

Applying GPGPU to Recurrent Neural Network Language Model based Fast Network Search in the Real-Time LVCSR

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Abstract

Recurrent Neural Network Language Models (RNNLMs) have started to be used in various fields of speech recognition due to their outstanding performance. However, the high computational complexity of RNNLMs has been a hurdle in applying the RNNLM to a real-time Large Vocabulary Continuous Speech Recognition (LVCSR). In order to accelerate the speed of RNNLM-based network searches during decoding, we apply the General Purpose Graphic Processing Units (GPGPUs). This paper proposes a novel method of applying GPGPUs to RNNLM-based graph traversals. We have achieved our goal by reducing redundant computations on CPUs and amount of transfer between GPGPUs and CPUs. The proposed approach was evaluated on both WSJ corpus and in-house data. Experiments shows that the proposed approach achieves the real-time speed in various circumstances while maintaining the Word Error Rate (WER) to be relatively 10% lower than that of n-gram models.

Index Terms: Recurrent Neural Network, Language Model, General Purpose Graphics Processing Units, Large Vocabulary Continuous Speech Recognition

1. Introduction

Recently, the Recurrent Neural Network Language Model (RNNLM) has gained its popularity in the field of Automatic Speech Recognition (ASR). Various academic research has reported the effectiveness of RNNLMs, which can train unseen contexts by sharing the statistics between words with syntactically and semantically similar contexts [1, 2, 3, 4, 5]. However, heavy computational load of RNNLM over traditional n-gram based approaches has been a hurdle in applying the RNNLM to diverse areas of ASR applications. Especially, when ASR systems are required to run under real-time constraint (i.e., less than 1xRT), the real-time decoder is hardly attainable with direct application of RNNLMs in place of traditional n-grams. In order to overcome such computational issues, most of the RNNLM systems adopt two-pass decoding strategy, which generates lattices or a set of n-best results based on n-gram in the first path, and then performs the rescoring on the hypotheses with RNNLMs.

Prior studies have investigated the possibility of implementing real-time decoder with RNNLM [5]. The study reduced computational complexity of the RNNLMs by caching the conditional probabilities of the words and the results of RNN computation and reusing the cached data. However, even though the computational load was minimized by introducing cache strategy and reducing redundant computations, the result was still far from achieving real-time performance with large vocabulary based RNNLM.

Recent studies have applied the General Purpose Graphic Processing Units (GPGPUs) in various fields of ASR [6, 7, 8, 9]. One of the studies applied the GPGPU to training RNNLMs, and showed that the outstanding parallelization capability of GPGPU was suitable in minimizing the computational load of probability normalization processes [9].

In this paper, we investigate the possibility of implementing a GPGPU-based real-time Large Vocabulary Continuous Speech Recognition (LVCSR) that utilizes RNNLM. Even though GPGPUs have powerful parallelization capabilities, obstacles such as their insufficient memory size and slow data transfer speed between GPGPUs and CPUs discourage the use of GPGPUs among RNNLM-based real-time decoders. Moreover, it is also important to balance the computation time between GPGPU and CPU, as the acceleration on GPGPU may not have a prominent impact on the overall speed if the GPGPU needs to wait for the CPU computation to finish.

In order to achieve real-time decoding of RNNLM-based LVCSR, we apply on-the-fly rescoring of RNNLM to GPGPU based network traversal technique proposed in [8]. We accelerate the speed of data exchange between the two heterogeneous processors and reduce redundant computations on CPUs by applying cache strategies. The resulting recognition system has shown almost twice faster than real-time speed when experimented under various conditions, while maintaining relatively 10% lower Word Error Rate (WER) than that of conventional n-gram models.

This paper is organized as the following. In section 2, the structure of RNNLMs is explained. Section 3 explains how we applied GPGPUs to RNNLM-based network search. Section 4 explains the RNNLM rescoring with caches. Section 5 evaluates the improvement of the proposed method, followed by the conclusion in Section 6.

2. Recurrent Neural Network

In order to speed up RNNLM computations, we apply an efficient RNNLM architecture described in this section, which consists of the hierarchically decomposed output layer [10], and Maximum Entropy (MaxEnt) strategy [11].

2.1. Hierarchical Softmax

In RNNLM-based ASR system, directly computing the conditional probability of an input word for a given word sequence has high computational complexity since the system needs to normalize probabilities over the all the words in the vocabulary. In order to alleviate the computational burden, the hierarchical softmax method was applied for our RNNLM implementation [12].

The output layer consists of a binary tree. We used Huff-

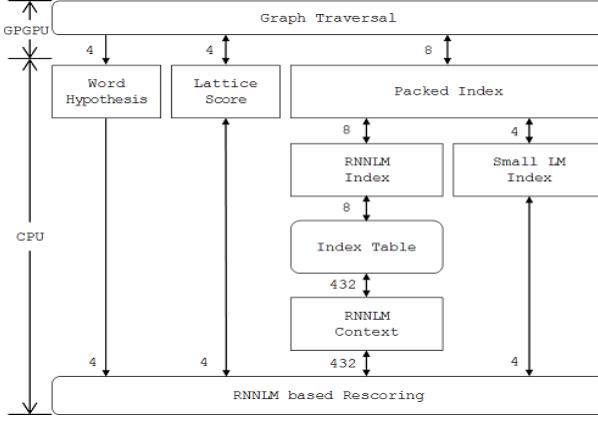


Figure 1: *The process of RNNLM-based graph traversals*

man tree method to build up the binary tree because it assigns shorter codes to more frequently used words and it leads to fast training and decoding speed [14]. In the output layer, the softmax normalization for computing the likelihood is performed only over the nodes on the path of the binary tree from the root to the input word node so that the computational cost is reduced from $O(n)$ to $O(\log n)$, where n represents the vocabulary size.

2.2. Maximum Entropy

In order to further reduce the computational cost, we interpolated hash-based MaxEnt models with the RNNLM itself. We have used n-gram based MaxEnt models, which has similar accuracy to traditional n-gram maximum likelihood model and is easy to integrate with neural network configuration [13].

Because the RNN-based and MaxEnt-based Language Models (LMs) are complementary to each other [11], interpolating both LM scores enables us to reduce the size of the number of nodes in RNNLM without loss of accuracy. Because the size of a hidden layer is a dominant factor for the computational complexity of RNNLMs, the amount of computation can be reduced.

3. GPGPU Acceleration in RNNLM-based Graph Search

GPGPUs have been successfully applied in various fields of ASR by virtue of their characteristics of the powerful parallelism. However, there are some obstacles in utilizing GPGPUs for accelerating RNNLM-based network search. First, GPGPUs have insufficient memory to load the whole content of large vocabulary RNNLMs. Moreover, the data transfers between GPGPUs and CPUs are very time consuming works. This section explains how we apply GPGPUs to RNNLM-based graph traversals.

3.1. On-the-fly RNNLM Rescoring

We employ the GPGPU-CPU hybrid architecture as noted in [8]. The RNNLM-based rescoring is deployed to both GPGPUs and CPUs in such a way that the Weighted Finite State Transducer (WFST) which is composition of HCLG networks. The G network is composed with a short span n-gram, which can be resided in the available GPGPU memory. While the

frame-synchronous Viterbi search is performed to generate lattices on the GPGPU side, the LM portion of the lattice score is simultaneously rescored with RNNLM in on-the-fly manner on the CPU side.

3.2. RNNLM Context Transfer

Whenever a new word hypothesis is output from the WFST graph traversal on the GPGPU, the word hypothesis and its prior RNNLM context are sent to the CPU side so that the RNNLM computation can be done on the CPU. After the RNNLM computation, the resulting rescored score and the updated RNNLM context are sent back to GPGPU.

The exact size of each RNNLM context may depend on the structure of the RNNLM, but it is generally larger than a few hundreds of bytes. Moreover, the number of new word hypotheses per each frame can be as high as a few thousands, and so millions of RNNLM lookups may be requested per an utterance. Considering the size of RNNLM context and the number of data exchange, the data transfer between GPGPU and CPU can cause speed degradation of RNNLM-based on-the-fly rescoring WFST traversals. We reduced the size of the data transfer by storing the RNNLM contexts on the CPU side, and only transferring the indices of the stored context to the GPGPU.

Figure 1 depicts the proposed RNNLM-based graph traversal processes. Each number and arrow represents bytes and the flow of data, respectively. We have created an *IndexTable* for storing and retrieving RNNLM contexts and put the table into the CPU memory. The *IndexTable* is in charge of converting a large-sized RNNLM context into an 8-byte index, and vice versa. Because both encoding and decoding of the contexts need to be performed in a short time, we have made *IndexTable* bidirectional to handle both purposes. In addition to the RNNLM index, the index of the small LM, which corresponds to an ngram of the LM used to build the WFST graph, also needs to be transferred in order to compute and replace the small LM score with the RNNLM score. Instead of exchanging the two index sequences separately, we concatenate the two indices into one numerical value in order to further reduce the data size per each transaction. With the indexing and packing method, we could reduce the exchanged data size to approximately 1/30 compared to transmitting the whole context information including a recurrent layer.

4. RNNLM Rescoring with Cache

In GPGPU-CPU hybrid architectures, the balance between the GPGPU and CPU speed is important, because relatively slower speed of CPUs can degrade the overall speed of RNNLM-based graph traversals since GPGPUs have to wait until the computations on CPUs are finished in order to work synchronously. Therefore, a fast RNNLM computation strategy on the CPU side is crucial in accelerating the overall on-the-fly rescoring time. This section explains the efficient method to speed up RNNLM-based graph search on the hybrid architecture.

4.1. The structure of RNNLM Context Cache

We have optimized the computation on the CPU side by reducing the number of redundant computations during RNNLM calculation. We use a cache strategy which stores the once-computed results and reuses them for the same input contexts.

Each element in the cache consists of a key-value pair: the key consists of a prior RNNLM context and a new word hypoth-

RnnlmProb(w, c)	
1	$\mathbb{I} \leftarrow (w, c)$
2	if Cache[\mathbb{I}] exists then
3	$\mathbb{O} \leftarrow \text{Cache}[\mathbb{I}]$
4	else
5	$\mathbb{C} \leftarrow \text{IndexTable}[c]$
6	$(p, \mathbb{C}') \leftarrow \text{ComputeRnnlm}(w, \mathbb{C})$
7	if IndexTable $^{-1}[\mathbb{C}']$ exists then
8	$c' \leftarrow \text{IndexTable}^{-1}[\mathbb{C}']$
9	else
10	$c' \leftarrow \text{lengthOf}(\text{IndexTable}) + 1$
11	IndexTable[c'] $\leftarrow \mathbb{C}'$
12	end if
13	$\mathbb{O} \leftarrow (p, c')$
14	Cache[\mathbb{I}] $\leftarrow \mathbb{O}$
15	end if
16	return \mathbb{O}

Table 1: The process of RNNLM computation with caches

esis, and the value consists of the resulting RNNLM score for the given word and the updated RNNLM context. The RNNLM context generally consists of the values in the previous hidden layer, but we also use the previous word sequence for computing the MaxEnt portion of the RNNLM. Since we are compressing the hundred bytes of context data into a 8-byte index by using *IndexTable* as explained in Section 3, we store the compressed indices instead of the whole context data.

4.2. RNNLM Probability Computation with Cache

Table 1 shows a procedure for the probability computation of a word hypothesis in the proposed RNNLM-based network search. \mathbb{I} represents the key structure of the *Cache* element and it consists of the current RNNLM context index c and the following word index w . \mathbb{O} represents the value structure of the *Cache* element and it consists of the LM probability p and the updated RNNLM context index c' . *IndexTable* compresses the RNNLM context data \mathbb{C} into an index variable c , and *Cache* stores the already computed pairs of inputs and outputs (\mathbb{I}, \mathbb{O}).

The context index c is associated with each path on the graph traversal on GPGPUs, and at every time the WFST network outputs a new word index w , the parameters w and c are sent back to the CPU side and fed into the RNNLM likelihood computation process. At line 1 of Table 1, the two input parameters are stored to the input structure \mathbb{I} . In lines 2–3, if \mathbb{I} is already cached, then the retrieved value of *Cache*[\mathbb{I}] is saved to \mathbb{O} and is returned without having to do any further computations. Otherwise, in lines 4–6, the \mathbb{C} is retrieved from the *IndexTable* with the index c , and the function *ComputeRnnlm* computes the conditional probability of w based on the prior context \mathbb{C} , outputting the RNNLM probability value p and the updated context \mathbb{C}' .

On a side note, the hidden layer value is initialized to a zero vector at the beginning of each utterance. The length of the word sequence in the RNNLM context \mathbb{C} is restricted to the order of MaxEnt model, and the latest word sequence is maintained by removing the oldest word from the sequence whenever the number of previous words in the context exceeds the predefined size.

In lines 7–12, the updated context \mathbb{C}' is stored into the *IndexTable* and its index value c' is retrieved. When the context

has been already stored before, the corresponding index is retrieved without adding it to the table again. In lines 13–15, p and c' are saved to \mathbb{O} , and \mathbb{I} and \mathbb{O} are cached as a pair of key and value for later use. Finally at line 16, \mathbb{O} is returned. Difference between the returned value and the score of short span n-gram will be sent back to the GPGPU side and will be used to rescore the partially decoded WFST lattice.

5. Result

5.1. Experimental Setup

The experiments were performed both with the Wall Street Journal (WSJ) database and with a much larger set of data collected within the company (*in-house*).

The acoustic model for evaluating the in-house data was trained on 2,000 hours of the fully-transcribed Korean speech data. All the speech data were sampled at 16 kHz and were coded with 40-dimensional mel-frequency filterbank features, plus an additional dimension for the log-energy. The frames were computed every 10ms, and was windowed by 25ms Hamming window. Five frames to the left and right of the given frame were concatenated to the features to make a 451-dimensional acoustic feature vector in total. All the acoustic models were trained with the Deep Neural Network (DNN) which consisted of 5 hidden layers with 2,000 nodes each. Rectified linear unit (ReLU) was used for the activation functions. The total number of output states was approximately 6,000.

The LM trained for evaluation of the in-house data was based on a total of 4GB text corpus, which amounts to approximately 74 million sentences with 475 million words, and the vocabulary size was about 1 million. The RNNLMs consist of one hidden layer with one hundred nodes, and the order of MaxEnt LM features was 3. As for the n-gram models used for the comparison to the RNNLM, the 3-gram back-off models with Kneser-Ney smoothing were used.

The WFST was compiled with a bigram LM and all the epsilon transitions were removed from the graph so that the computation on the GPGPU side can be optimized.

The evaluation tasks were performed on Intel Xeon X5690 3.47GHz processors with a total of 12 physical CPU cores and one Nvidia Tesla M2075 GPU equipped with 6GB memory.

5.2. Speed up by Cache

By considering that the number of resoring request per each utterance is as large as millions, it was expected that naively applying RNNLM-based on-the-fly resoring to ASR system would lead to high computational complexity.

As a matter of fact, our experiment showed that the naive application of the RNNLM to the on-the-fly resoring decoder resulted in the speed slower than 10xRT. However, the RTF was significantly dropped to much lower than 1xRT when the cache strategy explained in section 4 was adopted. The hit ratio of the cache was at least 88.66% over all the test cases, showing that most of the RNNLM computations were highly redundant.

5.3. Performance Evaluation

Figure 2 depicts the performance comparison between RNNLM and 3-gram in the in-house 1 million vocabulary evaluation set. Various beam widths were applied to each LM in order to investigate how the word error rate changes with respect to the decoding speed. The figure shows that while the lowest WER that 3-gram model can achieve is at around 8.49%, RNNLM

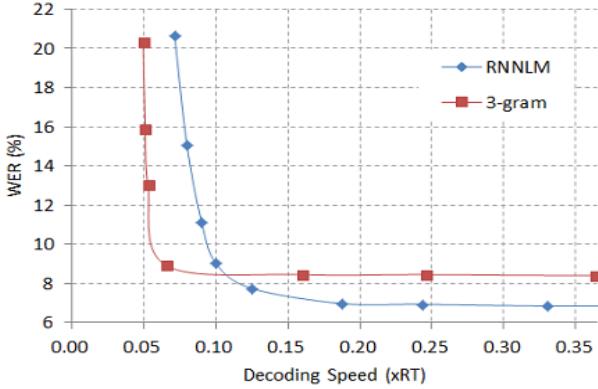


Figure 2: Comparison of decoding speed and WER for RNNLM and 3-gram (in-house)

Type Pass / Model	in-house		eval92		dev93	
	WER	xRT	WER	xRT	WER	xRT
1 / 3-gram	8.49	0.19	5.74	0.16	11.73	0.20
1 / RNNLM	6.83	0.64	4.15	0.43	10.80	0.40
2 / hybrid	7.57	0.33	5.74	0.25	11.31	0.27
2 / RNNLM	8.34	0.33	5.81	0.25	11.46	0.27

Table 2: Performance comparison of different types of LM scorings

can reach as low as 6.83% WER at the speed of 0.33 xRT.

Table 2 shows the performance comparison of four different rescoring methods with same decoding options which show the best performance all over the types of decodings. The one-pass types were computed by the proposed on-the-fly rescoring method, and the two-pass types were evaluated by rescoring the 1000-best hypotheses extracted from the lattices with 3-gram models. The two-pass hybrid type used interpolated score between 3-gram and RNNLMs.

Although the speed of the 1-pass RNNLM type was generally slower than that of other types, it was well within a real-time speed. This improvement shows that applying more accurate LMs at the WFST traversal stage at the first-pass leads to a better overall recognition result, instead of depending on the rescoring on the less accurate hypotheses generated from n-gram models.

5.4. Memory Efficiency

Another measure to consider is the memory footprint of the *IndexTable*. Whereas *Cache* elements consists of only four integer values, each element in *IndexTable* is as large as a few hundred bytes and may increase rapidly as the decoding goes on. In our experimental settings, each *IndexTable* item consists of four types of information and is as big as 432 bytes, as shown in Table 3. The size of the whole table increases during the decoding process and it is proportional to the number of unique elements.

During the in-house evaluation task, the average memory usage for *IndexTable* per utterance was 191.78MB. More than 80% of utterances over all evaluation data sets were shorter than 10 seconds, and average utterance length was about 7.69 sec. Considering that the size of the *IndexTable* will be generally proportional to the length of the utterance, we can reasonably assume that the memory footprint for the *IndexTable* is contained within acceptable size.

	Total Memory	# of Elem.	Size of Elem.
Hidden layer	400	100	4
Word sequence	24	3	8
MaxEnt Order	4	1	4
RNNLM Index	4	1	4

Table 3: The composition and the size of an element in *IndexTable* (in bytes)

Capacity(KB)	# of Cache	Mem.(MB)	xRT
0(=per utt)	69K	57.30	0.64
250	164K	135.43	0.59
500	282K	232.86	0.57
750	406K	334.70	0.57
1000	560K	461.49	0.57

Table 4: Cache memory usage and decoding speed depending on the capacity of cache (in-house)

5.5. Caching Over Multiple Utterances

We noticed that many speakers tend to repeat similar commands in different utterances, and so we hypothesized that maintaining the cache and *IndexTable* over multiple utterances may increase the hit ratio of the cache and will decrease the decoding speed further. Therefore, instead of resetting the caches for each utterance, we set a certain size boundary for the number of cache to be maintained, and kept the information over multiple utterances. We expected that a larger cache size will lead to a faster decoding speed, due to increased cache hit ratio.

Table 4 shows the decoding speed for different cache capacity. The memory usages of caches and the number of caches are averaged over all the utterances in the test set.

However, as can be seen from the table, the decoding speed did not get much faster than 1.12x even though the capacity of cache increased. We concluded that the result reflects the fact that even if the users are prone to speak the similar commands repeatedly, most of the word hypotheses are different for different utterances, and so the cache hit ratio does not get higher. Although the multi-utterance cache strategy only showed a marginal improvement, it would still be meaningful to adopt a smart cache strategy that limits the size of the cache by removing the cached items that are least frequently used, so that the size of the cache table does not overflow.

6. Conclusions

This paper explained how we applied RNNLMs to a real-time large vocabulary decoder by introducing the use of GPGPUs. We tried to accelerate RNNLM-based WFST traversals in GPGPU-CPU hybrid architectures by solving some practical issues for applying GPGPUs. Moreover, in order to minimize the computation burden on CPUs, we applied a cache strategy. The decoding speed of RNNLMs was still slower than that of n-gram models, but the proposed method achieved the real-time speed while maintaining relatively 10% lower WER as shown in Table 2, and so we could perfectly apply this approach to an on-line streaming speech recognition engine. The memory footprint for the cache method was small enough to perform the experiment on the large data set. However, it will be more desirable to employ efficient cache techniques to reduce the memory usage further.

7. References

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