Spotting Radio Transients with the Help of GPUs

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Abstract. Exploration of the time-domain radio sky has huge potential for advancing our knowledge of the dynamic universe. Past surveys have discovered large numbers of pulsars, rotating radio transients and other transient radio phenomena; however, they have typically relied upon off-line processing to cope with the high data and processing rate. This paradigm rules out the possibility of obtaining high-resolution base-band dumps of significant events or of performing immediate follow-up observations, limiting analysis power to what can be gleaned from detection data alone. To overcome this limitation, real-time processing and detection of transient radio events is required. By exploiting the significant computing power of modern graphics processing units (GPUs), we are developing a transient-detection pipeline that runs in real-time on data from the Parkes radio telescope. In this paper we discuss the algorithms used in our pipeline, the details of their implementation on the GPU and the challenges posed by the presence of radio frequency interference.

1. Introduction

The High Time Resolution Universe (HTRU) survey currently underway at Parkes Observatory using the 64m dish is an all-sky search for transient and periodic point sources. Its primary goals are to discover new pulsars and fast radio transients and it has so far discovered more than 65 previously unknown pulsars since it began in 2008 (Keith et al. 2011). The observing backend has 400 MHz of bandwidth over 1024 channels centered at 1381.8 MHz, and data products are produced with a time resolution of 64µs. The receiver is a multibeam design and contains 13 separate feed horns pointing at nearby locations on the sky (Staveley-Smith et al. 1996).

The current pulsar and transient search process begins by taking filterbank data (i.e., time series for each frequency channel) from the backend – stored using 2 bits per sample to give a data rate of around 4 MB/s per beam – and sending it via a fibre optic link from the telescope down to the Swinburne supercomputer in Melbourne (~700 km away). There it is written to disk for immediate processing (when possible) and also to tapes for longer term storage and future (re-)processing. The processing itself is then performed on a distributed cluster of multi-core central processing units (CPUs). Once the data are in memory, the current transient search pipeline takes more than 30 minutes to process a 10 minute observation.
While limitations in CPU computing power have necessitated offline processing of the survey data to date, ideally one would like to execute the pipeline in real-time with the observations. If this were achieved, several significant advances become possible. Among them is instant feedback and capacity for follow-up observations of significant events. This would eliminate the long delays incurred by the current off-site processing and undoubtedly increase the survey’s discovery power. Another promising possibility is triggered baseband data dumps. These would allow the capture of full-resolution baseband data during events of interest; the baseband data are currently not saved due to the high data rate, but could be kept for a short period in a buffer that is written to disk when deemed worthwhile.

CPU computing performance continues to increase year on year, but is still not up to the task of processing the survey data in real-time (for acceptable monetary, power and floorspace costs). However, the recent appearance of graphics processing units (GPUs) in high-performance computing presents a new opportunity to attempt to break the real-time barrier. These devices can provide an order of magnitude more compute power than CPUs at comparable costs, but pose considerable software challenges due to their unfamiliar architectures [see Fluke et al. (2011) for an introduction]. It is our aim to implement the transient detection pipeline on a GPU and to exploit the boost in processing power to achieve a real-time processing rate.

2. The Radio-Transient Detection Pipeline

The transient detection part of the software pipeline, which begins with filterbank data and ultimately produces a list of candidate events, involves five processes: RFI mitigation, incoherent dedispersion, baseline/red-noise removal, matched filtering and peak finding. With a special focus on the first two, we now introduce these algorithms and describe their implementation on the GPU. We base our approach on the algorithm analysis methodology of Barsdell et al. (2010).

2.1. RFI Mitigation

When searching for transient events in real time, one of the most significant obstacles to overcome is the presence of radio frequency interference (RFI). An event detection and recording system could easily be swamped with false positives if significant levels of RFI are allowed to pass through the pipeline. It is therefore necessary to apply RFI mitigation techniques to reduce the effects of these undesirable phenomena.

Several RFI rejection techniques have been used in the literature. These include simple sigma-clipping (where unnaturally loud signals are excised), statistical methods such as the use of spectral kurtosis (where non-Gaussianity is detected and removed) (Nita et al. 2007) and coincidence rejection via the use of one or more reference antennas (where non-localised signals are assumed to be RFI) (Fridman & Baan 2001). In this work we implement the coincidence rejection method using the 13 beams of the Parkes multibeam receiver as an array of reference antennas.

The simplest approach to implementing the coincidence rejection technique is to apply signal-to-noise and coincidence thresholds such that a) there is a good distinction between true signals and RFI, and b) there is a satisfactory constraint on the probability of falsely classifying noise spikes as RFI. An example of such thresholds might be “a signal exceeding $3\sigma$ in 4 or more beams”, which gives a probability of falsely classify-
ing a noise sample as RFI of \( p \leq \left( \frac{13}{4} \right) \times 0.01^4 = 7.15 \times 10^{-6} \). This is the method we chose for the initial version of the pipeline. The algorithm takes the form of a transform [see Barsdell et al. (2010)] of the multibeam time series, where for each sample the 13 beams are checked against the thresholds and the result is written as a boolean RFI mask. This maps trivially to the GPU as an “embarrassingly parallel” problem.

### 2.2. Incoherent Dedispersion

For transient search pipelines, dedispersion is typically the most computationally intensive process. The algorithm arises from the need to counteract the effect of the frequency-dependent time delay induced into the signal by interactions with the interstellar medium. This delay (or smearing) increases with the number of free electrons between us and the source. Given that the distance to new sources remains unknown, the amount of dispersion (the dispersion measure, DM) in the signal must be guessed prior to executing the remainder of the pipeline. Surveys typically compute many trial DMs – approximately 1200 in the case of the HTRU survey. The computation of each dispersion trial involves a complete integration over frequency channels, so it is clear that the process in its entirety requires a significant amount of computation.

While computationally intensive, the incoherent dedispersion algorithm is relatively simple to implement. Furthermore, as identified by Barsdell et al. (2010), the properties of the algorithm make it a very good match for the architecture of a GPU. Indeed, efficient implementations using NVIDIA’s CUDA\(^1\) GPU programming platform have appeared in the literature with reported speed-ups of an order of magnitude or more over multi-core CPU codes [Magro et al. (2011), Armour et al. (2012), Barsdell et al. (MNRAS submitted)].

Our GPU implementation of the most common ‘direct’ dedispersion algorithm [see Barsdell et al. (MNRAS submitted) for details] has reduced the processing time from around 20 minutes to 2.5 minutes for a 10 minute observation. While a significant speed-up in its own right, the more important aspect of this result is the fact that it has broken through the real-time barrier. Given that dedispersion consumes the largest fraction of the total execution time, the sub-real-time GPU implementation is a critical element for the real-time pipeline.

### 2.3. Other Algorithms

The recorded time series from the telescope often contain baseline wiggles (red noise), and these must be removed to ensure consistent behaviour in the detection pipeline. In the time domain, the most common approach is to compute a running mean for the data with a given window size (equivalent to convolving with a wide boxcar) and then subtracting this off the original data. One way to implement a running mean efficiently on a GPU is to exploit a parallel prefix sum algorithm. Once the ‘running sum’ has been computed, the running mean may be calculated by subtracting the points at plus and minus the window radius. We have implemented this algorithm using the Thrust library, which provides optimised implementations of the prefix sum and transform algorithms (among many others).\(^2\)

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\(^1\)http://www.nvidia.com/object/cuda_home_new.html

\(^2\)http://code.google.com/p/thrust/
In order to detect signals with a range of widths, the pipeline performs a series of matched filtering operations. This involves convolving the time series with boxcar functions of increasing sizes (e.g., 2, 4, 8 etc. samples) and passing each result through the remainder of the pipeline. The matched filtering algorithm is essentially identical to the baseline removal algorithm, and can be implemented in the same manner using the parallel prefix sum, which we have again done using the Thrust library.

The final step of the pipeline is to detect peaks in the reduced time series. We have implemented this process by first performing a sigma-cut and then gathering contiguous regions together into individual events. These algorithms map to the ‘transform’ and ‘reduce_by_key’ functions of the Thrust library, which makes their implementation on the GPU a trivial matter.

3. Discussion

Having successfully implemented each step of the transient detection process on a GPU, we are now working to integrate them into a complete GPU pipeline. Early benchmarks indicate that our target of processing one beam per GPU in real time is well within reach. Once the software pipeline is completely operational, we plan to deploy it on a small cluster of GPU nodes on-site at the Parkes radio telescope.

Our real-time radio transient detection pipeline promises to simplify the data processing procedure by performing it as observations are made. This new data reduction paradigm will enable immediate follow-up observations upon the detection of interesting transient events and provide unprecedented resolution of unique phenomena via baseband dumps.

References