SCALABLE POWER-EFFICIENT MULTI-TARGET TRACKING USING HYBRID ANALOG COMPUTATIONS

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Unconventional Processing of Signals for Intelligent Data Exploitation
(UPSIDE)

NICE Workshop
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Exploit existing and emerging analog-based computations to achieve state-of-the-art target tracking at ultra-low power levels

Key Challenges:
• Imperfections (noise, mismatch, non-linearity, inaccuracy, etc.)
• Mix between analog/digital components
System Architecture Overview

Analog computations based
Correlation-based analog filtering
Dealing with High-dimensionality

- Large visual field contains millions of pixels
- No classifier can handle such dimensionality
  \textit{Curse of dimensionality}
- Standard approach: three-phase process

ROI detection $\rightarrow$ Feature Extraction $\rightarrow$ Classification

$10^6 \rightarrow 10^4 \rightarrow 10^2$
Dealing with High-dimensionality

- Limitations of this approach:
  - Domain specific
  - Requires extensive hand-crafting of features
Deep Machine Learning*

• Biologically-inspired computational intelligence approach

• Goal: autonomously represent saliency in complex observations

• Hypothesis: brain represents the world by exploiting a hierarchy of abstraction

DeSTIN – DL Feature Extraction

Image data

Supervised Classifier

Classification

\[
\sigma\left(b + \sum_{i=1}^{n} a_i w_i\right)
\]
Inference Module (DeSTIN)

- Spatiotemporal pattern learning involves online clustering with feedback-based Bayesian inference.
State-of-the-art results

- MNIST digit recognition dataset
  - 3 layer DeSTIN architecture
  - Mean test classification accuracy of >98.8% was achieved
- Learning can be done off-line or on-line
  - Perceptron learning rule
  - Pre-trained off-line w/ fine-tuning online
The ADE Architecture

Inputs

Video/Image

Pattern

Voice

Raw Data

Belief States

Node

Rich Features

Transmission

Storage

Post-Processing

Classification

System Architecture
Clustering Algorithm
Node Architecture

1-D Conditional mean and variance learner is the core computational unit

- **AAE**: analog arithmetic elements
- **FGM**: floating gate memory

**2/24/14**

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Reconfigurable Analog Computation

- Includes wire-subtraction, absolute value, and $x^2/y$
- Configurable to calculate Euclidean or Mahalanobis distance; update for $\sigma^2$, $\mu$
Analog Arithmetic Element

- Absolute circuit rectifies the difference current \( o - \mu \)
- Translinear operator efficiently computes \( X^2/Y \)

\[
V_{GS1} + V_{GS2} = V_{GS3} + V_{GS4}
\]

\[
\rightarrow I_{D1} \cdot I_{D2} = I_{D3} \cdot I_{D4}
\]

\[
\rightarrow X^2 = YZ
\]
Distance Processing Unit

- IN converts $D_{MAH}$ to valid probability distribution $B$
  \[ B = \text{Norm} \left( \frac{1}{D_{MAH}} \right) \]
- WTA finds $\text{argmin}(D_{EUC})$
- Starvation trace addresses unfavorable initial condition
- S/H enables pipelined operation of all the layers
Transistor Size Scaling

- Robustness to static error inherent in learning algorithm allows aggressive device size reduction
- System modeling and simulation provides knowledge of the system’s tolerance to mismatch errors

Young, et al. TNNLS 2013
Clustering Test

- Input Data
- Cluster Means
- Evolution of Centroid Means
- Extracted Variance
- Data Cluster Parameters

\[ \mu = (3, 3) \quad \sigma^2 = (1, 1) \]

\[ \mu = (7, 7) \quad \sigma^2 = (1.5, 1.5) \]

\[ \mu = (7, 3) \quad \sigma^2 = (0.6, 0.6) \]

\[ \mu = (7, 3) \quad \sigma^2 = (1, 1) \]
Clustering Test – Starvation Trace

- Clustering test with unfavorable initial condition
Pattern Recognition

Input Pattern

Raw Data

ADE

4-D Rich Features

NN Classifier

Classification Result

100% Recognition Accuracy

95.4% Recognition Accuracy

10% Corruption

20% Corruption

Recognition Accuracy

Percentage Corruption

Measured

Baseline

Lu, et al. ISSCC 2014
Power Comparison

- Synthesized equivalent digital circuit for comparison
- Analog Implementation 288x more efficient

<table>
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<tr>
<th></th>
<th>Cents x Dims x Nodes</th>
<th>Area (um²)</th>
<th>Power @ Freq</th>
<th>Norm Energy</th>
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<tr>
<td>Digital</td>
<td>2x2x1</td>
<td>376x357</td>
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<td>7.7 nJ</td>
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<td>Analog</td>
<td>4x8x7</td>
<td>900x400</td>
<td>27 uW @ 4.5 kHz</td>
<td>27 pJ</td>
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Conclusions

- DL systems provide robust general purpose spatio-temporal feature extraction
- Analog computation offers substantial improvements in energy efficiency
  - No discernible degradation in performance relative to digital systems
- Tight coupling between algorithm and hardware/device physics
Acknowledgements

Sponsors

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Thank you