Online Pattern Recognition for the ALICE High Level Trigger

V. Lindenstruth, C. Loizides, D. Roehrich, B. Skaali, T. Steinbeck, R. Stock, H. Tilsner, K. Ullaland, A. Vestbø, T. Vik for the ALICE Collaboration

Abstract—

The ALICE High Level Trigger has to process data online, in order to select interesting (sub)events, or to compress data efficiently by modeling techniques. Focusing on the main data source, the Time Projection Chamber (TPC), we present two pattern recognition methods under investigation: a sequential approach (track follower and cluster finder) and an iterative approach (track candidate finder and cluster deconvolutor). We show, that the former is suited for pp and low multiplicity PbPb collisions, whereas the latter might be applicable for high multiplicity PbPb collisions, if it turns out, that more than 8000 charged particles would have to be reconstructed inside the TPC. Based on the developed tracking schemes we show, that using modeling techniques a compression factor of around 10 might be achievable.

I. INTRODUCTION

The ALICE Experiment [1] at the upcoming Large Hadron Collider at CERN will investigate PbPb collisions at a center of mass energy of about 5.5 TeV per nucleon pair and pp collisions at 14 TeV. Its main tracking detector, the Time Projection Chamber (TPC), is readout by 557568 analog-to-digital converters for the ALICE Collaboration

process the raw data performing track pattern recognition in real time. Based on the extracted information, clusters and tracks, data reduction can be done in different ways:

- **Trigger**: Generation and application of a software trigger capable of selecting interesting events from the input data stream.
- **Select**: Reduction in the size of the event data by selecting sub-events or region of interest.
- **Compression**: Reduction in the size of the event data by compression techniques.

As such the HLT system will enable the ALICE TPC detector to run at a rate up to 200 Hz for heavy ion collisions, and up to 1 kHz for pp collisions. In order to increment the statistical significance of rare processes, dedicated triggers can select candidate events or sub-events. By analyzing tracking information from the different detectors and (pre-)triggers online, selective or partial readout of the relevant detectors can be performed thus reducing the event rate. The tasks of such a trigger are selections based upon the online reconstructed track parameters of the particles, e.g. to select events which contain $e^+e^-$ candidates coming from quarkonium decay or to select events containing high energy jets made out collimated beams of high $p_t$ particles [3]. In the case of low multiplicity events such as for pp collisions, the online reconstruction can be used to remove pile-up events from the trigger event.

B. Architecture

The HLT system receives data from the front-end electronics. A farm of clustered SMP-nodes (~500 to 1000 nodes), based on off-the-shelf PCs and connected with a high bandwidth, low latency network provide the necessary computing power. The hierarchy of the farm has to be adapted to both the parallelism in the data flow and to the complexity of the pattern recognition.

Figure 1 shows a sketch of the architecture of the system. The TPC detector consists of 36 sectors, each sector being divided into 6 sub-sectors. The data from each sub-sector are transferred via an optical fiber from the detector front-end into 216 custom designed readout receiver cards (RORCs). Each receiver node is interfaced to a RORC using its internal PCI bus. In addition to the different communication interfaces, the RORCs provide a FPGA co-processor for data intensive tasks of the pattern recognition and enough external memory to store several dozen event fractions. A hierarchical network interconnects all the receiver nodes.
Each sector is processed in parallel, results are then merged in a higher level. The first layer of nodes receive the data from the detector and performs the pre-processing task, i.e. cluster and track seeding on the sub-sector level. The next two levels of nodes exploit the local neighborhood: track segment sending and track seeding on the sub-sector level. Finally all local results are collected from the sectors or from different detectors and combined on a global level: track segment merging and final track fitting.

The farm is designed to be completely fault tolerant avoiding all single points of failure, except for the unique detector links. A generic communication framework has been developed based on the publisher-subscriber principle, which allows to construct any hierarchy of communication processing elements [4].

### II. Online Pattern Recognition

The main task of the HLT system is to reconstruct the complete event information online. Concerning the TPC and the other tracking devices, the particles should ideally follow helical trajectories due to the solenoidal magnetic field of the L3 magnet, in which these detectors are embedded. Thus we model a track by an helix with 5(+1) parameters describing it mathematically. A track is made out of clusters. So the pattern recognition task is extract clusters out of the raw data and to assign them to tracks thereby determining the helix track parameters.

For HLT tracking, we distinguish two different approaches: the *sequential feature extraction* and the *iterative feature extraction*.

The sequential method – corresponding to the conventional way of event reconstruction – first searches the cluster centroids with a Cluster Finder and then uses a Track Follower on these space points to extract the track parameters. This approach is applicable for lower occupancy like pp and low multiplicity PbPb collisions. However, at larger multiplicities expected for PbPb at LHC, clusters start to overlap and deconvolution becomes necessary in order to achieve the desired tracking efficiencies.

For that reason, the iterative method first determines track candidates using a suitable defined Track Candidate Finder and then assigns clusters to tracks using a Cluster Evaluator possibly deconvoluting overlapping clusters shared by different tracks. In both cases, a helix fit on the assigned clusters finally determines the track parameters.

In order to reduce data shipping and communication overhead within the HLT, as much as possible of the local pattern recognition will be done on the RORC. We therefore intend to run the Cluster Finder or the Track Candidate Finder directly on the FPGA co-processor of the receiver nodes while reading out the data over the fiber. In both cases the results, cluster centroids or track candidate parameters, will be sent from the RORC to the host over the PCI bus.

### III. Sequential Tracking Approach

The classical approach of pattern recognition in the TPC is divided into two sequential steps: Cluster finding and track finding. In the first step the Cluster Finder reconstructs the cluster centroids, which are interpreted as the three dimensional space points produced by the traversing particles. The list of space points is then passed to the Track Follower, which combines the clusters to form track segments. A similar reconstruction chain has successfully been used in the STAR L3 trigger [5], and thus has been adapted to the ALICE HLT framework.

1) *The Cluster Finder:* The input to the cluster finder is a list of above threshold timebin sequences for each pad. The algorithm builds the clusters by matching sequences on neighboring pads. In order to speed up the execution time every calculation is performed on-the-fly: sequence centroid calculation, sequence matching and deconvolution. Hence the loop over sequences is done only once. Only two lists of sequences are stored at every time: the current pad and the previous pad(s). For every new sequence the centroid position in the time direction is calculated by the ADC weighted mean. The mean is then added to a current pad list, and compared to the sequences in the previous. If a match is found, the mean position in both pad and time is calculated and the cluster list is updated. Every time a match is not found, the sequence is regarded as a new cluster.

In the case of overlapping clusters, a crude deconvolution scheme can be performed. In time direction overlapping sequences are identified by a local minimum in a sequence, and is separated by cutting at the position of the minimum in time direction. The same approach is being used for the pad direction, where the cluster is cut if there is a local minimum of the pad charge values.

The algorithm is inherently local, as each padrow can processed independently. This is one of the main reasons to use a circuit for the parallel computation of the space points on the FPGA of the RORC [7].

2) *The Track Follower:* The tracking algorithm is based on conformal mapping. A space point (x,y) is transformed in the following way:

\[
\begin{align*}
x' &= \frac{x - x_1}{r^2} \\
y' &= -\frac{y - y_0}{r^2}
\end{align*}
\]

1The deconvolution can be switched on/off by a flag of the program.
\[ r^2 = (x - x_t)^2 + (y - y_t)^2, \]  
\[ \text{where the reference point } (x_t, y_t) \text{ is a point on the trajectory of the track. If the track is assumed to originate from the interaction point, the reference point is replaced by the vertex coordinates. The transformation has the property of transforming the circular trajectories of the tracks into straight lines. Since then fitting straight lines is easier and much faster than fitting circles (if we neglect the changes in the weights of the points induced by conformal mapping), the effect of the transformation is to speed up the track fitting procedure.} \]

The track finding algorithm consists of a follow-your-nose where the tracks are built by including space points close to the fit [6]. The tracks are initiated by building track segments, and the search is starting at the outermost padrows. The track segments are formed by linking space points which are close in space. When a certain number of space points has been linked together, the points are fitted to straight lines in conformal space. The tracks are then extended by searching for clusters which are close to the fit.

3) Track merging: Tracking can be done either locally on every sub-sector, on the sector level or on the complete TPC. In the first two scenarios, the tracks have to be merged across the detector boundaries. A simple and fast track merging procedure has been implemented for the TPC. The algorithm basically tries to match tracks which cross the detector boundaries and whose difference in the helix parameters are below a certain threshold. After the tracks have been merged, a final track fit is performed in real space.

4) Tracking performance: The tracking performance has been studied and compared with the offline TPC reconstruction chain. In the evaluation the following quantities has been defined:

- **Generated good track** – A track which crosses at least 40% of all padrows. In addition, it is required that half of the innermost 10% of the clusters are correctly assigned.
- **Found good track** – A track for which the number of assigned clusters is at least 40% of the total number of padrows. In addition, the track should not have more than 10% wrongly assigned clusters.

The tracking efficiency is the ratio of the number of found good tracks to the number of generated good tracks. The identical definitions have been used both for offline and HLT for comparison.

Figure 2 shows the comparison of the integral efficiency of the HLT and offline reconstruction chains for different charged particle multiplicities for a magnetic field of B=0.4T. We see that up to dN/dy of 2000 the HLT efficiency is ≥ 90%, but for higher multiplicities the HLT code becomes too inefficient to be used for physics evaluation. In this regime other approaches have to be applied.

5) Timing performance: The TPC analysis in HLT is divided into a hierarchy of processing steps from cluster finding, track finding, track merging to track fitting.

Figure 3 shows the foreseen processing hierarchy for 1 TPC sector (= 6 subsectors).

Figure 4 shows the required computing time measured on a standard reference PC \(^2\) corresponding to the different processing steps.

\(^2\)800MHz Twin Pentium III, ServerWorks Chipset, 256kB L3 cache
bars denote the standard deviation of processing time for the given event ensemble. For particle multiplicity of dN/dy=4000, about 24 seconds are required to process a complete event, or 4800 CPUs are required to date for the TPC alone at an event rate of 200 Hz. Table I compares the CPU time needed to reconstruct a TPC event (dN/dy=4000) for HLT and offline. For offline, loading the data into memory is also included in the measurement, while the HLT result only included the processing time as memory accesses are done completely transparent by the publisher-subscriber model.

A. Iterative tracking approach

For large particle multiplicities clusters in the TPC start to overlap, and deconvolution becomes necessary in order to achieve the desired tracking efficiencies. The cluster shape is highly dependent on the track parameters, and in particular on the track crossing angles with the padrow and drift time. In order to properly deconvolute the overlapping clusters, knowledge of the track parameters that produced the clusters is necessary. For that purpose the Hough transform is suited, as it can be applied directly on the raw ADC data thus providing an estimate of the track parameters. Once the track parameters are known, the clusters can be fit to the known shape, and the cluster centroid can be correctly reconstructed. The cluster deconvolution is geometrically local, and thus trivially parallel, and can be performed in parallel on the rawdata.

1) Hough Transform: The Hough transform is a standard tool in image analysis that allows recognition of global patterns in an image space by recognition of local patterns (ideally a point) in a transformed parameter space. The basic idea is to find curves that can be parametrized in a suitable parameter space. In its original form one determines a curve in parameter space for a signal corresponding to all possible tracks with a given parametric form to which it could possibly belong. All such curves belonging to the different signals are drawn in parameter space. That space is then discretized and entries are stored in a histogram. If the peaks in the histogram exceed a given threshold, the corresponding parameters are found.

As mentioned above, in ALICE the local track model is a helix. In order to simplify the transformation, the detector is divided into subvolumes in pseudo-rapidity. If one restricts the analysis to tracks originating from the vertex, the circular track in the η-volume is characterized by two parameters: the emission angle with the beam axis, ψ and the curvature κ. The transformation is performed from (R,φ)-space to (ψ,κ)-space using the following equations:

\[ R = \sqrt{x^2 + y^2} \]
\[ \phi = \arctan\left(\frac{y}{x}\right) \]
\[ \kappa = \frac{2}{R} \sin(\phi - \psi) \]

Each ADC value above a certain threshold transforms into a sinusoidal line extending over the whole ψ-range of the parameter space. All the corresponding bins in the histogram are incremented with the corresponding ADC-value. The superposition of these point transformations produces a maximum at the circle parameters of the track. The track recognition is now done by searching for local maxima in the parameter space.

![Figure 5](image)

Figure 5 shows the tracking efficiency for the Hough transform on a high occupancy event. The overall efficiency is above 90%.

Figure 6 shows the timing measurement of the Hough based algorithm for different particle multiplicities. The Hough transform is done in parallel locally on each receiving node, whereas the histogram adding, maxima finding and merging tracks across η-slices are done sequentially on the sector level. The histograms from the different subsectors are added in order to increase the signal-to-noise ratio of the peaks. For particle multiplicities of dN/dy=8000, the four steps require about 1000 seconds per events corresponding to 200,000 CPUs for 200 Hz event

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3 Estimate ignores any communication and synchronization overhead in order to operate HLT
4 For offline 17% of the time is needed for data loading.
processing rate. It should be noted that the algorithm were already optimized but some additional optimizations are still believed to be possible. However, present studies indicate that one should not expect to gain more than a factor of 2 without using hardware specifics of a given processor architecture.

The advantage of the Hough transform is that it has a very high degree of locality and parallelism, allowing the efficient use of FPGA co-processors. Given the hierarchy of the TPC data analysis, it is obvious that both the Hough transformation and the cluster deconvolution can be performed in the receiver nodes. The Hough transformation is particular I/O-bound as it create large histograms that have to be searched for maxima, which scales poorly with modern processor architectures and is ideally suited for FPGA co-processors. Currently different ways of implementing the above outline Hough transform in hardware are being investigated.

IV. DATA MODELING AND DATA COMPRESSION

One of the main goals of HLT is to compress data efficiently with a minimal loss of physics information.

In general two modes of data compression can be considered:

- **Binary lossless data compression**, allowing bit-by-bit reconstruction of the original data set.
- **Binary lossy data compression**, not allowing bit-by-bit reconstruction of the original data, while remaining however all relevant physical information.

Run-length encoding (RLE), Huffman and LZW are considered lossless compression, while thresholding and hit finding operations are considered lossy techniques that could lead to a loss of small clusters or tail of clusters. It should be noted that data compression techniques in this context should be considered lossless from a physics point of view.

Many of the state of the art compression techniques were studied on simulated TPC data and is presented in detail in [8]. They all result in compression factors of close to 2. However, the most effective data compression can be done by cluster and track modeling, as will be presented in the following.

A. Cluster and track modeling

From a data compression point of view, the aim of the track finding is not to extract physics information, but to build a data model which will be used to collect clusters and to code cluster information efficiently. Therefore, the pattern recognition algorithms are optimized differently, or even different methods can be used compared to the normal tracking.

The tracking analysis comprises of two main steps: Cluster reconstruction and track finding. Depending on the occupancy, the space points can be determined by a simple cluster finding or require more complex cluster deconvolution functionality in areas of high occupancy (see sec. III and III-A). In the latter case a minimum track model may be required in order to properly decode the digitized charge clouds into their correct space points. However, in any case the analysis process is twofold, clustering and tracking. Optionally the first step can be performed online while leaving the tracking to offline, and thereby only recording the space points. Given the high resolution of space points on one hand, and the size of the chamber on the other, would result in rather large encoding sizes for these clusters. However, taking a preliminary zeroth order tracking into account, the space points can be encoded with respect to their distance to such tracklets, leaving only small numbers which can be encoded very efficiently. The quality of the tracklet itself, with the helix parameters that would also be recorded, is only secondary as the tracking is repeated offline with the original cluster positions.

B. Data compression scheme

The input to the compression algorithm is a list of tracks and their corresponding clusters. For every assigned cluster, the cluster centroid deviation from the track model is calculated in both pad and time direction. This length is quantized with respect the given detector resolution, and represented by a fixed number of bits. In addition the total charge of

| Track parameters | Size (Byte) |
|------------------|-------------|
| Curvature        | 4 (float)   |
| $X_0,Y_0,Z_0$    | 4 (float)   |
| Dip angle,       | 4 (float)   |
| Azimuthal angle  | 4 (float)   |
| Track length     | 2 (integer) |
| Number of clusters | 1 (integer) |

| Cluster parameters | Size (Bit) |
|--------------------|------------|
| Cluster present    | 1          |
| Pad residual       | 9          |
| Time residual      | 9          |
| Cluster charge     | 13         |

The quantization steps have been set to 0.5 mm for pad direction and 0.8 mm for time direction, which is within the range of the intrinsic detector resolution.
the cluster is stored. Since the cluster shape itself can be parametrized as a function of track parameters and detector specific parameters, the cluster widths in pad and time is not stored for every cluster. During the decompression step, the cluster centroids are restored, and the cluster shape is calculated based on the track parameters. In tables II and III the track and cluster parameters are listed together with their respective size being used in the compression.

In figure 7 the offline tracking efficiency before and after applying the compression is compared. A total loss of ∼1% in efficiency and no significant loss in p_t resolution was observed. However, keeping the potential gain of statistics by the increased event rate written to tape in mind, one has to weigh the tradeoff between the impacts on the physics observables and the costs for the data storage.

For high occupancy events, clusters start to overlap and has to be properly deconvoluted in order to effectively compress the data. In this scenario, the Hough transform or another effective iterative tracking procedure would serve as an input for the cluster fitting/deconvolution algorithm. With a high online tracking performance, track and cluster modeling, together with noise removal, can reduce the data size by a factor of 10.

V. Conclusion

Focusing on the TPC, the sequential approach –consisting of cluster finding followed by track finding– is applicable for pp and low multiplicity PbPb data up to dN/dy of 2000 to 3000 with more than 90% efficiency. The timing results indicate that the desired frequency of 1KHz for pp and 200 Hz for PbPb can be achieved. For higher multiplicities of dN/dy ≥ 4000 the iterative approach using the Circle Hough transform for primary track candidate finding shows promising efficiencies of around 90% but with high computational costs.

By compressing the data using data modeling, results show that one can compress data of up to 10% relative to the original data with a very small impact on the tracking efficiency and the p_t resolution.

REFERENCES

[1] ALICE Collab., Technical Proposal, CERN/LHCC/95-71 (1995).
[2] ALICE Collab., Technical Design Report of the Time Projection Chamber, CERN/LHCC 2000-001 (2000).
[3] R. Bramm, T. Kollegger, C. Loizides, R. Stock, The Physics of the ALICE HLT Trigger Modes, hep-ex/0212050 (2002)
[4] T. Steinbeck et. al., An Object-Oriented Network-Transparent Data Transportation Framework, IEEE Trans. Nucl. Sci., Vol. 49, No. 2, April 2002.
[5] C. Adler et. al., The STAR Level-3 trigger system, Nucl. Instr. Meth. A499 (2003) 778
[6] P. Yepes, A Fast Track Pattern Recognition, Nucl. Instr. Meth. A380 (1996) 582
[7] G. Grastveit et. al., FPGA Co-processor for the ALICE High Level Trigger, Proceedings of CHEP03 La Jolla, California, March 24-28, 2003 (to be published)
[8] J. Berger et. al., TPC Data Compression, Nucl. Instr. Meth. A 489 (2002) 406

The compression scheme was applied to a simulated PbPb event with a multiplicity of dN/dy=1000. The input tracks used were tracks reconstructed with the sequential tracking approach (see Fig. 4). The remaining clusters, or the clusters which were not assigned to any tracks during the track finding step, were disregarded and not stored for further analysis. A relative size of 11% for the compressed data with respect to the original set was obtained. In order to evaluate the impact on the physics observables, the data was decompressed and restored cluster processed by the offline reconstruction chain.

Fig. 7. Comparison of the tracking efficiency of the offline reconstruction chain before and after data compression. A total loss of efficiency of ∼1% was observed.

Fig. 8. Comparison of the p_t resolution of the offline reconstruction chain before and after data compression.

The remaining clusters mainly originates from very low p_t tracks such as δ-electrons, which could not be reconstructed by the track finder. Their uncompressed raw data amounts to a relative size of about 20%.