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An Optimized DSP Implementation of Adaptive Filtering and ICA for Motion Artifact Reduction in Ambulatory ECG Monitoring

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Abstract— **Noise from motion artifacts is currently one of the main challenges in the field of ambulatory ECG recording. To address this problem, we propose the use of two different approaches. First, an adaptive filter with electrode-skin impedance as a reference signal is described. Secondly, a multi-channel ECG algorithm based on Independent Component Analysis is introduced. Both algorithms have been designed and further optimized for real-time work embedded in a dedicated Digital Signal Processor. We show that both algorithms improve the performance of a beat detection algorithm when applied in high noise conditions. In addition, an efficient way of choosing this methods is suggested with the aim of reduce the overall total system power consumption.**

I. INTRODUCTION

The fast improvement in microelectronic systems is having a large impact in the design of novel ambulatory electrocardiogram (ECG) monitoring devices. New advances in electronics allow more complex computational algorithms working in ultra low power consumption microprocessors [1]. Novel wearable systems extend the time of continuous monitoring from the 24-hours that was standardized about a decade ago to several days or even weeks. Ambulatory monitoring of the ECG has several clinical applications. It is widely used for the diagnosis of cardiac pathologies and in the assessment of therapy [2]. In addition, low cost ECG monitoring devices lead to other new non-clinical applications in sports and lifestyle. However, ECG recorded during daily activities have higher levels of noise as compared to when measured at rest. Noise due to motion artifacts can corrupt the signal making its interpretation difficult.

Several methods for noise reduction and motion artifact removal have been proposed in the literature. Some were based on traditional denoising techniques [3]. More recently, new and more effective techniques based on adaptive filtering [4] or blind-source separation techniques [5] have been proposed. However, this problem still remains a challenge and needs further research.

This paper describes an implementation and optimization of two algorithms for motion artifact reduction using Single-Instruction Multiple-Data (SIMD) instructions. The first algorithm method is an adaptive filter that uses skin-electrode impedance as a reference signal. The second method is based on Blind Source Separation (BSS) techniques, such as Principal Component Analysis and Independent Component Analysis (ICA).

After filtering the ECG signals by using these techniques, a robust beat detection algorithm based on continuous wavelet transform [6] is applied. The performance of the beat detection algorithm was used to evaluate the performance of the filtering techniques studied in this work.

II. BACKGROUND

A. *Adaptive Filter Based Motion Artifact Reduction*

Previously, we reported [9] a system that, alongside with 3-lead ECG recording is capable of measuring electrode-skin impedance (ETI), which has been shown to correlate with motion artifacts. The ETI signal can be used as a reference signal in an adaptive filter to reduce motion artifacts.

The least-mean-square sign-error algorithm (LMS-SE) is an alternative of the LMS algorithm [7]. The objective of the LMS-SE algorithm is to reduce the computation cost compared to the standard LMS algorithm. As its name indicates the equation of LMS-SE algorithm is given as:

$$\mathbf{w}(k+1)=\mathbf{w}(k)+2\mu\cdot\operatorname{sgn}\big(e(k)\big)\cdot\mathbf{x}(k) \tag{1}$$

$$\operatorname{sgn}(b)=\begin{cases}1 & b>0\\ 0 & b=0\\ -1 & b<0\end{cases} \tag{2}$$

where μ is the convergence step, x(k) is the reference signal, d(k) is the desired signal and e(k) is the error. For a linear and stationary system H, the quantization of the error vector can lead to a decrease in the convergence speed, and possible divergence. In the LMS-SE algorithm, the average gradient only uses a discrete set of directions. The limitation in the gradient direction may cause updates that result in frequent increase in the square error, leading to instability.

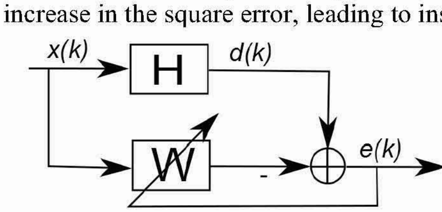

Fig. 1: Outline of the Least-Mean Square Sign Error algorithm

However, in the case of ambulatory ECG monitoring, H is changing continuously. When the error is small, the quantization of the error can provide a larger convergence step. It makes the adaptive filter converge faster than LMS

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to the minimum value of the new mean-square error surface. The filter is outlined in Fig. 1. To remove the baseline of the ECG and ETI signal before LMS-SE, we use a high-pass filter with passband 0.05 Hz.

B. ICA and PCA Based Motion Artifact Reduction

ICA and PCA are methods for separating mixed signals [8] and have been previously evaluated in the context of motion artifact reduction in ambulatory ECGs recordings [5]. ICA outperformed PCA in every metric, except for computational complexity, where ICA is more complex.

In this work we have chosen to work with three ECG leads. This is expected to provide a sufficient number of leads to apply statistical methods for ECG de-noising while minimizing the invasiveness of the system. The electrode position was selected [6] to maximize the amplitude of the R and P waves in the ECG. Electrodes are placed in positions V2, V3 and V4 (precordial lead positions), with reference electrode placed on the upper right portion of the chest.

In order to use ICA autonomously for motion artifact reduction in ECG recordings, an algorithm for the selection of independent components is necessary. This is one of the main challenges for using ICA for de-noising ECGs. Here, based on a previous study [5], the single independent component (IC) with the highest kurtosis is retained. The assumption is that this IC is the one that correlates the most with the ECG. The remaining ICs are set to zero before the inverse ICA transformation is performed to obtain the filtered ECG signals.

C. Digital Signal Processor

For the implementation platform, we used imec's CoolBio ultra low power biomedical signal processor [10], which at its core has NXP's CoolFlux BSP dual Harvard architecture. The CoolBio chip combines a 100 MHz 24/56-bit CPU, dynamic clock and power managers with an event-driven architecture. The 24-bit data path can either be used as 24-bit scalar or as 2x 12-bit Complex/SIMD with 56-bit accumulators (56-bit scalar or 2x 28-bit complex/SIMD). The dual architecture thus enables either 2x 24-bit or 4x 12-bit operations to be executed in parallel.

III. METHODS

A. Evaluating Motion Artifact Reduction

To evaluate the performance of the motion artifact reduction algorithms, we use the performance of a beat detection algorithm [6], in terms of sensitivity (Se) and Positive Predictivity (PP), applied on the unfiltered signals and the signals filtered by LMS-SE and ICA.

The evaluation database consists of 10 1-hour segments of ECG signals created from ECG template beats for V2, V3 and V4, using RR intervals collected from previous studies. Ten 1-hour ECG noise and impedance signals were recorded at the lower back of different subjects, above the lumbar curve, where the ECG is considered to be negligible. Each segment of clean ECG and noise is then combined to create 100 hours of motion artifact contaminated ECG. The noisy ECGs are split into 4-second segments where the SNR is calculated and the beat detection performance is evaluated.

B. Adaptive Filter Optimization

We calculate LMS-SE sample-by-sample on ECG and ETI both sampled at 256 Hz. From the initial 24-bit scalar implementation, the LMS-SE algorithm is optimized in two steps; first a cyclic buffer is introduced for addressing the regressor delay line. This avoids copying every element of the delay line when a new sample is inserted. The second optimization is to use SIMD instructions to update 4 filter taps in parallel. For both ECG and impedance, we use a 5 section cascaded biquad filter for high pass filtering.

C. ICA Optimization

We calculate ICA on 4 second input blocks of 3-lead ECG, sampled at 256 Hz. From the original 24-bit scalar implementation, the FastICA [8] algorithm is optimized mainly by focusing on converting functions to exploit the SIMD mode of the DSP. Special attention is given to the contrast function, which is the most critical part of the code. In this implementation, the cubic contrast function is chosen, which is used to measure the kurtosis of the independent components. The inner iteration loop for the cubic contrast function is defined as:

$$\mathbf{Y} = \mathbf{X} \times (\mathbf{w(k)} \times \mathbf{X^T})^3 \tag{3}$$

Where $\mathbf{X}$ is the multi-channel ECG matrix and $\mathbf{w(k)}$ the current weight to improve. The loop is repeated for every input channel until two consecutive iterations converge. The dataflow graph of the inner loop is illustrated in Fig. 2. The number of executions of this inner loop is dynamic, and has a large impact on the energy dissipated by the algorithm. Using SIMD instructions and 4 accumulators, the inner loop is processed 8 samples of $\mathbf{X}$ simultaneously. In the last stage of the inner loop, the accumulators are joined and appended to a second set of 48-bit accumulators in memory, which is again accumulated into 56-bit accumulators after the critical loop. To decrease the number of iterations required, we reuse the demixing matrix of the previous block as the starting point for the next block. The remaining computations of the ICA algorithm is dominated by matrix multiples and the calculation of kurtosis, both of which are also optimized with SIMD instructions.

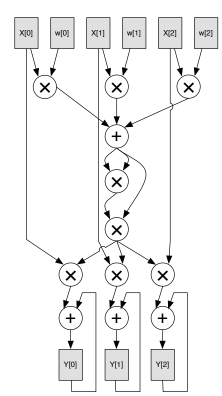

Fig. 2: Inner loop of the ICA algorithm using a cubic contrast function for 3-lead ECG

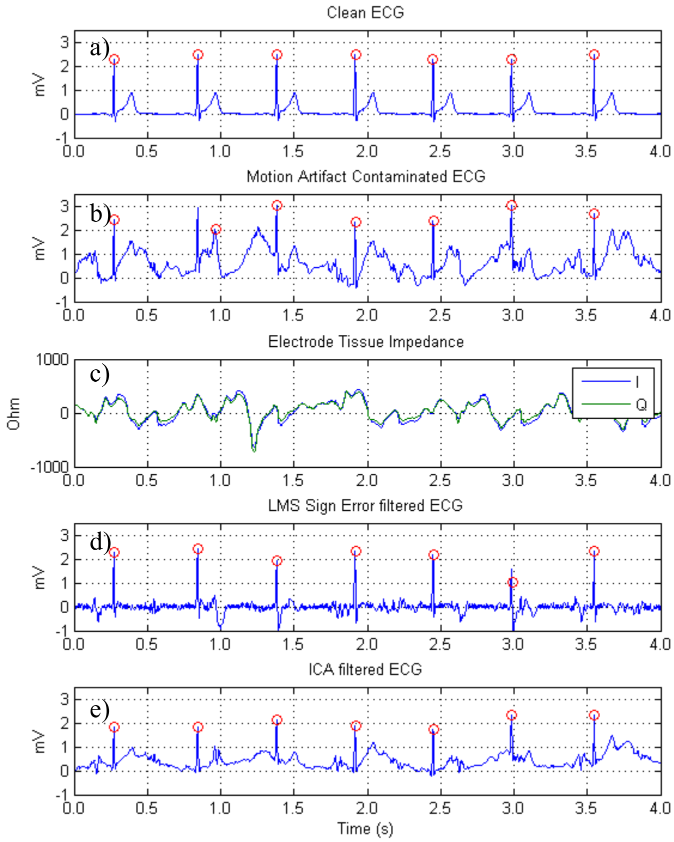

Fig. 3: a) Clean ECG signal b) ECG with added noise c) impedance signal corresponding to motion artifact d) LMS-SE adaptive filtered ECG, using imaginary impedance component as reference e) ICA filtered ECG using automatic component selection. The red circles indicate detections as reported by the beat detection algorithm.

D. *Energy Usage Estimation*

The cycle count is obtained from the R11 CoolFlux BSP Instruction Set Simulator (ISS). Based on profiling of the CoolBio DSP, we consider two cases of energy dissipation per clock cycle; the first is based on a non-optimized algorithm implementation, which does not fully exploit the capabilities of the DSP, which has been estimated to 46 pJ/cycle. Also, we consider the case of a highly optimized algorithm where all functional units of the DSP are active in every cycle, which has been estimated to 96 pJ/cycle. For the energy estimation, only energy spent inside the DSP is counted. This excludes any I/O and analog interfaces.

IV. Results

A. *Motion Artifact Reduction*

In Fig. 3, the different inputs and outputs of the algorithms are illustrated. In Fig. 4, the result of the beat detection is shown. $ICA_{optimal}$ is defined as using the theoretical component subset which gives the best beat detection performance, decided by computing all possible combinations, and keeping the best result. This shows the theoretical performance if we have a perfect component selection algorithm.

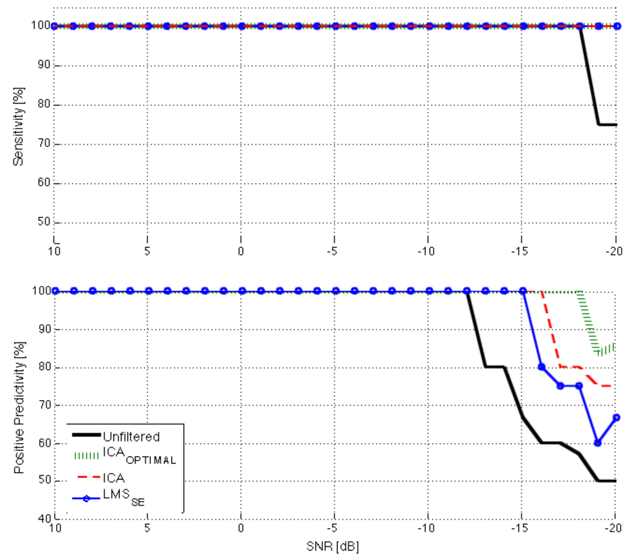

Fig. 4: Sensitivity and positive predictivity of a beat detection algorithm on the unfiltered vs. filtered signals

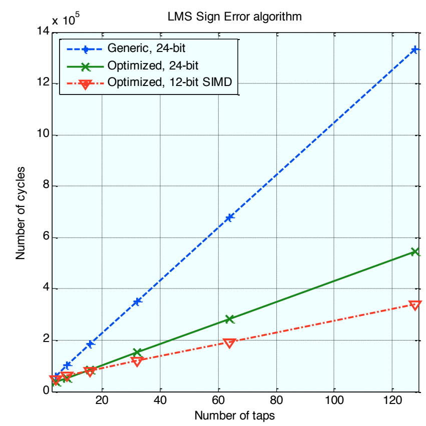

Fig. 5: Number of cycles spent for different tap lengths in the LMS-SE algorithm on filtering a 4-second ECG block (at 256 Hz) for three different CoolBio implementations.

B. *Adaptive Filter Optimization*

The cycle budget of three different LMS-SE implementations when adjusting the number of taps used for filtering the signals on a block of 4 seconds of input data is shown in Fig. 5. The first implementation does not use any DSP specific optimizations, while the second 24-bit uses a cyclic input buffer. The last implementation uses both the cyclic buffer and SIMD instructions.

In addition to this, the two biquad highpass filters are each using 9746 cycles per 4-second block. For the final implementation, 4 filter taps are used in the LMS-SE filter, as this was found to give the highest beat detection performance.

C. *ICA optimization*

In Fig. 6, a histogram over the number of iterations required to compute ICA on 4-seconds of ECG data is shown. The median-MAD number of iterations required did not change significantly (12-29.32 vs. 12-29.43) when quantizing the data from double precision floating point down to 12-bit SIMD data.

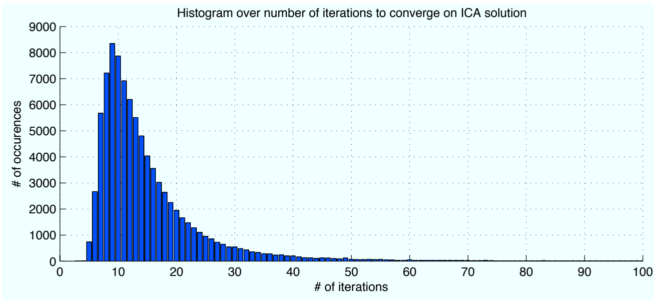

Fig. 6: Distribution of iterations needed to converge on ICA solution for 90000 simulations. The range between 0 and 100 iterations is shown above. Upper limit was set to 2000 iterations, epsilon was set to 0.0001.

TABLE I
CYCLE COUNT ESTIMATION FOR THE INNER LOOP OF THE ICA ALGORITHM

ICA Implementation	Cycles per iteration	Median-MAD iterations per block	Median-MAD number of cycles per block
Generic 24-bit FastICA	126 908	12 – 29.32	1 522 896 – 3 720 943
Optimized SIMD 12-bit FastICA	8 762	12 – 29.43	105 144 – 257 866

In Table I, the cycles spent in the inner loop of the ICA, and the median-MAD number of iterations required per block for each of the two algorithm implementations is shown.

D. *Energy Usage Estimation*

In Table II the energy estimation for both ICA and LMS-SE is summarized. With the CoolBio logic at 0.6 V and its memories at 0.8 V, and the frequency scaled to 10 MHz, we spend approximately 96 pJ/cycle, resulting in a median energy consumption of 13.8 µJ for each block processed for ICA with SIMD, and 4.9 µJ for each block processed by the LMS-SE. The energy dissipated by using 3-lead ECG vs. 1-lead ECG plus 1-lead ETI is considered to be comparative.

TABLE II
ENERGY ESTIMATION FOR ICA AND ADAPTIVE FILTER, EXCLUDING I/O

Algorithm	Static cycles	Est. dynamic cycles	Static + dynamic cycles	Energy per cycle	Energy per block
Generic 24-bit FastICA	688 874	1 522 896	2 211 770	46 pJ	102 µJ
Optimized SIMD 12-bit FastICA	38 167	105 144	143 311	96 pJ	13.8 µJ
Optimized LMS-SE (+ 2x IIR HPF) 24-bit	31 286 (+ 2x 9746)	0	50 778	96 pJ	4.9 µJ

V. CONCLUSION

The filtering performance and the DSP optimization of two different methods for motion artifact reduction were studied. Both algorithms improve beat detection results versus not filtering, and both algorithms were optimized using DSP optimization techniques. LMS-SE maintains 100% sensitivity and positive predictivity for the beat detection down to an SNR of -15 dB, vs. ICA -16 dB, an improvement over unfiltered ECG which is sensitive down to -12 dB. The optimized ICA implementation uses on average 13.8 µJ per 4-second block, vs. 4.9 µJ per 4-second block with LMS-SE.

For ICA, change in number of iterations per block is neglible when quantizing to the CoolBio SIMD mode from floating point. For LMS-SE, using the SIMD mode is more overhead than gain when the number of taps used is less than 16, which was the case in this study, where 4 taps were used.

As most of the time during ambulatory ECG monitoring, we do not need motion artifact reduction, the largest gain in energy efficiency would be to disable motion artifact reduction during periods of low noise, enable LMS-SE during periods of moderate noise, and enable ICA during periods of high noise. To estimate the amount of motion artifacts in the ECG, we could use the energy in the impedance signal as an indication.

As limitations of this study, only artificially generated signals were used to evaluate the performance of the algorithms. The beat detection performance was calculated in MATLAB on quantized versions of the algorithms, and the energy was estimated from the CoolBio instruction set simulator.

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