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Regulating Concurrency in Software Transactional Memory: An Effective Model-based Approach

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Nowadays **multi-core/processor systems** have become mainstream platforms

Hardware performance continues to improve mainly due to:

- even more cores in a single processor
- even more processors in a single machine



Single-threaded/process applications can not take advantage of such a hardware performance improvement.



need for multi-threaded/process applications





The **synchronization problem** in concurrent applications: code sections accessing shared data may have to be synchronized (e.g. critical sections)

using traditional synchronization techniques (i.e. locks, semaphores, monitors, ...) is not easy
fine-grained synchronization is a time-consuming task • pitfalls for programmers: deadlocks, livelocks, priority inversions, code composition is complex, scalability issues, ...

debug is complex



- programming paradigm for multi-core/processor systems
- simplifies the development of parallel and concurrent applications

key idea: hide away synchronization issues by using transactions



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Transactional Memories



The underlying transactional memory layer takes care of ensuring <u>atomic and</u> <u>isolated executions of transactions</u>







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The optimal concurrency depends on: application logic, workload profile, hardware architecture, ...

Additionally, the optimal concurrency level may change depending on the <u>application execution phase</u>.



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Goal:

enabling TM platforms to self-regulate the concurrency level

How:

1) a <u>parametric performance model</u> of TM applications is used to estimate the throughput of an application as a function of the:

- concurrency level (number of concurrent threads)
- the current workload profile of the application

2) <u>regression analysis</u> is exploited to customize the parametric performance model for a specific TM system (application + hardware platform)

3) a <u>controller</u> is integrated with the TM platform. At run-time, the controller exploits the customized model in order to decide, on basis of the observed workload profile, the number of concurrent threads to keep active





The parametric performance model estimates the <u>transaction abort</u> probability of transaction p_a as a function of:

- the average size of the transaction read-set (*rss*)
- the average size of the transaction write-set (*wss*)
- the average execution time of committed transaction runs (tt)
- the average execution time of code blocks outside of transactions (tntc)
- the read/write affinity (rw_a , i.e. the probability that an object read by a transaction is also written by other transactions)
- the write/write affinity (wwa, i.e. the probability that an object written by a transaction is also written by other transactions)
- the number of concurrent threads (k)

$$p_a = f(rs_s, ws_s, rw_a, ww_a, t_t, t_{ntc}, k)$$





Results from analytical modeling studies of transactional systems (e.g. [1,2]) :

$$p_a = 1 - e^{-\alpha}$$

where *α* is a complex function which is hard to identify unless making strong assumptions on workload profile, operations' execution speed, data contention, etc





Proposed approach:

- Simulation has been used to determine a parametric expression which captures the shape of the curve of the function p_a depending on the the workload profile

- The parametric expression has been validated using data achieved by executing TM applications on real systems

Basic equation:







Case of ρ : expressing ρ as a function of wss and wwa



fitting function:

$$[c \cdot (ln(b \cdot ws_s + 1)) \cdot ln(a \cdot ww_a + 1)]^d$$

fitting parameters: a, b, c, d





fitting function: $[c \cdot (ln(b \cdot ws_s + 1)) \cdot ln(a \cdot ww_a + 1)]^d$

Error evaluation with respect simulation data:

- fitting parameters (*c*, *b*, *a*, *d*) calculated through regression analysis (using 40 randomly selected workload profiles)

- average error (using 80 randomly selected workload profiles while varying *wwa* and *wss*): 5.3%







The same approach for ω and Φ , ...

Finally

$$p_a = 1 - e^{-
ho\cdot\omega\cdot\phi}$$
 , where:

expression of ρ :

$$\begin{split} [c \cdot (ln(b \cdot ws_s + 1)) \cdot ln(a \cdot ww_a + 1)]^d + \\ &+ [e \cdot (ln(f \cdot rw_a + 1)) \cdot ln(g \cdot rs_s + 1) \cdot ws_s]^z \end{split}$$

expression of ω :

 $h \cdot (ln(l \cdot (k-1)+1)$

expression of Φ :

$$m \cdot ln(n \cdot \theta + 1)$$
, where $\theta = rac{t_t}{t_t + t_{ntc}}$





Final average error with respect to simulation data: 4.8%







- Evaluation of the prediction error using <u>STAMP benchmark suite</u> [3] and TinySTM [4]

Hardware: HP ProLiant server with 2 AMD OpteronTM6128 Series Processor, 8 cores per CPU (for a total of 16 cores), 32 GB RAM, Linux kernel version 2.7.32-5-amd64.

- Evaluation of the <u>extrapolation capability</u> of the model: for each application, three regression analysis have been performed using three different sets of measurements. Each set of measurements includes 80 samples gathered observing the application running with:

- 2 and 4 concurrent threads (first set)
- 2,4 and 8 concurrent threads (second set)
- 2,4, 8 and 16 concurrent threads (third set)

Results (while varying application workload profiles and the number of threads between 2 and 16)

| | Observed concurrency levels for the regression analysis | | |
|-------------|---|------------------|------------------|
| application | 2/4 threads | 2/4/8 threads | 2/4/8/16 threads |
| Vacation | 2.166% (0,00089) | 1.323% (0,00028) | 1.505% (0,00032) |
| Kmeans | 18.938% (0,09961) | 2.086% (0,00100) | 2.591% (0,00109) |
| Yada | 2.385% (0,00029) | 2.086% (0,00016) | 2.083% (0,00022) |

abort probability prediction error (variance in brackets)





Comparison with a Neural Network-based Performance Model

Evaluation of the extrapolation capability with respect a <u>neural network-based model</u> (proposed in [5])



Results for Yada benchmark (using the first set of samples)



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Enabling STM to self-regulate the concurrency level:

architecture of CSR-STM (Concurrency Self-Regulating STM) available at URL http://www.dis.uniroma1.it/hpdcs/CSR-STM.tar







Periodically, the controller uses the performance model to calculate the expected abort probabilities $p_{a,k}$ while varying the number of concurrent threads k, i.e.:

 $\{(p_{a,k}), 1 \le k \le max_{thread}\}$

hence, the controller keeps active m threads, where m is the value of k such that the application throughput, i.e.



It can be calculated using the average number of transaction re-runs:

$$p_{a,k}/(1-p_{a,k})$$

Hardware scalability model used for validation [14]:

 $C(k) = 1 + p \cdot (k-1) + q \cdot k \cdot (k-1)$





Comparison Between CSR-STM and Tiny STM







• Analytical models of concurrency control protocols for transactional systems (e.g. [1,2,6,7,8]):

- strong assumptions on workload profile, operations' execution speed,

data contention, etc \rightarrow high prediction error with real applications

• Interpolation using different kind of functions (e.g. polynomial, rational, logarithmic functions) [8]:

- workload profile is not accounted \rightarrow variation of the optimal concurrency level along the execution of the application can't be captured

• Machine learning-based approach (e.g. [5]) \rightarrow low extrapolation capability (vs. the parametric performance model-based approach)

• Pro-active transaction scheduling schemes (e.g. [10,11,12])

- based on heuristic schemes \rightarrow require evaluating suitable heuristics and tuning a set of thresholds depending on the application workload





Thank you

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