Reconfigurable Analog Classifier For Knee-Joint Rehabilitation

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***Abstract*— We present a System-On-Chip Field Programmable Analog Array (FPAA) for analyzing and processing the signals off an accelerometer for a wearable joint health assessment device. FPAAs have been shown to compute with an efficiency of 1000 times, as well as area efficiencies of 100 times, more than digital solutions. This work presents a low power signal processing system which allows us to extract features from the output of the accelerometer. These features are used by the classifier, implemented using a vector matrix multiplication and a two output 1-winner-take-all, to detect flexion and extension cycles in the subject. The compiled design consumes 0.636 μW of power for the front end analog signal processing chain where as the single layer classifier uses 13 μW of power. Thus the system is highly suitable for wearable applications where power consumption is a major concern. The current FPAA is fabricated in a 0.35 μm CMOS process and is operated at a power supply of 2.5 volts. The Gm-C filters and other circuits are operated in the subthreshold regime of the transistor to obtain the highest transconductance to current ratio offered by the process.**

I. Reconfigurable Analog Processing for Wearable Devices

The paper presents a low power System-On-Chip (SOC) to interface with accelerometers and analyze and classify the data so as to make a decision on whether to enable a system which performs a real-time knee-joint health assessment [1] [2]. Joint disorders are one of the leading causes of disability among adults particularly active adults such as athletes and soldiers [3] [4]. Currently the assessment of knee-joint rehabilitation requires frequent physical exams which are subjective. Thus a non-invasive system which could operate outside the clinic could be highly beneficial for a faster recovery and could lead to improved therapies tailored towards the need of the patients.

A promising signal modality to analyze the knee-health condition non-invasively is joint sounds [5] [6]. In previous efforts using joint sounds to probe the status of the knee-joint health, various time- and/or frequency-domain features from acoustical emissions from the knee-joint under motion are extracted and through sophisticated off-line digital-signal-processing techniques such as single classifiers (e.g., classification using neural networks in [7]) or ensemble of classifiers (e.g., least-squares support-vector-machine fused with dynamic weighting in [8]), variability of the joint-sound features as well as correlation between the features and knee-health-status have been investigated. More recently we have shown that, for a given healthy-knee high-frequency acoustical features, namely clicks, of joint-sounds consistently occur at similar knee-angle locations for a variety of activities [2]. A distribution pattern of the clicks over the range of knee-angle, and an output measure based on the changes in the pattern due to knee-disorders could be a promising metric for the knee-health. To generate such a metric based on different activities and therefore different loading conditions and range-of-motions of the knee, a wearable system that can operate for hours throughout the day while the subjects perform daily activities is required.

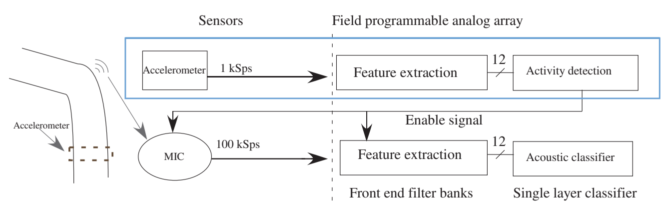

Fig. 1. The figure shows an overview of the knee joint rehabilitations system. The primary chain which is implemented in this work is highlighted in blue. The front end signal processing chain and the one layer neural network is implemented on a FPAA to detect the activity in the subject. The activity detector generates an enable signal for MEMS/piezoelectric microphone to start recording.

One major challenge towards designing such a system is the large power consumption associated with high data-rates required (f$\geq$50 kSps) to minimize information loss during the acquisition of knee-sounds. In fact, we have recently shown that a high sampling-rate data-acquisition system having a wearable form-factor can operate only for several hours for recording knee-sounds and inertial data for the knee-joint. It should be noted however that, most activities valuable in regards of knee-sound-emissions last for less than $\approx$15-20 sec. Therefore, by limiting the operation of a power-hungry data acquisition system to only these valuable activities, as long as the activity-detection could be achieved in a power-efficient manner, a system as such could be operated for days with limited or no user input. In this paper, towards achieving the ultimate goal of classifying a number of activities, we present an early version of a very-low-power real-time activity-classifier that can classify flexion-extension and sit-to-stand activities.

This work shows a system which could perform feature extraction from multiple sensors and process and analyze the data locally with very low power consumption. Fig. 1

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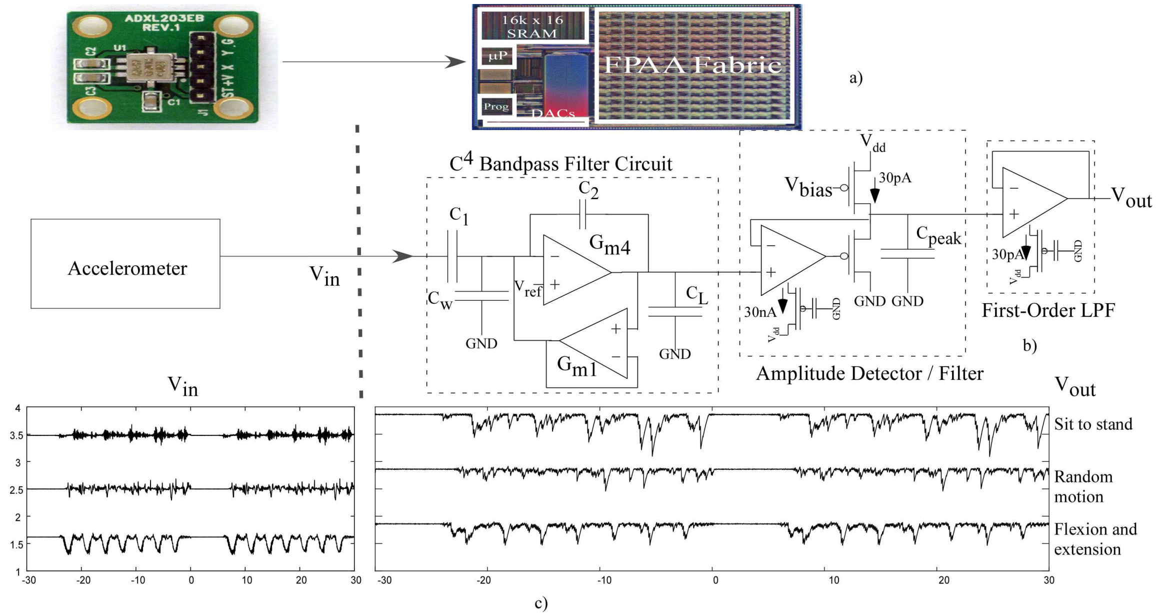

Fig. 2. a) Die photograph of a field programmable analog array and the dual axis accelerometer. b) The figure shows a signal processing chain to extract the average signal spectrum. The frond end is composed of 12 tap bandpass filters, with a Q=2 and frequencies scaled evenly from 700 mHz to 15 Hz, a amplitude detect and a low pass filter. c) The output of the accelerometer is recorded for three different activities by the subject. The output response of the fifth channel of the band pass and amplitude detect is shown.

shows a block diagram of the proposed system building on the previous work [1] [2]. The system consists of a low power signal processing chain which extracts the average of the signal spectrum and a classifier using Vector Matrix Multiplication (VMM) and Winner-Take-All (WTA). Here a dual axis accelerometer, ADXL203 from Analog Devices, is used for monitoring the activity of the subject. This work uses just one axis (x-axis) of the accelerometer for measurement. The accelerometer has a low sampling rate as opposed to the output of the MEMS and piezoelectric microphone and hence the system could operate at lower frequency and lower power compared to the signal chain of the microphone. Thus the accelerometer signal chain could be used to detect the activity and in turn enable the recording of acoustical emission from the knee joint via a microphone.

II. Signal Processing on FPAA

The signal chain used for the signal processing is designed and compiled on a Field Programmable Analog Array [9]. FPAA is a fully reconfigurable mixed signal integrated circuit which uses floating gate to program the design in a non volatile fashion. The FPAA consists of low power MSP430 microprocessor for programming the floating gates and communicating via a universal serial bus. These large-scale FPAA enables analog computation with energy efficiencies of 1000 as well as area efficiencies of 100 over digital solutions [10]. Such high efficiency allows us to effectively use these FPAAs in wearable devices where low power computation is a necessity. Also reconfigurability of signal processing chain allows us to account for the mismatch in the system and compensate for the changes due to temperature. This is significant because this allows for robust computation when the device is deployed in the field.

TABLE I

Power consumption of the front end

Component	Power (W)
Band Pass (C4)	36 nW
Amplitude Detect	0.3 μW
Low Pass Filter	0.3 μW
Total	0.636 μW

The front end consists of 12 Gm-C filter banks followed by amplitude detect and a low pass filter. A more detailed analysis of linearity, distortion and dynamic range of the second order band pass filter can be found in [11]. The band pass filter have their frequencies evenly scaled from 700 mHz to 15 Hz with a quality factor of 2. As shown in the Fig. 2b the output of the band pass is passed through a minimum detector and low corner low pass filter. The accelerometer is used to monitor different activities of the subject under a control environment. Fig. 2c shows the output of the accelerometer during flexion and extension, walking, and sit to stand activities. These outputs are then passed through the front end signal processing chain implemented on the FPAA. Fig. 2c shows the response of the fifth channel, from 12 parallel channels, to these activities. The bandwidth of the low pass filter could be further reduced to have a smoother response at the output. The power consumption of the front-end processing chain is summarised in the table I. Power is of the compiled front end analog processing circuit, that is the filter bank chain, used for feature extraction.

III. Vector Martix Multiplication and Winner-Take-All

There has been significant efforts for using machine learning and neural network to perform accurate diagnosis and/or prognosis [12]. But most of this work involves performing data acquisition and analyzing it off chip, using clusters of servers, which usually require large storage and bandwidth for transmission. Such a method would not scale, when taking into account multiple devices generating data from multiple users. Thus there is a need for a robust as well as low power computing method which could effectively be used on a wearable device.

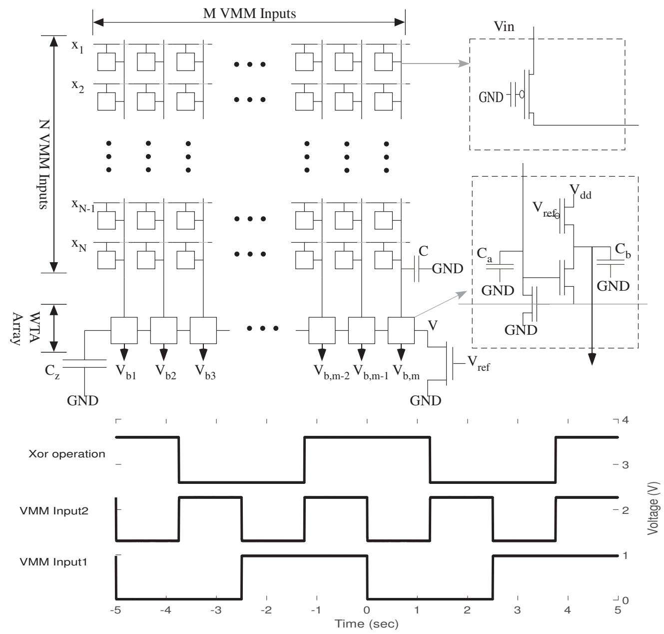

Fig. 3. a) Shows a general NxM VMM and WTA. The weights for the classifier are implemented using the charge on the floating gate of the transistor. Input is at the source of the floating gate transistor. b) The figure shows the output of 3x3 VMM-WTA implementation of an XOR function)

Classification on FPAA has been shown to be power efficient and robust [9]. A single layer VMM and WTA is a universal approximator, in that it can be used to perform a XOR functionality. The VMM is implemented in the routing fabric of the FPAA thus allowing for a high area density. Fig. 3a shows a generic NxM VMM block and WTA. The multiplication is performed by storing the charge onto the gate of the floating gate transistor, which are part of the routing fabric and work as a switch during normal operation but could be target programmed when required [13]. The weight update on the VMM follows the simple transistor equation in subthreshold regime given by equation 1.

$$\begin{aligned} I_s &= I_{th} e^{\frac{\left(\kappa_p (V_{dd} - \Delta V_{fg} - V_{T0})\right)}{U_T}} e^{\frac{(V_{dd} - V_{in})}{U_T}} \qquad (1) \\ I_s &= I_{th} e^{\frac{\left(\kappa_p (V_{dd} - \Delta V_{fgref} - V_{T0})\right)}{U_T}} W e^{\frac{(V_{dd} - V_{in})}{U_T}} \\ W &= e^{\frac{\left(\kappa_p (V_{dd} - \Delta V'_{fg})\right)}{U_T}} \end{aligned}$$

Here κ_p is the fractional change in the pfet surface potential due to change in $\Delta\ V_{fg}$, U_T is the thermal voltage. Here ΔV_{fg} which is the charge on the floating gate is given by $\Delta V_{fg} = \Delta V_{fgref} + \Delta V'_{fg}$. So the weight of the VMM is given by the change in $\Delta V'_{fg}$ and is adapted using electron injection where as Fowler-Nordheim tunneling is used as global erase. V_{in} is the source voltage of the pfet transistor and is used as an input to the matrix. The output of the VMM is a current signal and is an input to the winner-take-all circuit, first introduced by Lazzaro et. al. [14], to perform classification. The output of the Fig. 3b shows a XOR functionality performed by the single layer of VMM and WTA.

IV. Single Layer Classification

Fig. 4 shows the output for the proposed system. A vectorized representation of the signal chain, the way it is implemented in the open source FPAA design tools [15], is shown in the Fig. 4a. A shift register, controlled using general purpose input/output registers of the MSP430 microprocessor, is used to characterize the signal processing chain. The root mean square voltages of the 12 filter banks for two different activities is plotted in the Fig. 4b.

The weights for the VMM were adapted outside and programmed on the floating gate. Here a 12x2 VMM-WTA is implemented for detecting flexion and extension cycles. Instead of implementing a K-WTA, which could have K winners, the winner-take-all circuit is designed to have just one winner. Due to the particular topology of the winner-take-all the output is low when it wins. For the purpose of testing, a dataset consisting of accelerometer output during flexion and extension cycles and sit to stand cycle was created. This dataset was passed through the signal processing chain and a single layer of VMM-WTA. As seen in Fig. 4c WTA1 has its weights programmed to the values where it wins when there is no flexion and extension cycles and WTA2 is where the detection takes place. Due to finite sampling of the oscilloscope for the time scale used in Fig. 4c some of the wta wins are not captured correctly which can be seen clearly in the experiment performed with the smaller time scale in Fig. 4d. The VMM-WTA structure with its adapted weights, for which the detection takes place, consumes 13 μW of power.

V. Discussion

We present a system which classifies the signal from an accelerometer and consumes 13.63 μW of power. The system is designed and compiled on a field programmable analog array fabricated on a 0.35 μm CMOS process. Reconfigurability of these ICs allows us to compensate for the mismatch and temperature variation. The compiled signal chain is shown to efficiently detect the flexion and extension cycle of the knee-joint, by processing and classifying the output of the accelerometer. Multiple band pass and amplitude detect circuits are used to extract the features, average signal spectrum, from the data. These features are used by a single layer VMM and WTA circuit to perform classification.

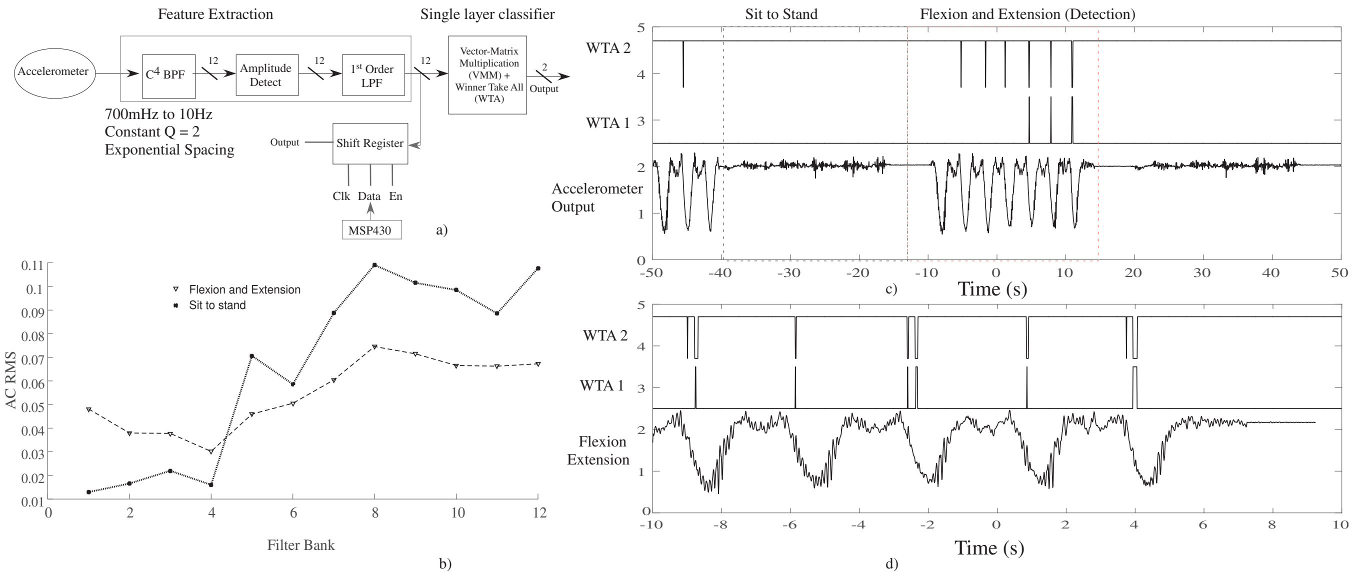

Fig. 4. a) Shows the signal chain used to characterize the output of the accelerometer. Shift register is used to scan out the 12 channels of the front end. Shift register is controlled by general purpose input/output registers from the MSP430 processor on the IC. b)The figure shows AC RMS of two different activities performed by the subject. c) A dataset of two activities, sit-to-stand and flexion detection, was created with goal of detecting flexion and extension cycles in the subject. WTA1 is clustered around a null and wins when the subject is not performing flexion and extension cycles. WTA2 output corresponds to detection of flexion and extension cycles. d) Figure shows the detection of flexion and extension cycles on a smaller time scale.

The low power consumption of the system allows us to operate it and collect the data for several days while the subject performs their daily activities. Also, this signal processing chain would work in conjunction with the acoustic recording of knee-joint sounds via a MEMS/piezoelectric microphone. Future work and direction would be to feed the system with data from several subjects and allow it to process, analyze and classify the data. Training the weights using the data from several subjects will make the system more robust and reduce the rate of errors. A similar signal processing chain could be used to analyze the acoustic data from the microphone, to classify the clicks and sounds from the knee-joint. We believe that the whole system would lead to a better and more precise assessment of the knee-joint and which could lead to tailoring the rehabilitation process towards the need and activities of the patients.

REFERENCES

[1] C. N. Teague, S. Hersek, H. Treyin, M. L. Millard-Stafford, M. L. Jones, G. F. Kogler, M. N. Sawka, and O. T. Inan., "Novel methods for sensing acoustical emissions from the knee for wearable joint health assessment," *Transactions on Biomedical Engineering*, 2016.

[2] H. Treyin, H. K. Jeong, S. Hersek, C. N. Teague, and O. T. Inan, "Quantifying the consistency of wearable knee acoustical emission measurements during complex motions," *IEEE Journal of Biomedical and Health Informatics*, In press.

[3] M. Majewski, H. Susanne, and S. Klaus, "Epidemiology of athletic knee injuries: A 10-year study," *The knee*, vol. 13, pp. 184–188, 2006.

[4] G. S. Smith, A. L. Dannenberg, and P. J. Amoroso, "Hospitalization due to injuries in the military. evaluation of current data and recommendations on their use for injury prevention," *Am. J. Prev. Med.*, vol. 18, pp. 41–53, 2000.

[5] Y. Wu, S. Krishnan, and R. M. Rangayyan, "Computer-aided diagnosis of knee-joint disorders via vibroarthrographic signal analysis: a review," *Crit. Rev. Biomed. Eng.*, vol. 38, pp. 201–24, 2010.

[6] R. Mollan, G. McCullagh, and R. Wilson, "A critical appraisal of auscultation of human joints," *Clinical orthopaedics and related research*, vol. 170, pp. 231–237, 1982.

[7] Y. Zhang, R. Rangayyan, C. Frank, G. Bell, K. Ladly, and Z. Liu, "Classification of knee sound signals using neural networks: a preliminary study," *Proceedings of IASTED Int Symp Expert Systems, Honolulu*, pp. 60–2, 1990.

[8] S. Cai, S. Yang, F. Zheng, M. Lu, Y. Wu, and S. Krishnan, "Knee joint vibration signal analysis with matching pursuit decomposition and dynamic weighted classifier fusion," *Computational and mathematical methods in medicine*, 2013.

[9] S. George, S. Kim, S. Shah, J. Hasler, M. Collins, F. Adil, R. Wunderlich, S. Nease, and S. Ramakrishnan, "A programmable and configurable mixed-mode FPAA SOC," *Accepted to IEEE Transactions on VLSI*, Oct 2015.

[10] J. Hasler and H. B. Marr, "Finding a roadmap to achieve large neuromorphic hardware systems," *Frontiers in Neuroscience*, vol. 7, no. 118, 2013.

[11] D. W. Graham, P. E. Hasler, R. Chawla, and P. D. Smith, "A low-power programmable bandpass filter section for higher order filter applications," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 54, no. 6, pp. 1165–1176, June 2007.

[12] W. G. Baxt, "Use of an artificial neural network for the diagnosis of myocardial infarction," *Annals of Internal Medicine*, vol. 115, no. 11, pp. 843–848, 1991.

[13] S. Kim, J. Hasler, and S. George, "Integrated floating-gate programming environment for system-level ics," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. PP, no. 99, pp. 1–9, 2016.

[14] J. Lazzaro, S. Ryckebusch, M. Mahowald, and C. A. Mead, "Winner-take-all networks of o(n) complexity," in *Advances in Neural Information Processing Systems 1*, D. Touretzky, Ed. Morgan-Kaufmann, 1989, pp. 703–711.

[15] M. Collins, J. Hasler, and S. George, "An open-source tool set enabling analog-digital-software co-design," *Journal of Low Power Electronics and Applications*, vol. 6, no. 1, p. 3, 2016.