Development of a New EMG Wearable Sensor for Myoelectric Control

Clive Seguna, Steve Buhagiar, Jeremy Scerri and Kris Scicluna
Institute of Engineering and Transport, Electrical and Electronics, MCAST, Corradino Hill Paola, Malta

Keywords: e-Health, Wireless, Wearable, Sensing, EMG, ECG, Telemetry.

Abstract: The application of wireless technology to monitor and record high quality real-time signals is playing an important role in today`s world. Various applications such as electromyography and electrocardiography require low-power and low-voltage portable wireless sensors for remote e-health monitoring. The use of such technology allows patients with muscle or heart problems to be monitored from the comfort of their home. Additionally, wireless implantable electromyogram sensing is also integrated in the design of intelligent myoelectric control for powered prostheses. The specifications within such applications constrain the design and development of wearable electromyographic sensors. This work presents a low-cost, portable, wireless non-invasive 8-channel system to monitor and classify electromyographic signals related to hand or finger movement. The proposed system operates at 1.0 V and draws a current of 1 mA in power-down mode. The paper also discusses the hardware and software implementation details and presents various measurement results. This work concludes through feature comparison with other similar technologies in the market.

1 INTRODUCTION

Wearable technology has been trending in healthcare and myoelectric applications for the last decade. Electromyography (EMG) sensors have been succesfully used in assistive and therapeutic healthcare. Such applications impose several challenges on the development of such wearable technology for the continuous daily health monitoring; these include small form factor, minimal power consumption, portability and extended battery life. EMG signals are distributed in a frequency range between 10 to 500 Hz. Additionally, EMG sensors are also used in motion therapies in order to track patient motion and applied forces (Nikolic, 1994), (Suster, 2007), (Cong, 2009), (Kamali, 2014).

EMG sensor which are expensive and have a large form factor are already available in the market. However, researchers are finding challenges in designing and developing low-cost, low-voltage, and small form-factor sensors that are able to detect finger and hand movement (Nair, 2010), (Lui, 2000).

Such requirements are critical for wearable and portable applications. Various EMG-based control techniques apply the use of pattern recognition, mapping techniques or models (Burke, 2004), neural nets and time domain (Nagaraju, 2010), (Benatti, 2017), (Teng, 2014) analysis for the classification of hand or finger movement (Cappellari, 2018), (Berezhnoy, 2018), (Bembli, 2019), .This work presents a new low-cost, low-voltage EMG sensor designed to classify finger and hand movement in a patient. Through the use of an LPC824 based microcontroller system and the implementation of custom signal conditioning circuitry the developed non-invasive EMG wireless sensor is able to capture and process 8 multiplexed EMG signals. The pre-processed EMG data is then trasmitted wirelessly over Bluetooth for the control and activation of a robotic manipulator. Such features makes this sensor suitable for various applications including muscle movement and myoelectric control at low-cost by just using commercial off-the shelf components. Classification of finger and hand movement is implemented through amplitude and time-domain analysis (Mert et al., 2018).

Section 2 presents the circuit design for the wireless EMG sensor. Section 3 describes the adopted time-domain procedure for the classification and detection of hand or finger movement. A detailed description related with the measurement results is given in Section 4.

Seguna, C., Buhagiar, S., Scerri, J. and Scicluna, K.
Development of a New EMG Wearable Sensor for Myoelectric Control.
DOI: 10.5220/0008979501600164
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 1: BIODEVICES*, pages 160-164
ISBN: 978-989-758-398-8; ISSN: 2184-4305

2 EMG SENSOR CIRCUIT DESIGN

This section describes the design and implementation details related with the developed EMG sensory module. The acquisition of the 8-channel EMG signals is performed through the use of wet electrodes connected in uni-polar configuration and then to an instrumentation amplifier (IA) with a common-mode rejection ratio (CMRR) of 120 dB, followed by amplification and filtering stages. This arrangement contributes to the reduction of common mode noise which is present on both electrodes while retaining the signal of interest. Further reduction in circuit design is achieved through the use of a multiplexing circuit that allows the switching between the 8-channel selectable electrode signals. The instrumentation amplifier circuitry shown in Figure 1 (gain of 3300), yields a maximum output voltage of 3.3 V peak to peak. A DC offset of 1.65 V is introduced so that the full range of the 3.3 V Analogue-to-Digital Converter (ADC) on the LPC824 microcontroller is used. The DC offset circuit is followed by an first order low-pass filter (bandwidth f_{3dB} = 15 kHz) as shown in Figure 2. The adopted LPC824 ARM based Cortex M0+ microcontroller operates through an internal RC oscillator running at 12 MHz, pre-scaled to 30 MHz using an internal PLL. Additionally, this microcontroller supports Direct Memory Access (DMA), thus enabling the processing of 14^{th} order band-pass digital filter at a sampling frequency of 1.5 kHz. The dual rail supply voltage for instrumentation amplifier is ± 5.0 V.

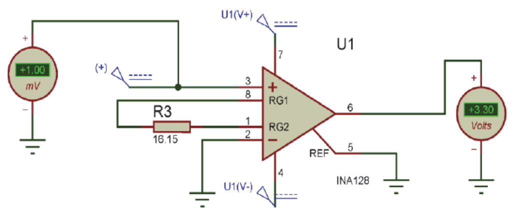

Figure 1: EMG Instrumentation Amplifier Circuit.

The TPS6122 buck-boost DC-DC converter circuitry has a minimum input voltage of 0.7 V and output voltage range of 1.8 to 5.5 V with a quiescent current of 5.5 µA.

The analog stage requires a dual rail supply, therefore a buck-boost convertor (negative supply) is used to achieve the required voltages of ± 5.0 V. The ADM8829 charge-pump voltage inverter changes the input voltage outputted from the TPS6122 device into

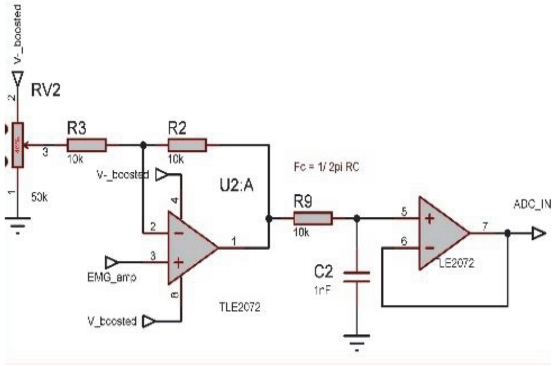

Figure 2: DC offset and Low Pass Filter circuitry.

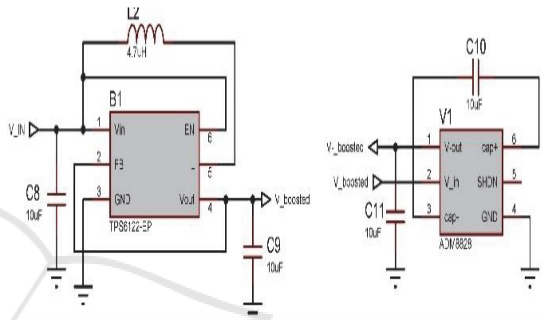

Figure 3: Buck-Boost Converter.

a negative voltage, creating a dual rail supply voltage for the IA and op-amps.

The ADG708 multiplexer is used to switch between selectable 8-channel electrodes whose output is to be sampled by the ADC, and then filtered through the 14^{th} order digital infinite-impulse response (IIR) band-pass digital filter using the LPC824 microcontroller (bandwidth $f1_{3dB}$ = 25 Hz, $f2_{3dB}$ = 225 Hz). The filtered EMG data is then transmitted from the LPC824 device to the HC06 bluetooth module and then received by a wireless client device.

The maximum switching time in between multiplexer channels is 14 ns when running on 5 V and a typical power consumption of 1 µA.

Figure 5 illustrates the top and bottom views for the manufactured system with a small form-factor of 33 by 20 mm. Two switch push-buttons, are used to program the microcontroller. The internal LPC824 direct Memory Access (DMA) module allows transfer of digital EMG data at a high transfer rate with the intervention of very few CPU cycles. Test pins were included in the module so to directly monitor and record the amplified and filtered EMG signals through an oscilloscope.

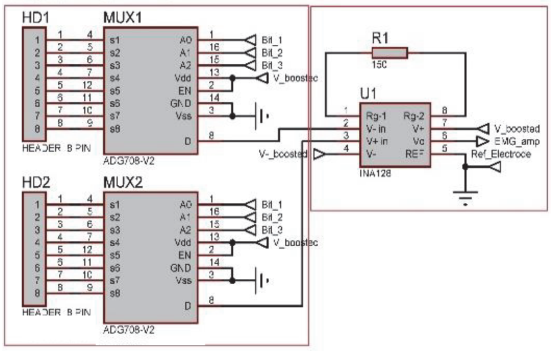

Figure 4: INA128 and multiplexing stage.

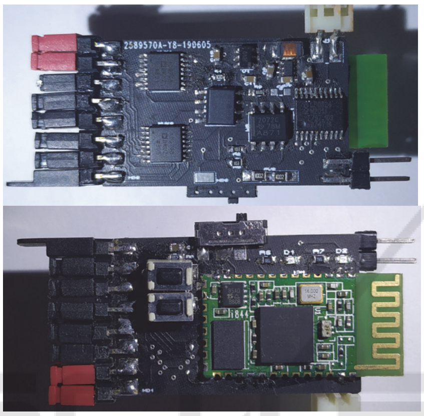

Figure 5: Top and bottom view of the wearable EMG sensor with dimension 33mm by 20 mm.

3 EMG SENSOR CLASSIFICATION

Analysis of EMG signals was performed using two pairs of electrodes placed over the forearm muscle, which is mostly active when moving the arm wrist. The raw EMG signal was processed through root mean square calculation. Classification of wrist and hand movement was done through time-domain amplitude analysis. A system calibration procedure shown in Figure 6 allows the recognition of wrist or hand movement via amplitude analysis. The implementation for amplitude analysis identifies and configures the thresholds measured when certain hand gesture movements are made. Calibration process follows electrode placement. This process consisted of contracting the wrist in three different positions multiple times and one at a time. With each contraction, the amplitudes acquired from all electrodes being recorded. This process was repeated for a pre-defined amount of repetitions so to establish the required thresholds. The amplitude analysis is performed prior to the signal being filtered and then Root Mean Squared; a moving average can be applied to the signal if needed.

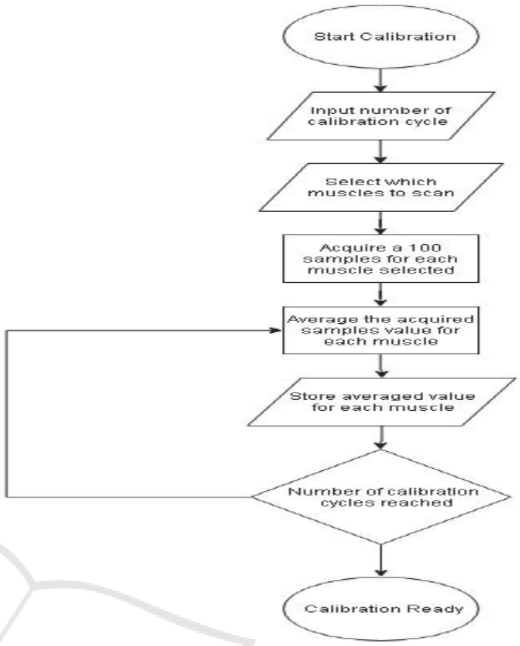

Figure 6: Calibration Procedure for the classification of hand movement.

4 MEAUREMENT RESULTS

An illustration of the amplified raw, DC shifted EMG signal for various hand movements is shown in Figure 7. This signal represents the electrical currents generated by the muscle activity being controlled by the nervous system and is also depended on the anatomical and physiological properties of the muscles. Additionally, the shown EMG signal in Figure 7 has been filtered from noise being generated from various tissues. For testing purposes, a 3D-printed five degrees of freedom robotic manipulator is to be controlled through six analogue or PWM inputs located on the robot controller.

The acquired EMG myoelectric signals from 4 different channels are shown in Figure 8. The calibration procedure was performed for adaptively setting the required channel amplitude thresholds needed for the classification of three hand movements. Classification data is wirelessly transmitted to a bluetooth client device located on the robotic manipulator and controlled using an embedded controller.

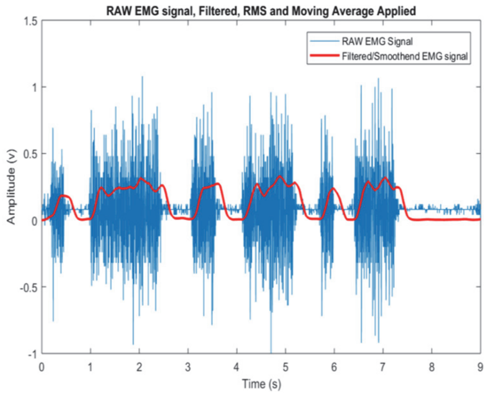

Figure 7: Amplitude response of filtered and smoothened Raw EMG signal.

Examples of three different classified hand motions are shown in Figure 9. The fist motion will control the opening and closing of the claw actuation, while two other hand movements rotates are used to control the angular position robotic arm that is clockwise or counter-clockwise. The same classification procedure has also been tested and adopted for the classification of finger movement. Through exstensive experimentation repetitive measurement and performance results were noted.

5 DISCUSSION AND CONCLUSION

In this work, the successful development of a low cost and wearable 8-channel sEMG data acquisition system was presented along with the implementation of an adaptive threshold setting algorithm for the classification and contraction detection of hand or wrist movement. A feature comparison of the proposed system with other similar sEMG sensors including commercially available products in terms of bandwidth, operating voltage, size, and contraction detection is shown in Table 1. Such comparison, illustrates that the developed non-invasive wearable sEMG sensor has the smallest form factor operates and operates at a low supply voltage of 1.0 V using just one single-cell AAA battery. The developed EMG sensor has also a very low weight of 6 grams, four times less when compared to other similar work.

Additionally, through exstensive testing and from the illustrated measurement results the threshold setting amplitude analysis classification algorithm is satisfactorily detects contractions and recognizes wrist or finger movement.

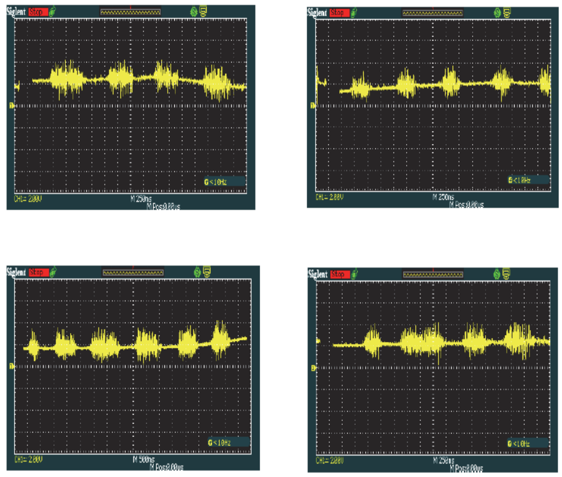

Figure 8: EMG measurements for four EMG channels (mV versus time ms).

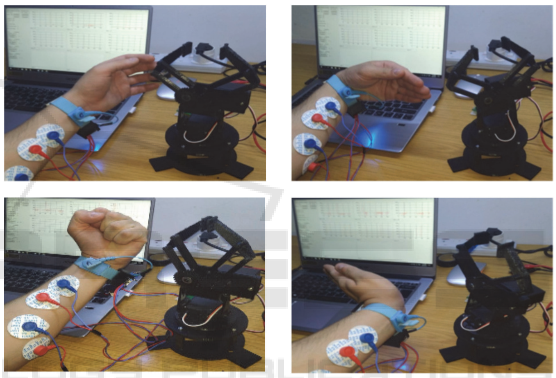

Figure 9: Control of robotic manipulator through developed EMG sensor.

Table 1 : Comparison with other similar Systems.

	This work	sEMG Sensor (Seguna, 2018)	Myo Armband	Hercules (Mert, 2018)
Classification of Hand/Finger Movement	Yes	Yes	No	No
Contraction Detection	Yes	Yes	No	Yes
Wearable	Yes	Yes	Yes	Yes
Bandwidth (Hz)	1200	20-589	-	20-500
Supply Voltage	1.0 V	2.5 V	3.7 V	3.7 V
Dimensions L x W (mm)	20 x 33	45 x 25	190 x 340	-
Weight (grams)	6	24	93	-
Battery Type	AAA (x1)	-	Built-in lithium Ion	AA (x2)

REFERENCES

Nikolic, R., et al.,“Instrumentation for ENG and EMG recordings in FES systems”, IEEE Trans. Biomedical Engineering, v. 41, nr. 7, pages 703-706, 1994.

Suster, M., et al., “A Wireless Strain Sensing Microsystem with External RF Powering and Two-Channel Data Telemetry Capability,” ISSCC, 2007, pages 380-381.

Cong, P., et al., “A Wireless and Batteryless 130 milligram 300µW 10-bit Implantable Blood Pressure Sensing Microsystem for Real-time Genetically Engineered Mice Monitoring”, ISSCC, 2009, pages 428-429.

Kamali, T., et al., ,“A multi-classifier approach to MUAP classification for diagnosis of neuromuscular disorders,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 22, no. 1, pages 191–200, Jan. 2014.

Nair, S., et al., “The application of machine learning algorithms to the analysis of electromyographic patterns from arthritic patients,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 18, no. 2, pages 174–184, Apr. 2010.

Liu, W. and Humayun, M. S, “Retinal Prosthesis”, ISSCC, 2004, pages 218 – 225.

Burke, M., et al., “A micropower dry-electrode ECG preamplifier,” Biomedical Engineering, IEEE Transactions on, vol. 47, 2000, pages 155 –162.

Nagaraju, M., et al., “Circuit techniques for wireless bioelectrical interfaces,” in 2010 International Symposium on VLSI Design Automation and Test (VLSI-DAT), 2010, pages 117 –120.

Benatti, S., et al., “A prosthetic hand body area controller based on efficient pattern recognition control strategies,” Sensors, vol. 17, no. 4, pages 2-17–4-17, 2017.

Teng, S., L, et al., “Programmable EXG biopotential front-end IC for wearable applications”, IEEE Trans. Biomed. Circuits Syst., vol. 8, no. 4, pages 543–551, Aug. 2014.

Cappellari, P., et al., “Identifying Electromyography Sensor Placement using Dense Neural Networks”, in Proceedings of the 7th International Conference on Data Science, Technology and Applications – pages 130-141, 2018.

Berezhnoy, V., Popov D., Afanasyev I. “The Hand-gesture-based Control Interface with Wearable Glove System”, in Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics - Volume 2: ICINCO, pages 458-465, 2018.

Bembli, S., et al., “A Terminal Sliding Mode Control using EMG Signal: Application to an Exoskeleton-Upper Limb System”, in Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics - Volume 2: ICINCO, pages 559-565, 2019.

Seguna, C., et al., “Development of a New Low-Cost EMG Monitoring System for the Classification of Finger Movement”, 2018 New Generation of CAS (NGCAS), pp. 126-129, 2018.

Mert, E., et al., “An Embedded, Eight Channel, Noise Cancelling, Wireless, Wearable sEMG Data Acquisition System with Adaptive Muscle Contraction Detection”, IEEE transactions on biomedical circuits and systems, 2018.