A Micropower Programmable DSP
Powered Using a MEMS-Based
Vibration-to-Electric Energy Converter

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Power Trends for DSP

Can we use ambient energy sources to power electronics?
Sources of Ambient Energy

- Solar Power
- Electromagnetic Fields
- Thermal Gradients
- Fluid Flow
- Mechanical Vibration
  - Machine mounted sensors
  - Body area sensors
Self-Powered System Block Diagram

- Ultra low power DSP enables operation using scavenged energy
- MEMS implementation compatible with future systems-on-a-chip
- DSP energy scalability enables tradeoff between quality and available energy
Can we get voltage constrained energy with easier implementation?

Voltage Constrained ACD:
\[
\left(\frac{1}{2} C_{\text{max}} - \frac{1}{2} C_{\text{min}}\right) V_{\text{max}}^2
\]

Charge Constrained ABD:
\[
\left(\frac{1}{2} C_{\text{max}} - \frac{1}{2} C_{\text{min}}\right) V_{\text{max}} V_{\text{start}}
\]
Modified Charge Constrained Conversion

\[ E_{\text{chrgconstr}} = E_{\text{voltconstr}} - \frac{(\Delta Q)^2}{2(C_{\text{par}} + C_{\text{max}})} \]

\[ E_{\text{chrgconstr}} \rightarrow E_{\text{voltconstr}} \]

0 if \( C_{\text{par}} \rightarrow \infty \)
MEMS Capacitor Transducer

- Vibration moves plates
- This is used as a transducer

- $C_{\text{min}} = 2 \text{ pF}$
- $C_{\text{max}} = 258 \text{ pF}$
- Device size: 1cm X 0.5cm
Power Electronics (Single Phase)

1: Charge L from $C_{res}$
2: Charge $C_{MEMS}$ from L
3: Vibration moves $C_{MEMS}$ fingers apart
4: Charge L from $C_{MEMS}$
5: Charge $C_{res}$ from L

- Mechanical vs Electrical $\tau$
  
  \[ T_{LC} \sim 500\,nS \]
  
  \[ T_{vibration} \sim 400\,\mu S \]
Energy Harvesting Module

MEMS Transducer

- Fingers
- Support Beam
- Proof Mass

Power Electronics

- Control Core
- Power Switches

Core Power: (measured) 456nW
Switch Power: (measured) 3.87µW
Power Output: (predicted) 4.29µW

Functional and being characterized
Detection & Classification Algorithm

Matched Filter Template

Volts (V)

Time (s)

Preprocessing

Linear Filtering
H(z)

y[k]

Time Series Segmentation
S(y)

s

Feature Extraction
A(s)

f

Classification

z

- All Software Implementation: Preprocessing Dominates Hardware Use
- Preprocessing:
  - DA Unit implements matched filter efficiently
  - NLSL Filter Unit optimizes energy computation
  - Buffer stores preprocessed data

- Classification:
  - Microcontroller implements classifier
Distributed Arithmetic Implementation

X → D Q D Q D Q D Q D Q D Q D Q D Q D Q

Φ2 Φ2 Φ1 Φ0

Φ3 Φ3 Φ3 Φ3

Φ3 Φ3 Φ3 Φ3

Φ3 Φ3 Φ3 Φ3

Φ2 Φ2 Φ1 Φ0

/0/0/1/1

/0/0/1/1

/0/0/1/1

/0/0/1/1

/0/0/1/1

/0/0/1/1

/0/0/1/1

+/- MUX

TS

CLK Qualifying Signal

RESULT

x2

SRAM LUT
Distributed Arithmetic Filter

- Distributed bit serial filtering technique
  - Allows computation and power to scale with input data bitwidth
Power Scalable Classification

Recognition Performance vs. DA Unit Power

Recognition Performance (%) vs. Power (µW)

- 80.0
- 85.0
- 90.0
- 95.0
- 100.0

Power (µW)

- 0.5
- 1.5
- 2.5
- 3.5
Low Voltage SRAM Sense Amplifier
Power Scalable Preprocessing

Chip Power vs. Input Quantization Level

Power (nW)

Quantization Level (bits)
Sensor DSP Die Photo

- 0.6 µm CMOS process
- 4.4 mm x 5.8 mm
- 190K transistors
- $V_{dd} = 1.5V$
- 1.2 kHz/250 kHz clock
- Core Power: 560 nW
- Chip Energy: 26.6 pJ/sample
- StrongARM SA-110
  Energy: 11 µJ/sample
Conclusions

- Net power of 4 $\mu$W delivered from ambient mechanical vibration
- Ultra low power control framework enables positive delivered power
- Integrating energy scavengers into ultra low power DSP enables batteryless operation
- Energy scalable algorithms and architectures enable power/performance tradeoffs for sensor signal processing