence) is not obtained within the predefined number of generational cycles (100 cycles are used in this study), the solution obtained on completion of the predefined number of generational cycles still gives a better RMS error at the output compared with that of an LMS adaptive filter.

Table 4 Convergence time and SNR improvement for various levels of inteference at input

Level of interference compared with ECG signal peak, %	Convergence time in PC/Pentium, 133 MHz processor for SNR improvement of 99.96 dB, s	SNR improvement at output for 30 generational cycles (or 0.3 s), dB
10	0.65	39.0
20	0.36	54.4
40	1.0	37.0
50	0.4	43.0
100	0.6	34.5

Table 5 Comparison of results for input of ECG with sine wave interference and its third-harmonic distortion

	GA based cancellation	Adaptive filter with $\mu = 0.1$	FIR filter with -120 dB at 50 Hz
SNR improvement at output, dB	32.4	12.2	14.9
RMS error at output, mV	0.0094	0.096	0.0720

Table 6 Comparison of results for input of ECG without powerline interference

	GA based cancellation	Adaptive filter with $\mu = 0.1$	FIR filter with -120 dB at 50 Hz
RMS error at output, mV	0	0.0019	0.654

We conclude that the GA based cancellation method is adaptive to powerline interference in ECGs and gives very good SNR improvement compared with that of an LMS adaptive filter, at the expense of convergence time. This genetic-algorithm based powerline cancellation method is very suitable for a parallel-processing system.

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