# GPU version of the Polgraw all-sky F-statistic pipeline

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collaboration with

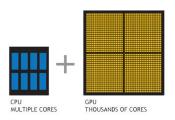
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#### Outline

- \* CPU vs GPU concept,
- \* description of the all-sky F-stat search for candidate signals,
- \* Implementation of the GPU version,
- \* CPU version performance testing.

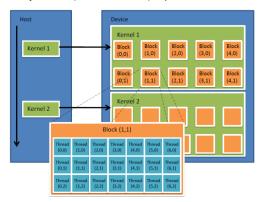
## Central Processing Units vs Graphics Processing Units

CPU: a **few** cores optimized for **sequential serial** processing



GPU: **thousands** of smaller (⇒ more efficient) cores designed for handling **multiple tasks simultaneously** 

\* Host (CPU) – Device (GPU) interaction, executing many kernels (device functions) in parallel



Platform & programming model for this project: CUDA (Compute Unified Device Architecture) of NVIDIA

## C vs CUDA: Hello world! example

```
#include (stdio.h)
                                                       #include (stdio.h)
      #define N 7
                                                       #define N 7
 3
                                                  3
                                                  4
 4
      int main() {
                                                       __global__ void add_arrays(char *a, int *b) {
                                                           a[threadIdx.x] += b[threadIdx.x]:
 5
                                                  5
 6
          char a[N] = "Hello ":
 7
          int b[N] = {15, 10, 6, 0, -11, 1, 0};
                                                       int main() {
 8
 9
          printf("%s", a);
                                                 10
                                                           char a[N] = "Hello ":
10
                                                           int b[N] = {15, 10, 6, 0, -11, 1,0};
11
                                                 11
          // adding int to char
12
                                                 12
13
          int i:
                                                 13
                                                           char *ad: int *bd:
14
          for (i=0; i<N; i++)
                                                 14
                                                           const int csize = N*sizeof(char);
              a[i] += b[i];
                                                           const int isize = N*sizeof(int);
1.5
                                                 1.5
                                                 16
16
17
          printf("%s\n", a);
                                                 17
                                                           printf("%s", a);
18
                                                 18
                                                           cudaMalloc((void**)&ad, csize);
19
          return 0:
                                                 19
20
                                                 20
                                                           cudaMalloc((void**)&bd. isize);
21
          // in ASCII
                                                 21
          // H 72, e 101, l 108, o 111
                                                           cudaMemcpy(ad, a, csize, cudaMemcpyHostToDevice);
22
                                                 22
         // W 87, r 114, d 100, ! 33
23
                                                 23
                                                           cudaMemcpy(bd, b, isize, cudaMemcpyHostToDevice);
      }
24
                                                 24
                                                           dim3 dimBlock(N); dim3 dimGrid (1);
                                                 25
                                                 26
                                                           // adding int to char
                                                 27
                                                           add_arrays <<< dimGrid, dimBlock >>> (ad, bd);
                                                 28
                                                           cudaMemcpy(a, ad, csize, cudaMemcpyDeviceToHost);
                                                 29
                                                 30
                                                           cudaFree (ad):
                                                 31
                                                           printf("%s\n", a);
                                                 32
                                                 33
                                                           return EXIT SUCCESS:
                                                 34
                                                                                                            4/14
```

#### Calculation of the F-statistic

To estimate how well the model matches with the data x(t), we calculate  $\mathcal{F}$ ,

$$\mathcal{F} = \frac{2}{S_0 T_0} \left( \frac{|F_a|^2}{\langle a^2 \rangle} + \frac{|F_b|^2}{\langle b^2 \rangle} \right)$$

where  $S_0$  is the spectral density,  $T_0$  is the observation time, and

$$F_a = \int_0^{T_0} x(t)a(t) \exp(-i\phi(t))dt, F_b = \dots$$

and a(t), b(t) are amplitude modulation functions (depend on the detector location and sky position of the source),

$$h_1(t) = a(t)\cos\phi(t), \quad h_2(t) = b(t)\cos\phi(t),$$

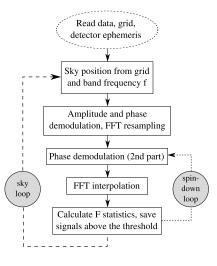
$$h_3(t) = a(t)\sin\phi(t), \quad h_4(t) = b(t)\sin\phi(t),$$

related to the model of the signal  $(h_i, i = 1, ..., 4)$ 

$$h(t) = \sum_{i=1}^4 A_i h_i(t).$$

For triaxial ellipsoid model: dependence on extrinsic  $(h_0, \psi, \iota, \phi_0)$  and intrinsic  $(f, \dot{f}, \alpha, \delta)$  parameters.

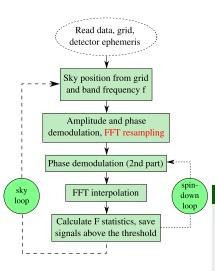
## F-stat all-sky search description



Main parameters in coherent search for continuous wave signals:

- ★ bandwidth 1Hz
- ★ sampling time 0.5 s
- ★ data length N = 344656 (two sideral days)
- $\star$  4D grid:  $\alpha,\,\delta,\,f,\,\dot{f}\,$  sky positions, frequency and spindown
- \* Uses the F-statistic defined in Jaranowski, Królak & Schutz (1998), algorithm described and tested in Astone et al. (2010)
- $\star$  No. of F-statistic evaluations  $\propto f^3$  (no. of sky positions  $\propto f^2$ , spindown  $\propto f$ )

## F-stat all-sky search description



## Basically the whole loop over sky $(\alpha, \delta)$ can be computed in parallel since the sky positions are independent of each other

The majority of computing is spent on

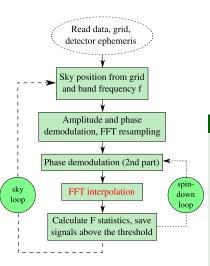
- ★ calculating the phase (trigonometric functions,  $\gtrsim 30\%$ )
- **★** FFT (≳ 50%)

Efficient FFT requires  $2^N$  data points  $(N_{data}=344656<2^{19}) \rightarrow$  padding with zeros to  $N=2^{19}$ 

#### FFT: resampling

- \* Resampling to barycentric time FFT and inverse:
  - $\star$  nearest-neighbour ( $\simeq 5\%$  error),
  - $\star$  splines ( $\simeq 0.1\%$  error)

## F-stat all-sky search description



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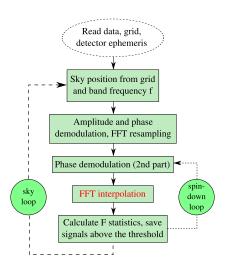
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#### FFT: Interpolation

Grid coincides with Fourier frequencies - possible loss of signal (max. 36.3% when *f* is half way between the Fourier frequencies)

- \* FFT (length N) & interbinning (max.  $\simeq 13\%$  error): DFT component in the middle of two Fourier frequencies approximated by  $X((k+1/2)\simeq (X(k+1)-X(k))/\sqrt{2}$
- $\star$  FFT zero-padding (length 2N, max.  $\simeq$  10% error)

## F-stat: parallelization strategy



#### How to do FFT with GPU:

- ★ use CUDA cuFFT library:
  - well-optimized (Cooley-Tukey, Bluestein), 1D/2D/3D double precision complex/real transforms, multiple transforms, in- and out-of-place transforms,
  - cannot launch many instances at the same time (at least not with every card/CUDA version).
- \* write custom kernel for FFT, launch concurrently.
- \* cuSPARSE (sparse matrix routines)

## Results of implementation on GPUs

- ⋆ Input data loaded to device once,
  - One detector version, but easy to generalize (CPU network-of-detectors version exists),
- ★ Sequence of kernels launched in a loop from CPU,
- Time resampling done using double precision, everything else (main spindown loop) using single precision,
- \* Asynchronous output transfer to host.

### Current GPU results: $\sim \times 50$ speedup with respect to the optimized CPU code

Estimated time  $\tau$  to match one template:

- $\star$  CPU (Intel(R) Xeon(R) CPU E5-2665 @ 2.40GHz)  $\simeq$  4  $\times$  10<sup>-2</sup> s
- ★ GPU (GeForce GTX Titan)  $\simeq 8 \times 10^{-4}$  s

#### Also testing on:

- ⋆ Intel(R) Core(TM) i5, 2.8GHz
- \* GPUs:
  - ⋆ GeForce GTX 560 Ti
  - \* GeForce GTX 480

Performance scaling - favorably for high frequencies (fast spindown loop on GPU).

## Profiling the CPU version with perf

Initially we were using gprof and Callgrind/KCachegrind, but later learned about perf (of linux-tools) and found it much more useful to estimate performance in FLOPS:

- \* perf stat -e r5300c0 -e r530110 -e r532010 -e r534010 -e r538010 -e r531010 -e r530111 -e r530211, where the switches correspond to different operations on a Sandy Bridge processor:
  - \* r530111 SIMD\_FP\_256:PACKED\_SINGLE
  - \* r530211 SIMD\_FP\_256:PACKED\_DOUBLE
  - \* r530110 X87
  - \* r531010 SSE\_FP\_PACKED\_DOUBL
  - \* r532010 SSE FP SCALAR SINGLE
  - \* r534010 SSE\_PACKED\_SINGLE
  - \* r538010 SSE SCALAR DOUBLE

(SIMD - Single Instruction Multiple Data, SSE - Streaming SIMD Extensions)

Estimated performance is 25% of peak performance on Sandy Bridge

## Profiling the CPU version with perf

Also useful to locate the time-expensive parts of the code (with a direct view into the assembly code):

```
* perf record -B -e
  task-clock:u,cycles:u,
  instructions:u
```

\* perf report

```
Samples: 59K of event 'cycles'. Event count (approx.): 44758302322
                 [kernel.kallsyms]
                 libveppp.so
                                        sincos@plt
                                          libc memalign
                                        init arrays
                                          printf fp
                                        fftw twiddle awake
```

### Fast libraries for commonly used functions in CPU version

- Obvious choice is icc Intel compiler + Math Kernel Library (MKL), with optimizing flags
  - -march=native -mtune=native -Ofast -unroll-agressive -ipo
    -use-intel-optimized-headers -opt-prefetch
- We also have a good experience with gcc, FFTW3 and optimized math libraries (using latest SSE & AVX instructions):
  - \* SLEEF (SIMD Library for Evaluating Elementary Functions) trigonometric functions (among others) in double precision without table look-ups, conditional branches etc. http://shibatch.sourceforge.net or
  - \* YEPPP high-performance SIMD-optimized mathematical library for x86, ARM, and MIPS processors. http://www.yeppp.info
- ★ FFTW3 Planner Flags FFTW\_PATIENT instead of FFTW\_MEASURE
- \* compiler flags: -03 -ffast-math -funsafe-loop-optimizations -funroll-loops -march=native -mtune=native -mavx

Changing the libraries from standard math to optimized ones + remembering about FFTW3 planner flags ->30% speedup in case of CPU.

## Summary/references

We have a quite well-optimized CPU code ( $\pm$  memory access optimizations), and a working GPU code that may still need some optimization (+ extenstion to a network of detectors).

- P. Astone, K. M. Borkowski, P. Jaranowski, M. Piętka and A. Królak, PRD, 82, 022005 (2010)
- ► https://developer.nvidia.com/cuFFT
- P. Jaranowski, A. Królak, and B. F. Schutz, PRD **58**, 063001 (1998).
- https://github.com/mbejger/polgraw-allsky.git