A Proof-of-Concept Classifier for Acoustic Signals from the Knee Joint on a FPAA

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***Abstract*—A proof-of-concept low-power analog classifier for assessing acoustic signals from the knee joint on a reconfigurable Field Programmable Analog Array (FPAA) is presented in this paper. Knee joint sounds are measured using piezoelectric (contact) microphones and processed using the front end analog filters. A single layer of neural network composed of Vector Matrix Multiplication (VMM) and Winner-Take All (WTA) is used for the classification. A simple classifier detecting an anterior cruciate ligament injury is implemented here. Measurement from a single subject's healthy and injured knees are used here as an input. The FPAA is fabricated in a 350nm CMOS process. A bank of 12 parallel filters is used for feature extraction and a 12x2 VMM-WTA is used as a classifier. The compiled system, front-end and the classifier, consumes a power of 15.29μW with a power supply of 2.5 V.**

I. Signal Processing for Wearable Devices

Knee injuries, ranging from simple sprains to ligament tears, are widely prevalent among all ages of Americans. Current techniques for assessing knee joint rehabilitation involve multiple visits to a clinic. To reduce strain on the health care system and to perform continuous monitoring of the subject, there has been work towards using wearable devices as a non-invasive method for assessing the health information of the knee [1]. It has been shown that acoustical signals could be used to non-invasively measure in-depth information about joint health [2][3]; wearable devices with embedded acoustical sensors placed around the knee could thus be used as a point-of-care solution for potentially enabling personalized treatment for the patients.

Such approaches could greatly benefit from the use of on-board, real-time classifiers for allowing information regarding knee health to be presented to the user and care-giver alike. From a classification point of view, there has been significant progress in implementation of neural networks and machine learning partly due to the availability of faster devices and partly due to innovation in algorithms. They have been effectively used to solve problems in the field of speech processing, computer vision, and big data to name a few. They have also shown promising results in the field of bioengineering and biomedicine to perform medical diagnosis and prognosis [4]. However, most of this work involves performing data acquisition and analyzing it off chip which usually require large storage and bandwidth for transmission. Such a method would not scale, when taking into account multiple devices generating data for multiple users. Thus a system which could perform efficient and robust computation is necessary where the data could be analyzed and processed locally and in real time.

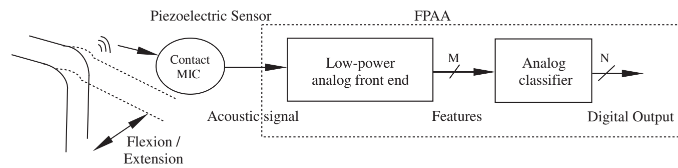

Fig. 1. Top level of the proposed acoustic classifier. The system is compiled on the FPAA. The output of the analog front end and the classifier are vectorized. In this work M is 12 and N is 2. In general, reconfigurability offered by the FPAA allows N and M to be a variable depending on the application.

This work presents a proof-of-concept low-power analog classifier for knee joint health assessment compiled on a large scale reconfigurable FPAA [5]. The system can be used for real time signal processing with very low power consumption. The classifier is used to automatically separate acoustical signatures for a joint with an acute ($<$ 7 days prior) Anterior Cruciate Ligament (ACL) tear compared to the healthy, contralateral side. A piezoelectric sensor (SDT, Measurement Specialties, Hampton, VA) is used as a contact microphone to measure these acoustic emissions. Measurement from a single subject are used as an input for the analog classifier. A top level block diagram of the proposed system is shown in Fig. 1. The contact microphone recorded an acoustic signal while the subject performed unloaded, seated flexion / extension of the knee. These signal are analyzed by the compiled system comprising of 12 parallel second-order band pass filter, amplitude detectors, LPFs and a single layer classifier implemented using VMM-WTA. The WTA used in this work has a digital output and could be easily stored.

II. Reconfigurable SoC

Floating gate FPAAs offer reconfigurability and programmability which allow for low-power computation with high efficiency [5]. Floating gate can be programmed to a target current using hot-electron injection and erased using Fowler-Nordheim tunneling. FPAA consists of Computational Analog Blocks (CAB) and Computational Logic Blocks (CLB) and are connected using manhattan style routing. CAB consists of several OTAs, NFET current mirrors, transmission gates, and capacitors which could be routed globally and locally. Programming infrastructure is composed of DACs and ADCs which measure and control the FG transistors. These DACs

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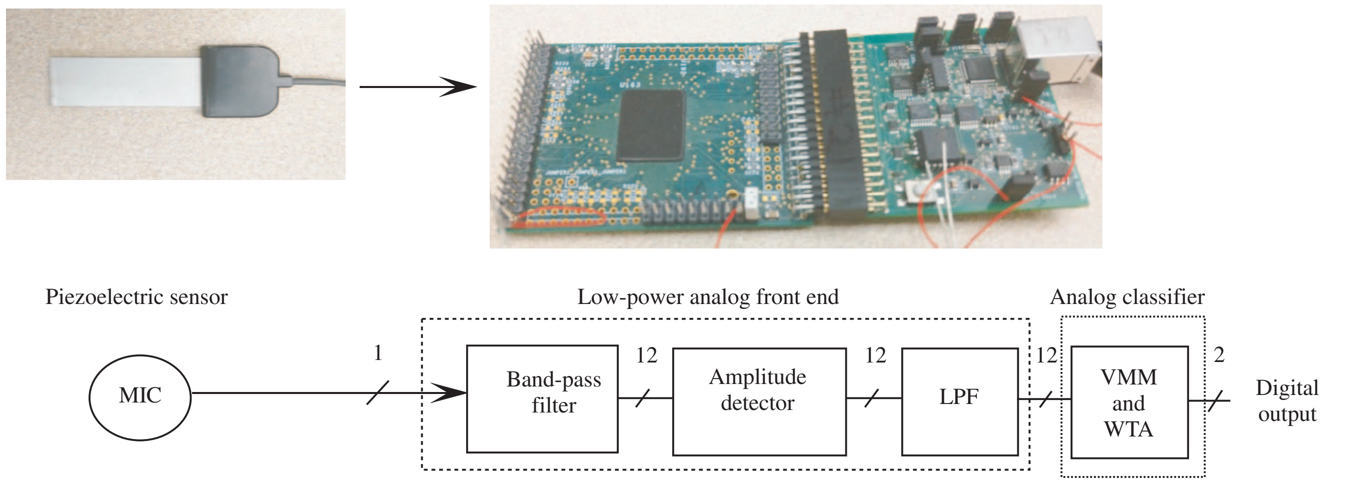

Fig. 2. General architecture of the compiled system. A contact microphone (piezoelectric sensor) is used to record the acoustic signals. The front-end analog chain is compiled on the FPAA. Front-end is composed of 12 parallel band-pass filters, amplitude detectors, and LPFs. The features extracted by the front-end are used by a single layer of VMM-WTA.

and ADCs could be routed to the FPAA fabric to work as a arbitrary waveform generator and data acquisition. A shift register which is a part of the routing infrastructure could be used for observing and measuring multiple outputs and inputs.

Figure 2 shows a general architecture of the compiled system on the chip. Acoustic signals from the piezoelectric sensor are analyzed and processed for relevant features. Analog front-end comprising of 12 parallel band-pass filter, minimum detector and Low Pass Filter (LPF) is compiled on the FPAA, using an open source open-source Xcos/Scilab tools [6]. In this work a band-pass filter is designed using a G_m-C OTA, a capacitively coupled current conveyer (C^4) structure, present as a part of the CAB elements. Inputs of the OTA has a floating gate, coupling through a capacitor, which allows for a higher dynamic range and input offset compensation at the cost of reduced gain. The second-order band-pass filter have a programmable G_m which allows us to control the higher frequency and lower frequency pole. They were programmed to have a Q of 2 and with a gain of 10 dB. The band-pass filter extracts the features, in this case the frequency content, from an acoustic signal and this forms an input to the amplitude detector. The amplitude detector measures the minimum amplitude of the signal. The amplitude detector are tuned to work with a bandwidth of 5 kHz. The LPF is biased to have a cut-off of 100 Hz, which allows us to reduce the ripples caused by the minimum detector. Current biases for all the OTAs are set using a floating gate PFET transistor which could be programmed to a target current value. All the elements of the analog front-end are biased in subthreshold regime to reduce the power consumption of the system. The front-end consumes a power of 3.096μW. Where the power consumed by 12 band pass filters is 36.3nW and the LPFs consume 60nW. Amplitude detectors consume a power of 3μW, because they are biased to operate at higher bandwidth.

A single layer analog classifier, composed of Vector Matrix Multiplication (VMM) and Winner Take All (WTA) uses the features extracted by the analog front-end for classification. In this system, a simple classifier is designed which detects the presence of ACL injury in the knee joint. Reconfigurability of a FPAA allows compiling a NxM VMM in the routing infrastructure. The FG transistors in the routing infrastructure are used to store the weights of the classifier by storing a charge on the floating node. Subthreshold current in a PFET floating gate is given by $I_s = I_{th} e^{\frac{\left(\kappa_p(V_{dd}-\Delta V_{fgref}-V_{T0})\right)}{U_T}} W e^{\frac{(V_{dd}-V_{in})}{U_T}}$ where U_T is the thermal voltage, κ_p is the fractional change in PFETs surface potential with change in V_{fg}, V_{T0} is threshold voltage, and the weight $W = e^{\frac{\left(\kappa_p(V_{dd}-\Delta V_{fg})\right)}{U_T}}$. Source of the FG PFET transistor is used as an input (V_{in}) to the VMM. Here a 12x2 VMM is used for the classification. Current output of the VMM is compared using WTAs, which is a current comparator with non-linear properties [7]. A 1-WTA, which could only have a single winner, is used instead of K-WTA which could have multiple winners. The design of WTA is such that it wins with a zero and loses with a one at the output.

III. Classification of ACL injuries

A single layer VMM-WTA can be used to perform non-linear classification, such as a XOR classification [7]. In this work, a single layer of 12x2 VMM-WTA is used to design a classifier for detecting the presence of ACL injury prior to reconstructive surgery. Figure 3 shows the recording system and sensor placement during subject testing. Recording from a single subject with an injured and healthy knee is analyzed and used an input to the FPAA system.

Acoustic recording of a healthy and a injured knee is passed through the analog front-end, and their outputs are used for training the weights of the VMM. Inputs to the VMM are observed using a 16-bit shift register on the chip. The training of the VMM is done off-chip by clustering the weights around their input. The FG PFET transistors in the VMM are biased in subthreshold regime to reduce the power consumption. The schematic of the 12x2 VMM-WTA is shown in Fig. 3. A common bias for the WTAs is generated using a FG PFET transistor and a NFET current mirror.

A dataset comprising of the injured and healthy knee was created for the purpose of testing the classifier. Figure 3 shows

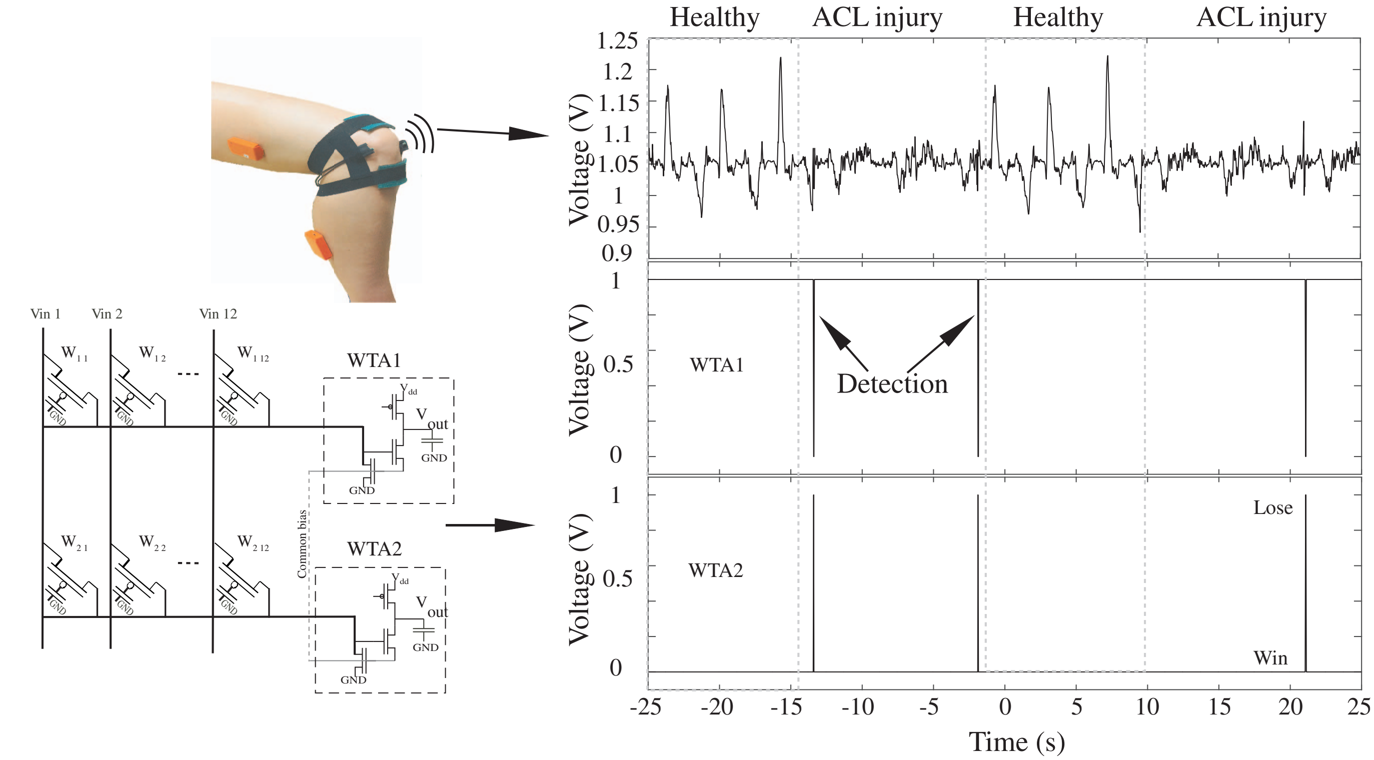

Fig. 3. Output of VMM-WTA along with recording and sensor placement. Two 1-WTA are used for the classification of ACL injury. The data was recorded from a single subject having a ACL injury on one of the knees. WTA1 predicts the injury by winning when an injured acoustic signal is presented to it. WTA2 wins when the signal is from a healthy knee joint.

part of the dataset being used for testing the classifier. WTA1 detects when it is presented with features from an injured knee whereas WTA2 wins for the rest of the input. The classifier consumes a power of 12.2μW. The buffers used at the output of the WTA, to drive I/O pads, consumes a power of 10μW and dominates the power consumption of the classifier.

IV. Discussion

In this work, we show a proof-of-concept low-power analog classifier compiled on a large-scale SoC FPAA. This work shows that such a system could classify acoustic signals, that are recorded using a contact microphone (piezoelectric sensor). These signals are analyzed and processed through a analog front-end, and the features are extracted. These extracted features are used by a single layer VMM-WTA for classification. A dataset comprising of both injured and healthy is used to test the classifier. The system consumes a power of 15.29μW with a power supply of 2.5 V.

In general, such a system can be scaled to work in real time for detecting and classifying the knee joint sounds, assessing the knee-health and rehabilitation. Patterns of the clicks over the range of knee angle and an output measure based on the changes of thes pattern due to knee-disorders could be a promising metric for the knee-health. For generating such a metric based on different activities, loading conditions, and range-of-motions of the knee, a wearable system that can operate for several hours while the subjects perform daily activities is required. An activity detector, shown in [3], could be used in conjunction with our system. This would allow us to reduce the power consumption by only recording when relevant activity is being performed.

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