

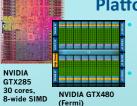
Exploring Recognition Network Representations for Efficient Speech Inference on Highly Parallel Platforms

Parallel Computing Lab

Jike Chong, Ekaterina Gonina, Kisun You, Kurt Keutzer, Department of Electrical Engineering and Computer Science, University of California, Berkeley

PAMAS

Maturing Highly Parallel Platforms



15 cores 16-wide

- Architecture trend:
- · Increasing vector unit width
- Increasing numbers of cores per die

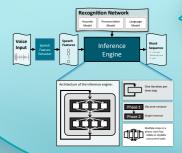
Maturing HW architecture:

 Including caches as well as local stores that benefit irregular accesses

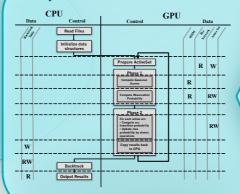
Ongoing work investigates performance of alternative approaches to speech recognition on these highly parallel platforms

Speech Recognition Inference Engine Characteristics

- Parallel graph traversal through Recognition network
- Guided by a sequence of input audio vectors
- · Computing on continuously changing data working set
- Implementation challenges
 - Define a scalable software architecture to expose fine-grained application concurrency
 - Efficiently synchronize between an increasing number of concurrent tasks
 - Effectively utilize the SIMD-level parallelism



Implementation Architecture



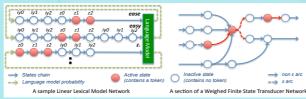
Evaluation of the Recognition Network Representations



18

- To achieve the same accuracy:
- LLM traverses 22x more state transitions than WFST
- On GTX285, LLM is faster
- On GTX480. WFST is faster
- On Grado, Wish is laster
- Looking at detailed timing:
- LLM takes 3-5x more time in Graph Traversal, but evaluates 22x more transitions
- 51% of the execution time in WFST is spent in gathering data from its irregular data structure

Two Recognition Network Representations



LLM Network

- Chain of triphone states for each pronunciation
- Each chain constructed using a separate copy of triphone states – many duplications
- Evaluate possibility of transition from one word to all other words at the end of each triphone chain

WFST Network

ESM of composed pronunciation and language models

12 14

18

22

GTX285 Results

0.20

0.10 0.15

Real Time Factor

- Across-word transitions explicitly represented
- Encapsulates large amount of information with little redundancy
- · Fewer tokens required to be maintained for target accuracy

	LLM Pruned	LLM	WFST Pruned	WFST
# States	123,246	123,246	1,091,295	3,925,931
# Arcs	537,608	1,596,884	2,955,145	11,394,956

Wall Street Journal 1 Corpus

- Based on a 5,000 word vocabulary, 1,350,392 bigrams (291,116 pruned)
- · 3000 16-mixture acoustic models, 39 dim features based on 13 dim MFCC
 - WFST network is an HCLG model compiled and optimized offline



GTX480 Results

— WFST Pruner

-A-- IIM

0.15 0.20

Conclusions

- Simpler LLM network representation performs competitively with highly optimized WFST representation
- WFST representation is a more concise representation requiring traversal of 1/22 number of state transitions to achieve the same accuracy
- Per state transition LLM gathers data 53-65x faster and evaluates transitions 4.7-6.4x faster than WFST
- Uncoalesced memory accesses are still a major bottleneck in implementations using the WFST representation

Emergence of highly parallel platforms brings forth an opportunity to reevaluate computational efficiency of speech recognition approaches.

Thanks to Nelson Morgan, Andreas Stolcke, and Adam Janin at ICSI for insightful discussions and continued support in the infrastructure used in this research.

This research is supported in part by an Intel Ph.D. Fellowship.