ABSTRACT

Hardware acceleration of database query processing can be done with the help of FPGAs. In particular, they are partially reconfigurable during runtime, which allows for the runtime adaption of the hardware to a variety of queries. Reconfiguration itself, however, takes some time. As the affected area of the FPGA is not available for computations during the reconfiguration, avoiding some of the reconfigurations can improve overall performance. This paper presents optimizations based on query sequences, which reduces the impact of the reconfigurations. Knowledge of coming queries is used to (I) speculatively start reconfiguration already when a query is still running and (II) avoid overwriting of reconfigurable regions that will be used again in subsequent queries. We evaluate our optimizations with a calibrated model and measurements for various parameter values. Improvements in execution time of up to 21% can be obtained even with sequences of only two queries.

Keywords Query sequence · Optimization · Hardware accelerator · Reconfiguration · FPGA

1 Introduction

There are already a couple of projects addressing the acceleration of database query processing with the help of FPGAs, e. g. [1,2,3], and their integration into a DBMS. The ReProVide project [4] is one of them. The particular approach of this project is to use dynamic reconfiguration of the FPGA in a combination of a novel DBMS optimizer and accelerated data storage units called ReProVide Processing Units (RPUs). On these RPUs, a library of query-processing modules is available, which can be configured onto the FPGA in the order of 15ms. Due to the limited amount of logic resources on an FPGA, not all modules can be made available simultaneously. So at some point in time, only a subset is ready for use in query processing. Hence, reconfiguration of one or more region of the FPGA is needed to process an incoming query optimally, if the required modules are not loaded already.

The idea presented in this paper is that when a sequence of queries to be executed repeatedly is known, information about this sequence can be given to the RPU via so-called hints. The RPU can use this information to reduce the overall execution time of the sequence of queries.

In the following, we will indicate where such sequences of queries may come from. They are assumed to be part of an application program that e. g. fills the frames of some modular screen output from different parts of an underlying database.

2 The ReProVide Processing Unit (RPU)

This section gives some more detail on how the ReProVide system does the query processing. It is a “system on chip” (SoC) with own storage (SSD), an ARM processor, and some memory (DRAM)—in addition to the FPGA. So the RPU
Figure 1: Sequence diagram of an example query sequence \( S \) on top and our proposed optimizations for this sequence below, namely (I) speculative reconfiguration and (II) accelerator reordering.

“owns” data tables, which means that any access to these tables goes through the RPU. The RPU is attached to a host running a (relational) DBMS via a fast network. It is important to note that streaming the table data through the FPGA comes at no additional cost.

However, reconfiguration may be required before the RPU can process the data in the way a particular query demands. The FPGA of a RPU contains various static hardware modules, like a storage controller, a network controller, data interconnects, and local memories, as well as multiple partially reconfigurable regions (PRs). Data is processed by so-called accelerators loaded into these PRs. RPUs execute a partial query by streaming the tables from the storage at line-rate through one or multiple accelerators to the network interface. Operations like sorting or joining of larger tables cannot be implemented in an efficient way on such a streaming architecture and are therefore left to the DBMS.

As the accelerators are optimized for line-rate processing, and FPGA resources are limited, not all available operator modules can be combined into a single accelerator. E.g., implementations of arithmetic operators differ not only in the operation they implement (mult, add, . . . ), but also in the type they operate on (float, int32, int64). Dynamic partial reconfiguration allows to offer support for more and more operators with a growing library of available accelerators, each implementing a reasonable subset of all available operators.

This means the RPU has a state, which consists of the set of accelerators configured, and a cost of changing that state, introduced by the time it takes to exchange accelerators through the reconfiguration of PRs.

A special approach of the ReProVide project is that the interface of the RPU will allow to send some hints in addition to the query-execution request. These hints do not change any functionality, but give some information to the RPU so it can optimize the execution further. This paper introduces one such hint to avoid unnecessary reconfiguration or to begin with reconfiguration for coming queries while still executing the current one.

The optimizer of the DBMS that hosts the RPU identifies the filter operations that can be pushed down to the RPU. Since the data has to be retrieved from the table storage anyway, and since the processing is almost for free, all operators that can be executed by the RPU are pushed down. This may greatly reduce the amount of transferred data, and thus not only relieves the network of unneeded traffic, but also reduces the load on the DBMS, as less data needs to be processed by it.

3 Related Work

The Hybrid Query Processing Engine (HyPE) is a self-tuning optimizer framework. As the name indicates, it allows for hybrid query processing, that is, utilizing multiple processing devices. CoGaDB has used it to build a hardware-oblivious optimizer, which learns cost models for database operators and efficiently distributes a workload to available processors. It is hardware- and algorithm-oblivious, i.e. it has only minimal knowledge of the underlying processors or implementation details of operators. To achieve this, HyPE has three components: estimation component, algorithm selector, and hybrid query optimizer. Simple regression models are used to estimate the behavior of hardware w.r.t. properties of input data like size and selectivity. Runtime monitoring allows verifying the predictions. The

\[ \text{In this paper, we neglect the caching of tables in a host system.} \]

\[ \text{We assume data rate_{network} \leq data rate_{storage}} \]
optimizer must select an algorithm (including the processor), estimate the cost, and decide on a plan according to heuristics. In contrast to this work, HyPE does not address multi-query optimization and hints.

The ADAMANT project [8] enhances a DBMS with extensible, adaptable support for heterogeneous hardware. The main objectives are to find a useful abstraction level that considers the fundamental differences between the heterogeneous accelerators, the development of an improved optimization process that copes with the explosion of search space with new dimensions of parallelism, and to fine-tune device-dependent implementation parameters to exploit the different features available in heterogeneous co-processors. The project mainly uses OpenCL and emphasizes GPUs, but is also beginning to look into FPGAs.

Multi-query optimization has been studied for some time already [9][10][11]. In all cases, however, the queries to be optimized are available at the same time. Here, we receive the queries one after the other, with some time gap in between. The template of the coming queries is known, but the parameters, e. g. the constants used in comparisons, are not. So we can use the techniques for identifying common subexpressions, but we do not consider to change the ordering of the queries in this work.

Query processing using FPGA-based hardware accelerators has been studied extensively since a few years [12][13][14][15][16]. Offloading query operations for reducing energy and for fast execution is well investigated [14][15][16]. But the works are all focusing on the execution of a single query. Here we are interested in the execution of a sequence of queries.

4 Query-Sequence Model

The information base that drives the optimization is a sequence of (relational) queries to be executed repeatedly. It can be obtained from database query logs [17][18][19] or by code analysis [20][21], including the frequency and the time of arrival. The sequence can be adjusted manually to focus on the most important queries, if necessary.

We denote a query sequence $S$ containing $n$ queries as an ordered set of individual queries $Q_0, \ldots, Q_{n-1}$. All queries are run to completion before the next starts without any overlap in their execution. The time between two successive queries is estimated from experience or is learned by repeated observations. For any query sequence $S$, the time gap $t_{\text{gap},q}$ with $q \in \{Q_0, \ldots, Q_{n-2}\}$ gives the average time between two consecutive queries, namely $q$ and its successor. Please note that the optimization target in this model is not to optimize the execution time of a single query, but the time of the whole sequence, that is, the time from the arrival of $Q_0$ until the transmission of the last result of $Q_{n-1}$, including all time gaps.

The analysis of the queries in the sequence then determines

- the tables and attributes accessed, and in which order, as well as
- the operators they request on the attributes of the tables (arithmetic and/or comparisons)

While the proposed approach is suitable for arbitrary operators, we focus on filters (selections) together with arithmetic for now. They can easily be extracted from query-execution plans (QEPs). The constants used in the arithmetic or in the comparisons may come from program variables, so they will be different in future executions of the query sequence. We will introduce parameters here, as known from prepared queries and stored procedures.

The query sequences are generated by application programs that e. g. compose output from various parts of a database. Imagine an e-mail client displaying overview lists together with a preview of the first e-mail on the list and maybe some attachments. The first query retrieves the list elements with selected information such as sender and subject line. Using the id of the top line, the second query fetches more details, e. g. the list of other recipients and the first 10 lines of attachments. The first query retrieves the list elements with selected information such as sender and subject line. Using the id of the top line, the second query fetches more details, e. g. the list of other recipients and the first 10 lines of the body. The third query finally obtains previews of the attachments. One can easily imagine other client interfaces consisting of frames filled with related contents extracted by queries from a database.

5 Execution Model

In order to keep the model simple, we only use a single partial region within the RPU and do not overlap table scanning with accelerator execution. We, however allow the parallel scanning of tables and reconfiguration of the partial region. The upper part of Fig 1 depicts the execution of a query sequence $S$ with two consecutive Queries ($Q_0, Q_1$). The execution time of a Query $t_q$ is the sum of the needed accelerator runtimes ($t_{\text{acc},X}$) and network transport time ($t_{\text{trans}}$). As the table scan can be executed while the first accelerator is reconfigured ($t_{\text{acc},X}$), only the maximum value of $t_{\text{scan}}$ and $t_{\text{acc},X}$ is added to the execution time of its particular Query.

Build on top of cost models from Ziener Etal. [15], a software emulator was built to test the behavior of different optimizations strategies. We used 15 example Queries to evaluate the correctness of the implemented emulator. The
6 Optimization

The optimizer of the DBMS analyzes the sequence of pushed-down operations for similarity, that is, common subexpressions [10]. Since the goal at this point is to avoid unnecessary reconfigurations, only information about subsequences of common comparisons is passed to the RPU as hints. This information can be organized with the help of the query repository [13].

There is no scheduling of queries; a query sequence may begin at any time. The DBMS optimizer tries to recognize the first query of a sequence and then retrieves the relevant sequence information, i.e. the similarities in the sequence of pushed-down comparisons.

From that, the optimizer generates the hints to the RPU in order to avoid reconfiguration and thus reduce the execution time of the pushed-down query plans. The RPU should then

I speculatively load accelerators for subsequent queries, once other accelerators are no longer used by the current query, and

II avoid the replacement of reusable accelerators.

The effect of optimization I is shown in the middle of Figure[1]. While the processing of the first query of the sequence (Q0) has not changed, the reconfiguration back to Accelerator 0 (acc0) is speculatively started as soon as Accelerator 1 (acc1) has finished. In this example, the reconfiguration—which runs in parallel to the result transmission—has completed before the subsequent query (Q1) arrives. This is the optimal case for this optimization. Query Q1 can start immediately when it arrives, without any waiting time introduced by reconfiguration.

Optimization II tries to avoid the third reconfiguration at all by swapping the accelerator invocations of Q0 if possible. For instance, two accelerators implementing filters can be swapped safely. The local optimizer would invoke the filter with the lowest selectivity first to reduce the data volume early. This may be revoked by the swapping. In the lower part of Figure[1] one can see the consequences. Query Q0 now needs more time than without optimization II, as the second accelerator acc0 takes longer to process the data produced by acc1. While this looks detrimental to the goal of optimization, the third reconfiguration has in fact vanished and thus the execution time for the complete sequence is reduced.

Of course this only makes sense, if the RPU actually reacts to the hints, that is, if the optimization works on the RPU side as well, because it can skip some time-consuming action or exploit waiting times.

7 Evaluation

We have evaluated our proposed optimizations using the calibrated emulator from Section[5]. A parameterized version of the query sequence S as presented in Fig.[1] is used for the evaluation. It is a minimum-size sequence and hence,
any other sequence with more accelerator runs or queries will only enhance the possibility to apply the optimizations presented here. We vary the size of the relation to be processed by the two queries (scale factor) and the time gap between the queries ($t_{gap,Q_0}$).

Fig. 3 shows the improvement in execution time for each proposed optimization with varying relation size. Two different time gaps between the queries are included.

![Figure 3: Execution-time Improvement vs. Relation-size scaling for an average reconfiguration time $t_r$ being drastically smaller or drastically higher than the average time gap between the two queries ($t_{gap}$)](image)

It can be clearly seen that no single optimization is superior. While II drastically outperforms I for small relation sizes where $t_{trans} + t_{gap,Q_0} \leq t_{r,acc}$, up to a relation size with a scale factor of 2, I dominates from that point on, as the reconfiguration time can be hidden completely.

A similar behavior can be found in Fig. 4 where $t_{gap,Q_0}$ has been varied. For small relation sizes and only very little time between the two queries, optimization II is preferable and can lead to a runtime improvement of up to 22%.

![Figure 4: Execution time Improvement vs. $t_{gap}$ for two relation size scales](image)

While the result sizes vary with the parameter values in the queries, the time gap $t_{gap,Q_0}$ obtained by the sequence analysis gives a good indication of the case where the speculative reconfiguration approach should be used.

8 Conclusion

The paper has introduced the utilization of information on query sequences in the optimization of processing them on reconfigurable accelerator hardware. The ReProVide Processing Unit (RPU) is such a system that can filter data on their way from storage to DBMS. The reconfiguration required to adapt to the next query can be substantially reduced by
taking the sequence of coming queries into account. It can (I) be done in parallel to the result-data transfer of a running query and can (II) be avoided completely by swapping accelerators. The second optimization has strong improvement effects for smaller relations, while the first overtakes for larger relations and/or rising time gaps between queries.

The optimizations done by hand in these evaluations already show promising results. So we will be built them into the optimizer.

For further optimizations, we will use query-analysis graphs similar to those proposed in [10]. The idea is to keep result data in the memory of the RPU, if they can be reused in subsequent queries. For instance, if one query asks for tuples with \( A > 100 \) and the next asks for \( A > 200 \), the result of the first can be used to generate the result of the second.

More hints can be imagined to optimize the RPU further: We could synthesize other accelerators by combining other arithmetic and comparison operators, depending on the frequency of these combinations in the query sequences.

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