

# Analog Front-Ends comparison: on the way to a portable, low-power and low-cost EMG controller based on Pattern Recognition

Enzo Mastinu, Max Ortiz-Catalan, Bo Håkansson

**Abstract— Compact and low-noise Analog Front-Ends (AFE) are becoming increasingly important for the acquisition of bioelectric signals in portable system. In this work, we compare two popular AFEs available on the market, namely the ADS1299 (Texas Instruments) and the RHA2216 (Intan Technologies). This work develops towards the identification of suitable acquisition modules to design an affordable, reliable and portable device for electromyography (EMG) acquisition and prosthetic control. Device features such as Common Mode Rejection (CMR), Input Referred Noise (IRN) and Signal to Noise Ratio (SNR) were evaluated, as well as the resulting accuracy in myoelectric pattern recognition (MPR) for the decoding of motion intention. Results reported better noise performances and higher MPR accuracy for the ADS1299 and similar SNR values for both devices.**

## I. INTRODUCTION

Although modern knowledge in matter of mechanical and robotic engineering is a consolidated reality, the available options for the control of prosthetic devices limits the utilization of advanced robotics. So far, the control of artificial limbs has been mostly made possible by the use of analog circuits. These are based on the amplification of EMG signals and the switching of motor actuators depending on overcoming voltage thresholds [1], [2]. The use of RMS-to-DC converters in this direct control strategy has been a good option for many examples in the state of art. In the literature it is also common to find examples of hybrid control circuits [3], where the analog part concerns about amplification, filtering and acquisition of EMG, while the digital part focuses mainly on checking the signal levels and driving motor units. Recently, a new approach has emerged, representing the main interest of this and future work. It has its foundations on digital controllers programmed with their own decision intelligence able to predict the motion intent of the amputee. Particular training protocols can be developed to achieve the intuitive control of the prosthesis based on the principle that specific EMG patterns recorded from residual limb muscles are associated with specific hand movements and grip functions, also known as MPR. The control complexity and efficiency can be truly increased by developing a proper custom artificial intelligence based on MPR. The ever-increasing computing power of modern microcontroller units (MCU) allows digital solutions to handle conventional and complex signal processing and MPR

algorithms. However, before algorithms can take over, signal acquisition hardware must provide the source signals, which is the focus of this work.

### A. ADS1299 vs RHA2216

Despite the two ICs used in this study have the aim to record low amplitude bioelectric signals, they still have relative big differences. The TI's ADS1299 has 8 differential acquisition channels and each channel is equipped with a programmable gain amplifier, up to 24 times, and with an analog to digital delta-sigma converter of 24 bits resolution [4]. Intan Technologies provides devices with 16, 32 and 64 channels with a fix gain of 200. In this work we have focused on RHA2216 with 16 differential channels [5], [6]. It has built-in high-pass and low-pass filters configurable by external resistors, and as opposed to the TI's device the RHA2216 must be interfaced to an external data converter to obtain the signals in digital format. Intan also provides AFEs with digital output. The RHA2216 is equipped with an internal multiplexer that, driven externally, allows all 16 amplifiers to share one analog-to-digital converter with sampling rate up to 30kHz. In the ADS1299 the oversampling technique is used to reduce the noise, spreading it on a wider band of 1.024 MHz. The only filtering achievable is a digital low-pass decimation filter with the cut-off frequency that depends on the output data rate: lower data rate means narrower bandwidth and turns in higher SNR, higher data rate means wider bandwidth and thus more noise is included in the signals. This decimation filter introduces a pass-band trend that repeats itself on the multiplies of the oversampler frequency. For this reason the use of an anti-aliasing filter is recommended to eliminate all possible high frequency interferences. A DC block filter is recommended as well to avoid any bio-potential drift from the recorded signals. The ADS1299 is totally customizable via software modifying its internal registers and it introduces some useful features for EMG, EEG and ECG applications, such as the possibility to check the state of connections of the electrodes; the possibility to measure the bias voltage of the subject; and the option to drive this bias to increase CMR in a configuration close to the classic RLD circuit.

## II. METHODS

The RHA2216 must be interfaced with an external analog-to-digital converter. The AD8221 (Analog Devices) with 16 bits of resolution was used for this task as recommended by the manufacturer. In all experiments and for both devices the sample rate was set on 2000 Hz. The data acquisitions were obtained interfacing both chips to a TI MCU with ARM CortexM4 core. The MCU was programed to acquire the EMG and transfer it to a PC via UART-to-USB interface. The data transfer protocol was SPI for both devices. With the

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E. Mastinu is with the Dept. of Signals and System, Chalmers University of Technology (CTH), Gothenburg, Sweden (e-mail: enzo@chalmers.se).

M. Ortiz-Catalan is with the CTH, the Centre for Advance Reconstruction of Extremities (C.A.R.E.), Sahlgrenska University Hospital (SUH), and Integrum AB (e-mail: maxo@chalmers.se).

B. Hakansson is with the Dept. of Signals and System, Chalmers University of Technology (CTH), Gothenburg, Sweden (e-mail: boh@chalmers.se).

same SPI lines it was possible to setup the ADS1299 configuration registers. A Matlab GUI was used for receiving and saving data on the PC side. The AFEs test began with the measure of two of the major important features for bioelectric signals acquisition, CMR and IRN. The ADS1299 offers an internal amplifier which can be used for drive the bias signal in way to increase the CMR, and this mode was also evaluated. Moreover, the bias driver circuit was tested also in an open loop configuration. Then we tested the performances of both devices when used for MPR. All the accuracies calculations were done offline using BioPatRec [7], an open source platform for MPR implementation based on Matlab. Finally the same data set was used for SNR analysis.

### A. IRN and CMR

For the initial section of experiments, 10 seconds recording time was used. The IRN was tested shorting together all input terminals and tying them to ground. Every channel revealed an input offset which was deleted by subtracting the mean of that channel. Resulting data were plotted on histogram graphs and the values of the IRN, in peak to peak representation, were computed from the standard deviation. The CMR tests were done by shorting together the positive and negative input terminals of every channel and then tying all channels together to a relative big common mode voltage. This common mode signal was set to be a sinusoid with 50 Hz frequency, centered in the middle supply of the devices with amplitude able to reach the supply limits. The supply configurations were dual 2.5V for ADS1299 and single 3.3V for RHA2216. Finally, the CMRR was computed as the ratio of differential gain power over the common-mode gain power, measured in decibel. The differential gain was set as the maximum for both devices, or rather 24 times for ADS1299 and 200 times for the RHA2216. As afore mentioned, the ADS1299 offers the possibility to improve CMR driving the bias of the user. This is based on a flexible internal multiplexer with which it is possible to lead the common mode voltage of every input channel to the inverting input of a built-in amplifier. The inverting input is then forced to the reference voltage by the non-inverting terminal and a feedback loop net composed by  $R_F$  and  $C_F$ . The bias driver test setting was different, and as suggested in [8], it was based on a circuit used to model the body's response to power lines stimulus. This circuit, shown in Fig. 1, is basically a resistor and capacitor net with equivalent impedance that emulates the mismatch introduced in the differential channel by the electrode/body system. This set allows to test one channel for each time: the channel is used for sense the bias oscillations inducted by a signal generator in the parallel net that simulates body's impedance. Then, an inverted version of these bias drifts is sent back to the electrode/body system through another analogue parallel net, with the aim of delete the common mode voltage fluctuations. The  $R_F$  and  $C_F$  values were chosen in order to get a cut off frequency two time bigger than the stimulus frequency [9]. The test was repeated for every input channel. Finally, with the same test setting this bias driver loop was tested with an open loop configuration. In this mode, the

common mode driver signal is delivered to the body's model through a resistance connected to the output of the amplifier, instead of using the RC net to close the feedback loop.

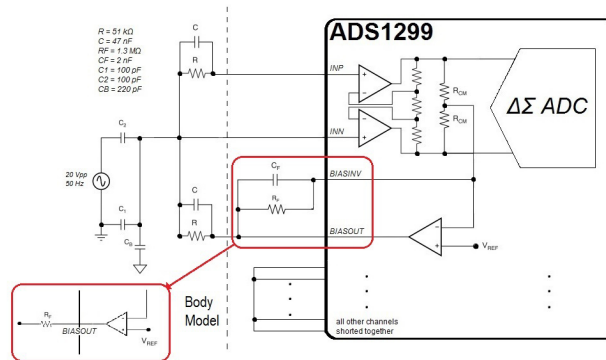


Figure 1. ADS1299 bias driver test setup, close and open-loop configuration.

### B. MPR and SNR

MPR tests were done on a set of eight able-bodied subjects, six males and two females, with age ranging from 23 to 32 years old. Four of them were already familiar with the BioPatRec system and the rest were novices. Four pairs of Ag-AgCl electrodes were equidistantly placed around the forearm of the subjects, forming four differential channels. The inter-electrode spacing was approximately 2 cm, set along the muscle fibers. A reference electrode was placed in the elbow. The subjects were seated and asked to find their most comfortable position, then, placed in front of a screen where the BioPatRec recording sessions were run. The recording sessions consisted in a sequence of ten movements, which the subjects were asked to execute doing three repetitions for each, alternately three seconds contraction time with a three seconds rest time. The movements were: open hand, close hand, flex hand, extend hand, pronation, supination, side grip, fine grip, agree and pointer. Three sessions were recorded from every subject, using three different acquisition sets: Intan's RHA2216, TI's ADS1299 and TI's ADS1299 with bias driver circuit enabled. The order was randomized for every subject. The subjects were trained, before start the experiment, with one dummy recording session. The classifier used to decode the performed movement was Linear Discriminant Analysis (LDA) using four time domain features: absolute mean, waveform length, zero crossing and slope changes [7]. The total number of time windows per movement was 121 with 200 ms length and 50 ms time increment. These time windows were then assigned randomly to training, validation and test sets by 40%, 20% and 40% of the total feature vectors, respectively. The randomize sets were used to train the classifier in One-Vs-One topology. This operation was repeated 10 times and the average accuracy between all movements for all iterations was taken as the result.

The last part of this experiment regards the SNR. A statistic ratio of signal and noise powers was calculated using the previous recording sessions. From every of the three

repetitions in the same movement recording, the central three seconds were extracted, from contraction and from resting time slots. These portions were then concatenated in two different arrays and considered as signal and noise data, respectively. RMS values were calculated and used in (1) to get the SNR.

$$SNR_{dB} = 10 * \log_{10} \frac{S_{RMS}^2}{N_{RMS}^2} = 20 * \log_{10} \frac{\sqrt{\frac{1}{n} \sum_1^n S_i^2}}{\sqrt{\frac{1}{n} \sum_1^n N_i^2}} \quad (1)$$

For every movement, the channel with strongest muscle activation was taken in consideration. This procedure was repeated for all subjects.

The results are summarized in Table 1. Average CMRR was: 116 dB for the ADS1299, 135 dB for the ADS1299bias, and 84 dB for the RHA2216. The values are mostly equal to the values reported in the respective datasheets. Moreover, it was found, as expected, a performance improvement using the bias driver functionality. On the other hand, the ADS1299bias with open-loop configuration resulted in a CMRR of 97 dB with a resistance of 1.3 MΩ.

The average IRN expressed in peak to peak volts was: 2.58 μV and 9.58 μV for the ADS1299 and RHA2216, respectively. These results can be seen in histogram form in Fig.4. In both cases were found no surprising values, perhaps a slight and favorable variation from the datasheet value for the Intan device.

The accuracies found with BioPatRec LDA classifier are reported in Fig. 2. For all configurations tested, the average accuracies found were over 90%. The 0.05 statistic significance of the results was tested with Wilcoxon signed-rank test.

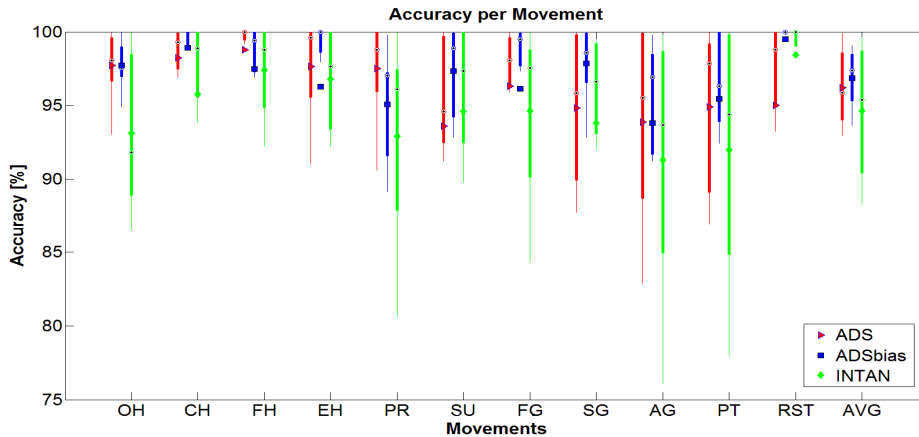


Figure 2. Results for accuracies per movements.

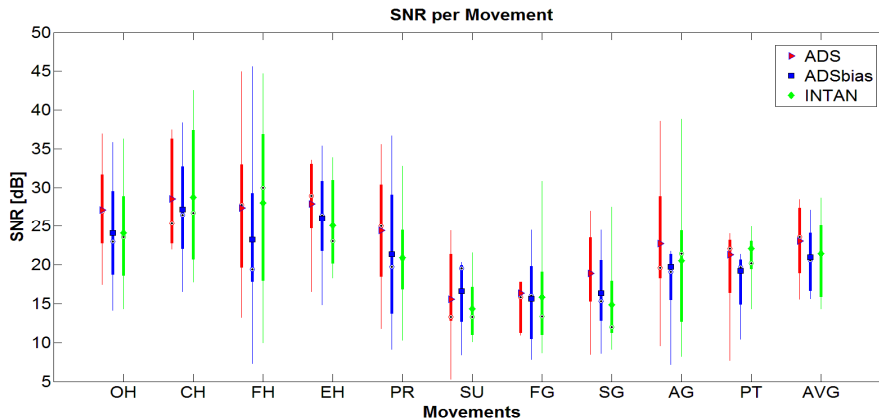


Figure 3. Results for SNR per movements.

The SNR results are shown in Fig. 3 and it is possible to note close values for all three configurations. It was surprisingly found a lower SNR for the ADS1299 with bias driver system although it was expected to be the highest before start the experiment.

#### IV. CONCLUSION

According to the CMRR and IRN results reported in Table I, it is possible to argue that the ADS1299 can achieve better performances against noise. The CMRR performance increased with the bias driver feature, but not in the open-loop configuration. The CMRR was obtained using a model circuit, but the natural body response to surrounding interferences is more complex, and therefore it could potentially lead the system to worse performance. It is interesting to note how the bias driver circuit increased the MPR accuracy although presenting a lower SNR. One can speculate that perhaps the feedback loop forces changes in the signal waveforms from which the result is higher descriptive features while worsening the average SNR. Further work is necessary to investigate this particular contradiction.

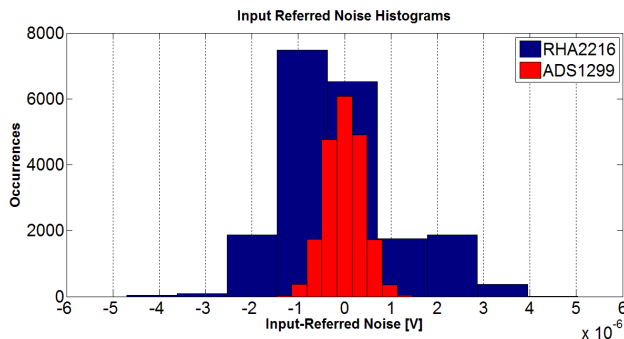


Figure 4. IRN histograms.

TABLE I. DEVICES COMPARISON

Features	Devices		
	ADS1299	ADS1299 bias driver	RHA2216
n. Differential Channels	8		16
Power x Ch. [mW]	5		0.5
Supply Voltages [V]	5 and 3.3		3.3
Gain [V/V]	1,2,4,6,8,12,24		200
Signal BW Range [Hz]	0 ÷ 4093		0.02 ÷ 20k
IRN [ $\mu$ Vpp]	Measured	2.58	9.58
	Datasheet	2.79	13.2
CMRR [dB]	Measured	-116	-84
	Datasheet	-120	-82
SNR [dB]	23.02	20.94	21.45
BioPatRec Accuracy [%]	96.22	96.88	94.62

Although the RHA2216 was found to be more sensitive to noise, it still has favorable points like the 16 acquisition channels, the built-in filters with a wide selectable range of band-pass frequencies, low power consumption, and the low operating voltage of 3.3 V. Additionally, ADC with higher resolution and performance could be used with this IC. Comparing these two ICs it should appear clearly how they are inherently different, even though aimed for the same purpose. Intan provides an IC able to reach acceptable results in EMG context, relatively easy to use, and ready to work at maximum performance. On the TI side, the ADS1299 needs more effort to get it working at the best level, an effort that is heavier on the software side. For instance, the absence of an inner input filter for DC rejection, forces designers to look into filter solutions, analog or digital as well. Despite this, ADS1299 digital side gives more flexibility and options like bias driving or lead-off detection, provided that the time to market of the application in question is sufficient to take advantage of it. In sum, it is worth to point out the different design philosophies behind of these two ICs. RHA2216 is a low-power, low-noise and 16 differential channels device purely analog. The ADS1299 has comparable performance, it delivers a digital output, and it is less expensive. These two devices are valuable solutions for integration into artificial limbs controllers based in MCU and MPR, and the final selection would dependent on budget, available space on PCB, number of channels, and noise rejection capabilities.

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