

# Fast online predictive compression of radio astronomy data

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## ABSTRACT

TODO: add at end of writeup

## 1. INTRODUCTION

In this report we will investigate the feasibility of compressing radio astronomy data using a predictive compression scheme. All compression techniques build on the central concept of reducing redundant data. The exact definition of this redundancy is of course context dependent. It may take the form of repeated values, clustered values, wasteful encoding processes and many others. We also point out the difference between lossy and lossless compression, as well as online versus offline compression.

In a lossless compression scheme the compression is completely invertible with *no* loss of information after a decompression step is performed. Lossy compression on the other hand discards unimportant data and gives much higher compression ratios than lossless methods. Lossy compression is useful in many instances where subtle changes in data is not considered problematic. Some examples of this are the removal of high frequency data from images, sampling voice data at a lower rate than music or to employ a commonly used technique called *quantization* where data is simply binned into consecutive ranges (or *bins*).

An online compression scheme refers to a process of compressing data on-the-fly or as it is being transmitted on the wire. The results are sent off to subsequent processes such as transmission over a network or storage to disk. This is in contrast to an offline scheme where data is compressed as a separate process which doesn't form part of the primary work flow of a system. An online process are normally considered to be fast enough as not to slow the overall data processing capabilities of a system.

We will measure compression performance both in terms of effectiveness through a compression ratio described below [9, p. 10] and throughput speed. A compression ratio closer

to 0 indicates a smaller output file and values greater than 1 indicates that the algorithm inflated the data instead of shrinking it.

$$\text{Compression ratio} := \frac{\text{size of the output stream}}{\text{size of the input stream}} \quad (1)$$

$$\text{Throughput} := \frac{\text{input processed (in GB)}}{\text{difference in time (in seconds)}} \quad (2)$$

We will now discuss the relevance of our problem and give a breakdown of the most commonly used compression techniques. We will then discuss a detailed design of our predictive compression scheme, different implementation strategies along with technical details and a section with results and discussion.

## 2. BACKGROUND

### 2.1 KAT-7, MeerKAT and the SKA

South Africa and Australia are the two primary hosting countries for the largest radio telescope array in the world, known as the Square Kilometer Array. The SKA will give astronomers the opportunity to capture very high resolution images, over a wide field of view, covering a wide range of frequencies ranging from 70 MHz to 10 GHz. Upon completion in 2024 the array will consist of around 3000 dishes in the high frequency range and thousands of smaller antennae to cover the low frequency band. The South African branch of the SKA will be completed in 3 main phases. Phase 1 is a fully operational prototype 7-dish array called the KAT-7. The second phase, known as the MeerKAT, will consist of approximately 90 dishes to be erected in the central Karoo. The final phase add the remaining dishes and increase the baseline of the telescope to roughly 3000 km.

Due to the high signal sampling rate it is expected that each of these dishes will produce data rates up to 420 GiB/s while the lower frequency aperture arrays will produce up to 16 TiB/s. These rates, coupled with the scale of the SKA, will require a processing facility capable of handling as much as 1 Petabyte of data every 20 seconds, necessitating the need for massive storage facilities. Innovative techniques are required to deal with this complex requirement of high throughput rates while effectively reducing the large storage requirements by means of data compression.

### 2.2 Overview of data compression techniques

There are considered to be 4 broad categories of compression techniques [9]. These are some basic methods, Lempel-Ziv methods, statistical methods and transforms.

### 2.2.1 Basic methods

The more intuitive methods include commonly employed methods such as Run-Length Encoding (RLE) which, simply put encodes runs of characters using some reserved character and a number indicating the length of the run.

Another basic technique which is particularly relevant for application on numerical data a predictive compression scheme. Such a compression scheme encodes the difference between each predicted succeeding value and the actual succeeding value. This can be quite successfully employed to compress data generated from time series [4].

### 2.2.2 Lempel-Ziv methods

Also commonly referred to as LZ or dictionary methods is a class of algorithms with many variants and is one of the more popular adaptive techniques in modern compression utilities. In their simplest form these methods normally uses both a search and a lookahead buffer to encode recurrent phrases using fixed-size codes. An adaptive compression technique is useful in circumstances where the probability distribution of the underlying dataset is not known in advance or may change over time. One example of such an LZ method is the GNU compression utility Gzip which implements the Deflate algorithm [9, ch. 3].

### 2.2.3 Statistical methods

This class of algorithms normally uses variable length codes to achieve an optimal (or near optimal) encoding of dataset. In information theory this optimal encoding is described as an entropy encoding. Entropy is the measurement of the information contained in a single base- $n$  symbol (as transmitted per time unit by some source). Mathematically redundancy is defined as follows ( $n$  is the size of a symbol set and  $P_i$  is the probability that a symbol  $c_i$  is transmitted from a source)[9, p. 46 - 47]:

$$R := \log_2 n + \sum_{i=1}^n P_i \log_2 P_i \quad (3)$$

As the name may suggest the techniques uses the probability of occurrence to assign shorter codes to frequently occurring values in order to eliminate redundancy. The class of statistical methods include two widely employed techniques known as Huffman and Arithmetic coding respectively. Huffman coding assigns shorter *integral-length* codes, while arithmetic coding assigns *real-length* subintervals of  $[0,1)$  to frequently occurring symbols [12][9, ch. 2].

Both approaches lead to variable-size codes. Both techniques have adaptive versions which are useful in situations where the probability distributions change or have to be estimated. This approach is also applicable to the situation where the symbol table has to be computed on the fly, because it is impossible to perform multiple passes. Arithmetic coding is considered to approach a true entropy encoder and achieves higher compression ratios in both adaptive and non-adaptive cases. It should be pointed out that the decompression step of Arithmetic coding is slow and unsuitable for cases where fast access is required [8, 11][9, ch. 2].

### 2.2.4 Transforms

As the name suggest it can be useful to transform a dataset from one form to another in order to exploit its features for the purposes of compression. Such transformations includes, for example, wavelet transforms. As the name suggests a wavelet is a small wave-like function that is only non-zero over a very small domain and can be used to represent, for example, the high frequency components in an image (JPEG2000 and DjVu are popular formats using wavelet transforms). The coefficients within this transformation can then be further compressed using other techniques, for example, Huffman coding. If lossy compression (loss of accuracy which cannot be recovered after decompression) is tolerable, quantization can be used to discard unimportant values (for example the high frequency features of an image) [9, ch. 5].

Transforms are furthermore particularly useful where multiple levels of detail are desired. An example of this may include the transfer of scientific data over a network for real-time analysis and observation. Low resolution samples can be constantly transferred, while higher resolution samples can be transferred upon request [10].

## 2.3 IEEE 754

The IEEE 754 standard of 2008 defines 3 interchange formats (32-bit, 64-bit and 128-bit). See figs. 1 , 2. We will only refer to the 32- and 64-bit representations later in the paper. Each of these have a common construction with the following subfields:

- A 1-bit sign
- A  $w$ -bit length biased exponent
- A  $(d-1)$ -bit significand, where the leading bit of the significand is implicitly encoded in the exponent.

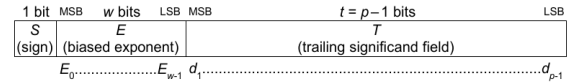


Figure 1: IEEE Interchange floating-point format [1]

Precision	Exponent width	Significant precision
32-bit	8 bits	23 bits
64-bit	11 bits	52 bits

Figure 2: Specifications for the 32-bit and 64-bit interchange formats

## 2.4 Overview of predictive compression

Previous research [7, 2, 4, 5, 6, 3] in this area has yielded good results both in terms of compression ratio and speed. The common line of thought is to predict successive values. Depending on the accuracy the difference between the predicted and actual value will hopefully be much smaller than the actual value itself. This difference can then be encoded using fewer bytes/bits of data (depending if compression occurs at a byte or bit level) by compressing the leading zeros after either an XOR or integer subtraction operation. Machine instructions to count the leading zeros can

be found on AMD and newer Intel Processors. The leading zero count is then encoded as a prefix stream while the remaining bits/bytes are encoded as a residual stream.

Previous research suggests several different constructions of predictors. The use of a Lorenzo predictor [5] generalizes a parallelogram predictor used by [4]. This approach is particularly useful to compress large meshes of structures. Other approaches include the use of prediction history (via a simple lookup table construction) as suggested in [7, 2, 3]. The later reports a throughput of up to 670 MB/s on a CPU implementation of their FPC compressor. An even simpler scheme [6] reportedly achieved throughputs of up to 75GB/s in its compression routine and up to 90GB/s in its decompression routine implemented in CUDA. In this scheme only the difference between successive values are encoded (this will clearly only work if the pairs of data points varies very little from one time step to the next). It is duly noted that the speeds achieved by [6] is on the post processing of results already stored in graphics memory. The implementations by [6, 7, 2, 3, 4] targets 64-bit IEEE 754 *double* precision floating-point data.

The primary scheme we propose takes its inspiration from [6], but will operate on 32-bit IEEE 754 *single* precision floating-point values. The uncompressed data itself is also structured slightly differently to the model used by [6]. Instead of compressing each consecutive value my compressor will compress consecutive blocks of data. Although the predictor itself is very simple and may not yield as good a compression ratio as the schemes suggested by the other authors it should obtain the required throughput. Additionally we will test the effectiveness of a parallelogram predictor, a Lagrange extrapolation predictor [4] and a moving mean and median scheme.

As pointed out in previous research [4, 5] using floating point operations in the prediction step can cause an irreversible loss of information due to floating point rounding errors. A simple approach is proposed by [4]. Floating point memory is simply treated as integer memory and all operations performed on that memory are integer operations. This approach assures us of achieving lossless compression and we will consequently only consider using schemes that conform to this approach. A simple case to illustrate this approach is made by [4]. It is clearly visible in fig. 3 that if two floating-point numbers are relatively close to each other in terms of magnitude it is possible to discard some repeated bytes of information after performing an XOR operation to extract the remaining, seemingly random, residual bits.

		byte	1	2	3	4	5	6	7	8
$a_1$	2.3667176745585676	->	40	02	ef	<b>09</b>	<b>ad</b>	<b>18</b>	<b>c0</b>	<b>f6</b>
$a_2$	2.3667276745585676	->	40	02	ef	<b>0e</b>	<b>eb</b>	<b>46</b>	<b>23</b>	<b>2f</b>
$a_3$	2.3667376745585676	->	40	02	ef	<b>14</b>	<b>29</b>	<b>73</b>	<b>85</b>	<b>6a</b>

Figure 3: Treating 64-bit IEEE 754 double precision floating-points as integer memory [4]

### 3. RESEARCH QUESTIONS

We are investigating the feasibility of adding a *online* predictive compression step to the existing KAT-7 / MeerKAT pipeline. Such a step has to meet at least two primary crite-

ria: high throughput and effective compression ratios. These are outlined below:

1. The technique must be fast. The algorithm should be able of achieving throughput rates of at least 40 GiB/s.
2. The technique should be effective. The algorithm should reduce the size of transmissions by several percent and hopefully this reduction can take the form of double digit figures. It has, however, been pointed out that the data may be too noisy to expect great reductions, while maintaining the throughput rate we mentioned above.
3. We will investigate the trade-off between throughput and size reduction.

## 4. DESIGN AND METHODOLOGY

## 5. IMPLEMENTATION

TODO

## 6. FINDINGS

TODO

## 7. DISCUSSION

TODO

## 8. CONCLUSION

TODO

## 9. FUTURE AVENUES OF RESEARCH

TODO

## 10. ACKNOWLEDGEMENTS

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Thirdly I would like to note that all tests were performed on the ICTS High Performance (*HEX*) cluster at the University of Cape Town. The cluster has 4 DELL C6145 nodes each boasting 4 16-core AMD Opteron 6274 CPUs, clocked at 2200 MHz with 16 MB L3 cache memory. There are two additional GPU nodes with 4 Tesla M2090 GPU cards each. Each GPU card has 6 GB GDDR5 and 2048 CUDA cores. I want to especially thank Andrew Lewis from ICTS for his assistance and support during testing.

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