Data compression in ALICE by on-line track reconstruction and space point analysis

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Data compression in ALICE by on-line track reconstruction and space point analysis

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Abstract. High resolution detectors in high energy nuclear physics deliver a huge amount of data which is often a challenge for the data acquisition and mass storage. Lossless compression techniques on the level of the raw data can provide compression ratios up to a factor of two. Higher compression ratios can be reached by introducing an appropriate model for the raw data and storing relevant information for the event reconstruction with respect to that model. In ALICE, a data compression technique has been developed for the Time Projection Chamber (TPC) to reach an overall compression factor suited for data taking in Heavy Ion collisions.

The ALICE High Level Trigger provides online calculation of the TPC clusters from the raw data, followed by tracking, thus producing a fully reconstructed event. Storing the reconstructed cluster data in an appropriate compressed format for utilization in the off-line reconstruction allows to discard the original raw data of the TPC. In the presented solution, compression factors of four to six are achieved without significantly affecting the physics performance. By associating space points to reconstructed tracks, all relevant parameters can be further transformed into a format suitable for Huffman compression. In a first conservative approach, all reconstructed clusters are kept in the data.

Data compression has been implemented for the ALICE TPC in 2011 for usage in the Heavy Ion data-taking. In this contribution the results on 2011 real data are presented for the first time.

1. Introduction

As size, granularity, and readout rate of particle detectors in high energy nuclear physics have grown constantly over the past years, the amount of data delivered by such devices imposes huge challenges to the processing and storage of the delivered raw data. There are various techniques for data compression which can be applied to reduce the data rate to a level digestible by data acquisition systems and suitable for storage. In ALICE [1], the dedicated detector for heavy ion collisions at LHC, the data volume is dominated by the Time Projection Chamber (TPC) [2], a gaseous detector measuring particle trajectories in three dimensional space.

From the Pb-Pb periods in 2010 the event size for the most central events has been measured to be about 80 MB/event. For such events the event rate is limited to approximately 200 Hz by the TPC readout electronics. For the 2011 Pb-Pb campaign an event rate for central collisions of 50 to 100 Hz was estimated from the LHC parameters. The resulting data rate would have exceeded the sustained limit of the ALICE Data Acquisition (DAQ) of currently 4 GB/s.

Lossless compression techniques on the level of the raw data can theoretically provide compression ratios up to a factor of two, modeling of the raw data with a lossy algorithm can increase that to a data reduction factor of three [3, 4].

Studies on simulated TPC data have earlier shown the potential for data compression [5, 6]. The application on real data is presented for the first time. With a combination of on-line cluster reconstruction from raw data, an appropriate fixed-point data format of sufficient precision, and a subsequent lossless data compression, the data volume can be reduced by a factor four to six depending on the data sample. The following sections describe the implemented data compression solution for the ALICE TPC using the computing facilities of the High Level Trigger.

1.1. Time Projection Chamber

Time Projection Chambers are gaseous tracking detectors which have been commonly used as tracking detectors in heavy ion collision experiments for more than three decades. TPCs provide a simultaneous three dimensional position measurement, together with the capability to measure the energy loss of the ionizing particle.

The electrons liberated in the primary ionization drift towards the end-caps of the detector in a longitudinal electrical field [7]. The readout at the end caps is realized by Multi-Wire Proportional Chambers. Here the primary electrons are multiplied in avalanches close to the anode wires. The remaining clouds of positive ions induce mirror charges onto the segmented cathode (pads). The two-dimensional pad information digitized in time steps of 100 nsecs is called a cluster. Since the drift velocity of the electrons in the TPC is known, the time measurement with respect to t_0 provided by trigger detectors allows to calculate the longitudinal coordinate.

The ALICE TPC is read out by more than 500000 channels, each providing 1000 samples of time measurement.

1.2. Data compression scheme

The ALICE High Level Trigger provides on-line reconstruction of the TPC data, involving the reconstruction of clusters from raw data - *clusterization* - and tracking. The reconstructed information can be used to categorize events and create trigger information for DAQ. The concept of HLT allows not only to produce trigger information but also to store additional payload in the HLT raw data, thus producing raw data like a normal detector. This ability is used for data compression where the original raw data of the detector are replaced by pre-processed data from the HLT like illustrated in Figure 1.

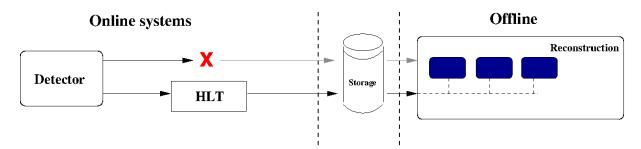


Figure 1. In the data compression scheme, original detector raw data are discarded and replaced by pre-processed data from the High Level Trigger. HLT data can enter offline detector reconstruction at different stages, e.g. clusterization and tracking.

In the presented solution for the TPC, clusters are reconstructed on-line in the HLT and recorded in an appropriate format.

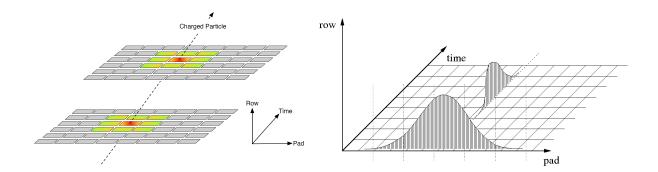


Figure 2. A cluster is defined by charge centroids in two dimensions, here pad and time coordinate. A pad row and the time direction span a 'virtual' pad-row plane, which is crossed by the particles (left). In the pad direction, clusters are distributed over several readout pads, the shape is determined by the detector and drifting process. In the time direction the signal shape is determined by the drifting process and the shaping electronics in the readout (right).

2. Data model

A Time Projection Chamber provides simultaneous measurement of three-dimensional track information, by using a two-dimensional readout of segmented pad planes, and drift time measurement of induced charges. The raw data consist of sampled charge measurements over a capture period for each channel.

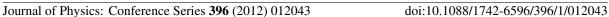
Clusters are charge centroids reconstructed from the raw data in the plane spanned by pad and time coordinates, see Figure 2. The properties are described by a) three position coordinates, b) the total and maximum charge, and c) cluster width in two dimensions. The shape of the clusters is determined by properties of the detector and the readout electronics, thus raw data is sufficiently described by reconstructed clusters. The clusters can now be recorded in an optimized storage format including lossless data compression techniques.

2.1. Raw cluster format

The reconstructed clusters are stored in raw coordinates which makes the recorded compressed data independent of drift time calibration and further corrections. Those are later applied in the offline reconstruction. In total 7 parameters are recorded, shown in table 1. The size for each parameter in both the raw cluster format and a fixed point format of sufficient precision has a big impact of the achievable compression ratio and is indicated in the table.

	HLT raw cluster format	bits	fixed point format	bits
padrow number	unsigned short	16	local padrow in partition	6
pad position	float	32	pitch $0.4/0.6 \text{ cm} \rightarrow 1/60$	14
timebin	float	32	$0.25 \mathrm{cm/timebin} \rightarrow 1/25$	15
y-width (σ_y^2)	float	32		8
z-width (σ_z^2)	float	32		8
total charge	short	16		10
max charge	short	16		16
		176		77
	22 Byte		10 Byte	

Table 1. Clusters are characterized by seven parameters.



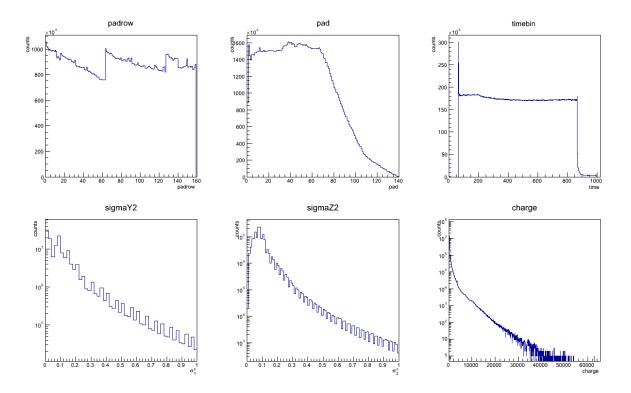


Figure 3. Distributions for six of the cluster parameters, the maximum charge is similar to charge. Note the logarithmic scale in the lower panels.

Each of the individual cluster parameters has a typical distribution as depicted in Figure 3. The distinct shape of the padrow and pad distributions is due to the three regions in the radial direction with slightly different geometries of the readout chambers.

2.2. Clusterization

Ionizations form clusters, which are calculated from the raw data as first step in the reconstruction. As described above the signal distribution in pad and time directions determine the cluster properties. There are two types of clusters. Normal clusters are distributed over several readout pads and fulfill required precision for tracking. Single-pad clusters have a deteriorated pad resolution, because the position is fixed to a single pad coordinate. Such clusters are not used in track momentum fits but carry useful charge information for particle identification (PID). It is thus important to record both types of clusters.

In the HLT, cluster reconstruction is performed in an FPGA co-processor in real-time. The details of the clusterization process, and its implementation in the co-processor are beyond the scope of this paper; however, descriptions can be found in [8, 9].

2.3. Data reduction in clusterization

The reconstruction of clusters from raw data is a lossy transformation, so the original raw data can not be restored. However, the loss in the required information for the event reconstruction is negligible for the physics analysis. A small data reduction factor is achieved in this step. Figure 4 shows the measurements for different event sizes. There is no exact linear dependence between event size and number of clusters. Slightly more clusters are found in events with high occupancy, which is a feature of the clusterization process and can be due to the splitting Journal of Physics: Conference Series 396 (2012) 012043

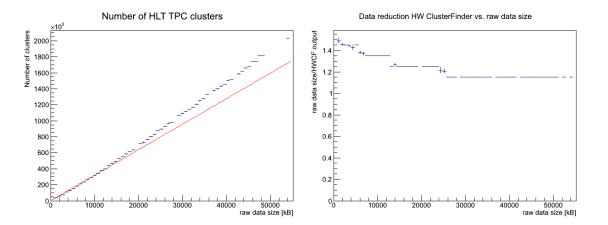


Figure 4. Number of clusters found for different event size, the line indicates a linear fit between 0 and 12000, extrapolated over the whole range to indicate the excess over a pure linear behavior (left); achieved reduction factor in the on-line clusterization (right).

of clusters. Data size is reduced by a factor of 1.1 to 1.5 depending on the event size. This dependence on the event size has a significant impact to the achievable compression ratio.

3. Data Deflation - Lossless data compression

Once the clusters have been reconstructed and the format has been adapted to the required precision, further compression can be applied before storing the data. While the two first steps are lossy and the original raw data can not be restored, the following data compression is lossless. Thus, independent of the technique or algorithm, the cluster data as produced by the on-line reconstruction is fully restored when unpacking the data.

Usually, members in data structures follow the granularity of bytes in memory. However, the parameters to be stored do not have a bit length of multiples of the byte size. In order to avoid unused bits, data members are stored in a bit stream. This is also a prerequisite for variable value length needed for compression algorithms based on entropy encoding. An abstract data deflater interface between data structure and data buffer supports multiple implementations.

3.1. Huffman compression

Currently, a Huffman implementation of the data deflater is in use in the ALICE HLT data compression. As can be seen from the parameter distributions in Figure 3, the charge and cluster width parameters are directly suited for entropy encoding. The compression ratio per parameter is shown in Figure 5.

Row numbers are stored differentially for sorted clusters in ascending row number which effectively requires 1 bit. The remaining parameters can not be compressed using that scheme but can be converted to a format better suited for Huffman coding, see below.

3.2. Track model compression

Since HLT provides not only the cluster reconstruction but also full tracking, the track information can be used to transform cluster coordinates into residual space. Time and pad coordinates are then expressed as deviations from the reconstructed tracks. The tracking algorithm assigns a number of clusters to every track. Furthermore, from the pool of unassigned clusters those in the vicinity of reconstructed tracks are associated with them as illustrated in Figure 6.

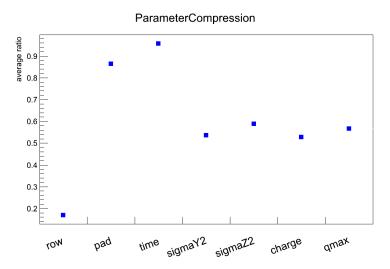


Figure 5. Huffman compression factor for individual cluster parameters.

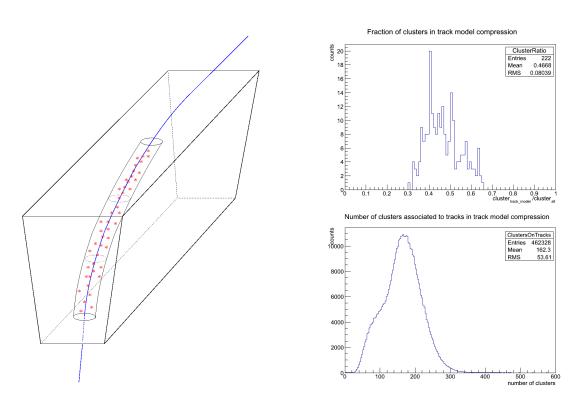


Figure 6. Illustration of the association of clusters to the track model (left), fraction of clusters in track model compression and number of associated clusters per track (right).

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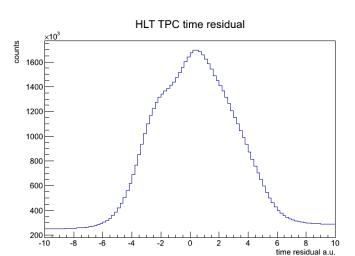


Figure 7. Distribution of cluster time residuals.

Approximately 50% of all clusters can be associated with tracks leaving a large fraction for which this optimization is not applicable. This has an impact on the overall compression factor if all clusters are recorded. In the current implementation, clusters not fitting into the track model are kept in separate data blocks.

The pad and time coordinates in residual format can be better compressed for two reasons:

- pad and time residuals have a smaller parameter range which allows to reduce required size \rightarrow pad from 14 to 10 bit
 - \rightarrow time from 15 to 9 bit
- Distributions of pad and time in residual coordinates are suitable for entropy encoding.

The resulting distribution of, for example, the time residual is shown in Figure 7. Clusters are transformed from raw coordinates into Cartesian space for tracking, including calibration and correction. This transformation is non-linear and non-uniform over the detector volume. In order to calculate the residuals in raw coordinates, the padrow crossings of reconstructed tracks are transformed back using a simplified linear transformation. The transformation has to be simple and deterministic in order to ensure the decoding of the data. The process broadens the distribution and has an impact to the possible compression by entropy encoders. Resolution in tracking, however, is not compromised as the compression is fully lossless.

4. Compression ratio

In the 2011 Pb-Pb data taking an average compression factor of 4.4 has been reached for TPC data. Figure 8 left shows the measured compression factors per event and raw data size accumulated on-line. In contrast to 2010, the trigger conditions have been changed, selecting a data sample with more central, i.e. bigger events. Track model compression has not been used in 2011, as the achieved data reduction factor with only Huffman compression on individual parameters was sufficient.

The performance of the different compression techniques has been studied in emulation on the 2011 data. A comparison of the compression ratios is shown in Figure 8 right.

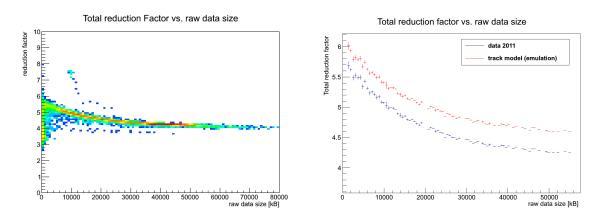


Figure 8. Left: compression factor in the 2011 Pb-Pb data taking, right: comparison of the compression ratios from 2011 data and emulation of track model compression.

5. Conclusions

In the presented solution, effective data compression is achieved by a combination of lossy transformation (cluster reconstruction), an appropriate data format of required precision and lossless data compression. Data compression for TPC data is operational and the default running mode in ALICE since 2011 Pb-Pb data taking. The 2011 data sample is biased by the physics trigger selection towards central, i.e larger events. An average compression factor of 4.4 has been measured.

Enhanced data compression factors can be achieved by further analysis of the space point properties and discarding clusters which are irrelevant for the measured observables. Furthermore, signal shaping and offline reconstruction code can be optimized to require only the calculated cluster charge instead of two charge values, thus reducing the number of parameters.

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