

# Parallel Odd-Even Sort

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## 1 Introduction

In this report we implemented two parallel versions of the Odd-Even Sort (OES) algorithm. The algorithm is pretty simple and works as follows: we proceed repeating identical iterations, each of which consists of two scans over the vector to be sorted; the first scan compare elements in even positions with their successors and, if out of order, swaps them, the same happens for odd-positioned elements in the subsequent scan. For the rest of this report we assume to sort a vector  $v$  of length  $n$ ; it can be proven (Wikipedia Odd-Even Sort) that  $n$  such identical iterations are sufficient to sort the vector, leading to a sequential complexity of  $\mathcal{O}(n^2)$ , sub-optimal with respect to the well known  $\mathcal{O}(n \log(n))$  alternatives. However this algorithm presents a strong data independence (i.e. its data flow graph is moderately interconnected), therefore we can aim at achieving interesting speedups with a parallel version.

## 2 Design Choices

The most trivial parallel implementation of OES exploits the data parallelism that is inherent to the inner for loops; we can simply run two parallel for (one for the even phase and one for the odd one) inside a sequential loop. An OMP implementation of this pattern is provided (`openmp.cpp`), however the experimental results showed that the parallel version introduce so much overhead that it is not even compensated by the speedup, so that the parallel version is slower than the sequential one. We implemented the exact same pattern implementing the barrier and the parallel for by myself (`pthread-barrier.cpp`) and again it yielded awful performances. Therefore

we decided to get rid of the barriers, it required some effort and we needed to add some additional structures and to disrupt the iterative form in which the sequential version has been describing. In the next section we describe two different patterns implemented respectively using native C++ threads and the Fastflow library.

### 3 Pthread Version

We refer to the file `pthread-async.cpp` that is widely commented, consider reading the source code for a thorough explanation of implementation details. The basic idea here is that, given  $nw$  workers, we can partition our vector  $v$  in  $nw$  chunks, so that each worker only deals with a single chunk. This is more or less what happens in our pthread implementation of the “barrier pattern” (i.e. the one employing a parallel for). In that case we synchronized our workers so that they waited each other once they finished a single pass over their chunk, but now we want to avoid the overhead arising from that. If we suppose that threads act really independently many problems open up: first we need to deal with data races (that we previously neglected, since the odd-even structure coupled with barriers prevented any data race); second we need to provide some stopping condition (since the theorem mentioned in the introduction and stating that  $n$  outer-loop iterations are enough holds only if the outer loop is sequential).

Now we explain how we managed to solve those problems, implementing a version of the algorithm in which each worker perform the OES iterations on its chunks until a global stopping condition is met.

#### 3.1 Data Races

Consider the vector  $v$  divided in chunks so that the  $i$ -th chunk is  $v[st[i]] \dots v[en[i]]$  where  $st$  and  $en$  are suitable vectors of indices denoting chunk boundaries. Our algorithm swaps elements with their successors, hence the only elements of  $v$  for which a data race occurs are  $v[en[i]] = v[st[i+1]]$  for some  $i = 1 \dots nw$ . We can use a vector of mutexes (one for each of those values) without incurring in a substantial overhead, in fact each pass over a chunk will only need two locks and unlocks: one for the left side and one for the right side boundary. In the next subsection more structure will be introduced that will need some synchronization mechanism to avoid data races, we exploited

the fact that those structures are often accessed simultaneously to boundary elements of  $v$  and employed the same mutexes. The only detail worth mention regards deadlocks, to prevent the deadlocks we adopted the “topological sort rule”: given the natural numeration of mutexes associated to elements  $v[st[i]]$ , we only nested mutexes so that the inner one is associated with the lower number.

### 3.2 Stopping Condition

Every thread only operates on its portion of the data performing a loop indefinitely, how can we set up a stopping condition? We define a boolean vector  $sorted[1 \dots nw]$  such that the following invariant holds:  $sorted[i]$  is true if and only if both an even and an odd pass over the  $i$ -th chunk have been completed and the following properties hold:

- no transposition was performed during the last odd-even phase by the  $i$ -th worker
- no transposition concerning elements at the boundary with the  $i$ -th chunk was performed by  $(i + 1)$ -th nor  $(i - 1)$ -th workers since the beginning of the last odd-even phase of the  $i$ -th thread

These two conditions together ensure that the  $i$ -th chunk is sorted, therefore if  $sorted[i] == true$  for each  $i = 1 \dots nw$  then the algorithm should terminate. This is handled through a global counter  $cnt$  counting how many entries of  $sorted$  are set to *true*; clearly  $cnt$  data races are prevented using a mutex. Finally some care should be taken to set and unset the *sorted* entries, in fact we need to both remember its state before the beginning of the current odd-even iteration and to annotate whether a neighbouring thread swapped any boundary element, this is achieved using another vector *meanwhile* that is true if and only if a boundary transposition happened since the beginning of the current odd-even iteration.

## 4 FastFlow Version

In the Fastflow implementation we implemented a different pattern. We used a master-worker pattern, namely we declared an emitter node and  $nw$  worker nodes, each equipped with a feedback channel feeding the emitter. A

first approach would be to synchronize all the workers so that the emitter handles the outer loop of the sequential OES and workers perform the inner loop exploiting the data parallelism. As noted above, this kind of barrier introduce a huge overhead, therefore we opted for a slightly more clever implementation: the key observation is that the interaction of chunks is only local, therefore to ensure sequential equivalence it is sufficient to guarantee that adjacent chunks have a “lag” of at most one odd or even iteration. More formally, we consider odd and even iterations as distinct and define the vector  $npass[1 \dots nw]$  counting how many odd (or even) passes have been performed over the  $i$ -th chunk; then we start the  $j$ -th pass over the  $i$ -th chunk only if  $npass[i + 1] \geq j$  and  $npass[i - 1] \geq j$ . We need lower bound of the number of passes in order to ensure correctness, hence in a first version of this pattern the emitter updated the number of passes (performing `++npass[i]`) when a worker signaled that has finished its work using the feedback loop. This was further improved, in fact it is sufficient to immediately perform the boundary transpositions (directly performed by the emitter) in order to increment  $npass$  without affecting correctness; in fact the external view of the chunk depends only on its boundary elements. In this way we achieved some decent speedups that we will see in the experiments section.

In the design of the FF version we checked that each thread was mapped to a different core of the Xeon Phi machine we run all our experiments on, this ensured that, using less workers than physical cores, the SPSC non-blocking FIFO was more efficient (although more power consuming) than the blocking version. Moreover we confronted different scheduling policies and found out that the default one (loose round robin) was the most efficient one.

## 5 Experiments

All the experiments have been performed on the Xeon Phi machine<sup>1</sup> whose access has been provided during the course. Our primary goal in the experiment was to evaluate the speedup and scalability achieved by our two implementations. For this reason we implemented a sequential version (`sequential.cpp`) and compared the performances.

We used vectors of random integers generated from a console-provided seed, so that we could guarantee the fairness of the experiments (reduce the random noise introduced by differently shuffled vectors). Although the code is written

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<sup>1</sup>Architecture: x86\_64, CPUs: 256, Cores 64, 1.30GHz, 64-bit.

for a vector of integers, it is very easy to generalize it to a generic type for which a total order operator  $<$  is defined. It is apparent that if we choose more costly comparison function speedup and scalability will get better (by Amdahl's law), therefore in this sense we explored a “worst case scenario”.

## 6 Conclusions