“ML using micro-electromechanical system (MEMS)”

Fadi Alsaleem, Ph.D – University of Nebraska - Lincoln

May 31, 2022
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* as of March 28, 2022; several more under final reviews
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<table>
<thead>
<tr>
<th>Date</th>
<th>Presenter</th>
<th>Topic / Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friday, July 3</td>
<td>Peter Ing, Senior Mechatronics Engineer, TFG Ambassador, Edge Impulse</td>
<td>TinyML South Africa Meetup Kickoff 2022</td>
</tr>
</tbody>
</table>

Webcast start time is 8:00 am Pacific time

Please contact [talks@tinyml.org](mailto:talks@tinyml.org) if you are interested in presenting
Reminders

Slides & Videos will be posted tomorrow

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Dr. Alsaleem joined the college of engineering at the University of Nebraska at Lincoln (UNL) in August 2016. Before this assignment, he worked for multiple years in the industry including four years as a Senior Lead Algorithm Engineer at Emerson Electric Inc to develop novel (cloud-based) sensor monitoring and learning algorithms used for fault diagnostics for mechanical systems. His current and future potential research goals are to vertically advance the fields of intelligent wearable sensing technologies and artificial intelligence algorithms and their use in many health and medical applications. In this research area, he has more than 10 awarded patents, more than 100 publications, presentations, and invited talks, and over 6 million total (near 1.5 million to his research team) of active funding to support his research work.
Objective: Develop ultra-power computing unit for tiny devices such as wearable devices to locally perform machine-learning algorithms.

How: The algorithms will be coded in the mechanical responses of multiple MEMS that also simultaneously capture the measurement of interest such as acceleration.

Potential:
(1) It will enable performing a complete ML algorithm at the sensor physical layer at a fraction of power requirement for an architecture with similar computational capabilities.
(2) Enable a novel simultaneous sensing and computing paradigm that eliminates the need for sensors interface and DSP to perform similar computation.
Team

- Prof. Siavash Pourkamali Anaraki
- Prof. Roozbeh Jafari
- Hamed Nikfarjam
- Muhammad Emad-Ud-Din
- Mohammad Hassan

1 The University of Texas at Dallas
2 Texas A&M University
3 Columbus State University

Special thanks for my PhD advisor: Dr. Mohammad Younis
Our team MEMS computing advancement summary

(a) Conventional MEMS operating as an analog sensor. The MEMS produces a voltage that requires multiple stages of conditioning before it can be read/processed by a processor. (b) My work: previous work of using MEMS as a self-activating threshold switch (TS) if acceleration exceeds a threshold value. (c) A small network of TSs engineered to produce digital acceleration measurement. (d) Our new work: for using a fully coupled small network of bi-stable TSs as a neural computing unit. This network can be trained to perform intelligent tasks like fall detection.
Accelerometer advancement

.75in*2in*8.5 in size and 1 lb weight

$420 in 1930!!!!!
How MEMS accelerometer works?

Capacitance = constant * A/d

Relative deflection of the structure

\[ |z(t)\omega_n^2| = |\dot{\ddot{y}}| \]

Acceleration of the base
Smart threshold acceleration switch

\[ V_{DC} = 0F_0 \]

\[ V_{DC} < V_{pull-in} \]

\[ V_{DC} > V_{pull-in} \]

Nonlinear Electrostatic Force + Shock Load = Early Dynamic Pull-in (Failure)

Switch On

Switch Off
Mechanical digital accelerometer!

<table>
<thead>
<tr>
<th>Acceleration</th>
<th>MSB Bit 1</th>
<th>LSB Bit 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 0.25 FSa*</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.25 FSa - 0.5 FSa</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0.5 FSa - 0.75 FSa</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0.75 FSa &lt;</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

*FSa: Full-Scale Acceleration

Data Table:

<table>
<thead>
<tr>
<th>Actuator Status</th>
<th>Sensor Mounting Angle (°)</th>
<th>Input Acceleration (g)</th>
<th>Measured Acceleration (g)</th>
<th>Sensor Binary Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSB Bit-6 Bit-5 Bit-4 Bit-3 Bit-2 Bit-1 LSB Bit-3 Bit-2 Bit-1 Bit-0 Bit-3 Bit-2 Bit-1 Bit-0 Bit-3 Bit-2 Bit-1 Bit-0 Bit-3 Bit-2 Bit-1 Bit-0 Bit-3 Bit-2 Bit-1 Bit-0 Bit-3 Bit-2 Bit-1 Bit-0</td>
<td>90</td>
<td>1</td>
<td>0.9918 ≤ g &lt; 1.0026</td>
<td>(01010101 )</td>
</tr>
<tr>
<td>65</td>
<td>0.963</td>
<td>0.9056 ≤ g &lt; 0.9164</td>
<td>(01010001 )</td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>0.68</td>
<td>0.6792 ≤ g &lt; 0.6900</td>
<td>(00111111 )</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>0.44</td>
<td>0.4313 ≤ g &lt; 0.4420</td>
<td>(00101000 )</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>0.259</td>
<td>0.2587 ≤ g &lt; 0.2695</td>
<td>(00010111 )</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.107</td>
<td>0 ≤ g &lt; 0.107</td>
<td>(00000000 )</td>
<td></td>
</tr>
</tbody>
</table>
Neural Network (Bio-Inspired Thing)

Hodgkin and Huxley model

\[ I = C_m \frac{dV_m}{dt} + \bar{g}_K n^4 (V_m - V_K) + \bar{g}_N a m^3 h (V_m - V_Na) + \bar{g}_l (V_m - V_l) \]

\[ \frac{dn}{dt} = -\nu(t) + \theta(t) + I(t) + w \sigma(y) \]

\[ \frac{dh}{dt} = \alpha_h (V_m)(1 - h) - \beta_h (V_m) h \]

CTRNN

Typical machine learning ignores the time temporal effect

\[ y(t) = I + w \sigma \]

The Nobel Prize 1963
How ML using MEMS?

MEMS naturally solve the neuron equation

\[ \tau \dot{x}(t) = -x(t) + J(\nu_c + \nu(t)) + \beta_g g_G(x) \]

You need a DSP to simulate

\[ \tau y(t) = -y(t) + \theta + I(t) + w \sigma(y) \]

The MEMS response, for example through gematric nonlinearities, can be engineered to match the response of a continuous recurrent neuron.
MEMS CTRNN

A network of coupled MEMS can mechanically perform machine learning calculation.

Why CTRNN?
Wrist trajectories


Our solution

A network of mechanically coupled MEMS can be designed to mechanically perform the calculation of a typical machine learning.
How to achieve coupling?

1. Full mechanical coupling (Only continuous)

So far we did it only for three MEMS
2-Through parallel fingers

Shared electrode (connected left or separated right) will simulate the weights of a ML
3- Though op-amp

Op-amp gains will simulate the weights of a ML
**Signal classification**

Problem: distinguish between two input waveforms; rectangular waveform and triangular waveform.*

One way to do it using MEMS switches

Works, but requires more neurons

And there is dithering
Other way (utilizing memory)

CTRNN neuron equation

\[
y(t) = -y(t) + \theta + I(t) + \omega |y|
\]

CTRNN neuron

\[
\tau \dot{x}(t) = -x(t) + T[V_0] + a(t) + wg(x)
\]
Application (Real hardware)
1-Signal classification

![Diagram of signal classification and mechanical components]

**Figure 5:** A SEM view of the fabricated device and details of the device structure.
2-Activity recognition (sit-to-stand detection)
Application (simulation):
3-Activity recognition (multiple events)

Acceleration profiles for different activities

Our MEMS solution matches state of art ML while consuming order of magnitudes less power

Ref
Active categorical perception problem. The agent (controlled unit), modeled as a circular object, is equipped with 7 proximity sensors, depicted as dashed lines, and is expected to categorize a falling object and act according to its shape. The agent is actuated via two motors attached to each side. (b) The recurrent neural network map used in this study, showing 14 total MEMS neurons: 7 input neurons, 5 computational recurrent neurons, and 2 output neurons.
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