



Kalman Filter Tracking on Parallel Architectures

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Introduction





- Reconstruction time diverges at large (≥ 100) PU
 - CPU frequency does not scale with Moore's law anymore
 - current model cannot be used at HL-LHC without compromises on physics!
 - both in online and offline processing
- The solution is a phase transition to highly parallel architectures
 - but code needs a hardware-specific design for optimal performance
 - algorithms cannot be ported in a straightforward way
 - initial target is the most time consuming algorithm, track reconstruction





• Xeon Phi as starting point, no real prejudice on architecture

- but more direct porting of optimizations to Xeon
 - in fact we test performance on both
- the name of the game is to keep the many **processors occupied** and the **vector units on sync**, performing the same calculations and thus minimizing branching points

• Standalone tracking code

- started with a simplified setup
 - Ideal barrel geometry, no material interaction, gaussian hit position smearing
 - Particle gun simulation, no interactions/decays
- prepared to increase complexity along the way





Kalman Filter tracking widely used in HEP, outstanding performance in LHC environment.

It consists in the reiteration of a **basic logic unit** for each tracker layer.



The track reconstruction process can be divided in 3 steps: track seeding, building and fitting.

The track fit is the bare repetition of the basic unit, ideal as a starting point. Track building is the most time consuming part – it involves branching points of variable size, with the simplest version degenerating into the track fit case. Track seeding under development but not included yet, for now seeds are defined using MC info.





Approach successful only if data structures are optimized for the specific architecture.

Kalman filter calculations based on small matrices. Intel Xeon and Xeon Phi have vector units with size 8 and 16 floats respectively. How can we efficiently exploit them?

Matriplex is a "matrix-major" representation, where vector units elements are separately filled by a different matrix: **n matrices work in sync**.

R1			M ¹ (1,1)	M ¹ (1,2)	 M ¹ (1,N)	M ¹ (2,1)	,	M ¹ (N,N)	M ⁿ⁺¹ (I,I)	M ⁿ⁺¹ (1,2)	
R2		rection	M²(1,1)	M ² (1,2)	 M²(1,N)	M²(2,1)	,	M²(N,N)	M ⁿ⁺² (I,I)	M ⁿ⁺² (1,2)	
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		fast m									
Rn	nit	↓ ↓	M ⁿ (I,I)	M ⁿ (1,2)	 M ⁿ (I,N)	M ⁿ (2, I)		M ⁿ (N,N)	M ²ⁿ (1,1)	M ²ⁿ (1,2)	

Matrix size NxN, vector unit size n





- Track fit implemented using Matriplex
 - same physics results and faster than SMatrix even in serial case
 - tested both on Intel Xeon and Xeon Phi (native application) with OpenMP, similar qualitative results
- Observe large speedup both from vectorization and parallelization.
 - Effective performance of vectorization is about 50% utilization efficiency.
 - Parallelization performance is close to ideal in case of 1 thread/core
 - some overhead with 2 threads/core
- Both issues related to L1 cache
 - Data availability and data packing in matriplex format





• Consolidate track fitting results

- identify bottlenecks for vectorization
- improve simulation towards a realistic setup

• Develop track building

- start with simple geometry setup
- target full vectorization and parallelization



Improving Vectorization

Comparison of input methods for fitting 1M tracks using Matriplex



- Relative fraction of time for data input is large with respect to total fit time
 - input consists of data transfer and repacking into Matriplex format
 - plot shown for Xeon Phi, single-threaded, using the vector units to the extent possible
- We explored different approaches (1-3) and different intrinsics (4-6) resulting in substantially different performance
 - 1, 6: Scatter data from tracks into Matriplexes, track by track, using for-loops or vscatter intrinsic
 - 2-5: Two stages: copy data into packed temporary, then use strided loads, MKL transpose, or intrinsics
 - Best method (#4) relies on two-stage copy and vgather intrinsic





- Progress towards implementation of the full tracking chain:
 - fit track obtained from building, not straight from simulation
- More realistic detector simulation:
 - Added option to include multiple scattering in simulation
 - Using USolids geometry package
 - implement different barrel-like layouts in a transparent way
 - still propagating track parameters to hit radius
 - timing and physics performance of track fit do not change!







- Same core calculations as in track fitting but adding two big complications
 - Hit set is not defined: hit on next layer to be chosen between O(10k) hits
 - For >1 compatible hit, combinatorial problem requires **cloning of candidates**
- The two issues can be **factorized** by dividing the development in two stages
 - first develop a simplified algorithm choosing only the best hit on next layer
 - deal with large number of hits, not with cloning study vectorization in this case first
 - then full implementation with combinatorial expansion
 - parallelization already using this version!
- Data locality is the key for reducing the Nhits problem
 - eta partitions are self consistent (no bending)
 - bins redundant in terms of hits, track candidates never search outside their eta bin
 - natural boundary for thread definitions
 - phi partitions give fast lookup of hits in compatibility window





Vectorization Results





- Run simplified track building (best hit option) on 10 events with 20k tracks each
 - pick hit in compatibility window with lowest chi2 at each layer
 - ▶ 70% (93%) of tracks found with \geq 90% (60%) of the hits
- Already much more difficult than fitting case, expect worse results:
 - test multiple (non pre-determined) hits per track
 - compatibility window and hits to process are not fully defined until propagation to layer
- Results show a maximum speedup of >2x both on Xeon and Xeon Phi
 - reasonable scaling on Xeon
 - overhead observed when enabling vectorization on Xeon Phi, then speedup
 - further gain from using prefetching and gathering instrinsics, but data input still takes a large fraction of the time!

Parallelization Results





- Run full track building with combinatorial expansion of candidates
 - ultimate physics performance, slower
 - ▶ 85% (95%) of tracks found with \geq 90% (60%) of the hits
- Parallelization is implemented by distributing threads across 21 eta bins
 - for nEtaBin multiple of nThreads, split eta bins in threads
 - for nThreads multiple of nEtaBin, split seeds in bin across nThreads/nEtaBin threads
- Large **speedup** achieved, both on Xeon and Xeon Phi
 - up to ~5x on Xeon and >10x Xeon Phi
 - speedup saturates above nThreads=42





- First version of vectorized and parallelized track building implemented!
- Significant speedup achieved both on Xeon and Xeon Phi
 - 2x from vectorization
 - 5x on Xeon and 10x on Xeon Phi from parallelization
- Ideal scaling indicates a large margin for further improvements
- More studies and developments are needed:
 - identify and solve bottlenecks in vectorization and parallelization performance
 - performance studies at different track occupancy values
 - improve data locality: optimize partition size, smart sorting of candidates
 - complete transition to more advanced tools for parallelization (TBB)
- While at the same time progressing towards a **fully realistic setup**
 - use full event simulation
 - complete the chain starting from track seeding





backup





- Xeon
 - CentOS 6.6, 2x6 core Xeon E5-2620 @ 2GHz, 64 GB RAM, turbo off, hyperthreading on
- Xeon Phi
 - Xeon Phi 7150, 16 GB RAM, 61 cores @ 1.24GHz, MPSS 3.4.3
- Intel compiler
 - icc (ICC) 15.0.2 20150121 with gcc-4.8.2 libstdc++/c++-11 support
- Open MP 4.0
- TBB 4.3.0
- Intel VTune 2015.2.0





- Intel VTune's metrics revealed that CopyIn, which distributes input data into a Matriplex, was underperforming
 - Assembler code showed lack of vectorization on Xeon Phi
 - Compiler was not converting strided for-loops into vectorized stores
 - Better: copy all data into a packed temp array, do strided loads
- Fastest Xeon Phi code uses Intel's _mm512 vector intrinsics
 - Vgather gave additional gains for strided loads
 - Vscatter was not as helpful with strided stores
- Underlying operation is equivalent to a matrix transpose
 - Intel MKL includes an optimized out-of-place transpose routine
 - It didn't work well; probably it is targeted for large-matrix operations



Details of Input Methods





- 1. CopyIn: scatter data from tracks into Matriplexes, track by track, using simple for-loops
- 2. CopyInContig + Plexify: copy 16 tracks into contiguous memory, transpose into Matriplexes via loops
- 3. CopyInContig + PlexifyMKLOut: copy 16 tracks into memory, use Intel MKL to transpose each Mplex
- 4. CopyInContig + PlexifyIntr (vgather): copy 16 tracks into memory, vgather into Matriplexes by rows
- 5. CopyInContig + PlexifyIntr2 (vscatter): copy 16 tracks into memory by rows, vscatter into Matriplexes
- 6. CopyInIntr (vgather + vscatter): scatter data into Matriplexes, track by track, using Intel intrinsics







- Algorithm parameters not tuned for ultimate physics performance yet
- But results already in very good shape
 - large hit collection efficiency
 - ▶ tracks with \geq 9 hits have <1% resolution



phiphi vs mic0





- looks like we do better on mic0?
- how come code is not the same?



BestHit on phiphi





- change vector unit size from 1 to 8
- not identical but very close



FindCandidates on phiphi





• change both vector unit size and number of threads

• not identical but very close



BestHit on mic0





- change vector unit size from 1 to 16 (with and without intrinsics)
- large difference going from 1 to 16
- small difference when turning on intrinsics



FindCandidates on mic0





- change number of threads with fixed vector unit size
- nthreads=1 and 7 are similar (nthreads<nEtaBins)
- nthreads=21 and 42 are similar (nthreads>=nEtaBins)



Prefetching in AddBestHit



	phiphi	phiphi noPF	mic0	mic0 noPF
Ι	3.49	3.44	18.47	19.49
2	2.90	2.78	23.11	24.32
4	1.90	I.84	22.46	17.63
8	I.68	I.58	11.89	13.43
8 int	I.60	1.61		
16			11.13	12.83
I6 int			8.28	10.24

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