Simulation and analysis of clustering for proton CT

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Abstract

A research team in Bergen in collaboration with others is working to develop a proton Computed Tomography (pCT) prototype. It is an image modality that uses proton rather than x-ray to create a CT-image. This can lead to a more precise dose calculation when used in proton therapy.

The proton CT system uses a Digital Tracing Calorimeter (DTC) consisting of multiple layers of ALPIDE chips with the aim of measuring where the protons stops in the calorimeter. The objective of this thesis is to simulate particle hits on a single ALPIDE chip using a realistic data collection of pixel cluster shapes and then use different approaches to reconstruct the clusters. The challenge when reconstructing the clusters is to find a satisfying approach to separate the overlapping clusters. The reconstruction was done by experimenting with various cuts, which had different ways to distinguish abnormal clusters.

The basic method was a template for all the cuts when reconstructing clusters. 3 different cuts were tested: fill percentage cut, asymmetric cut and inactive pixels cut. The different cuts had various parameters to optimise in order to improve the percentage of perfectly reconstructed clusters.

The optimal cut, based on the cuts tested in this thesis, was divided into 3 parts. These include the optimal solution for 0-100 clusters, 100-300 clusters and 300-500 clusters, respectively, in the detector. The inactive pixels cut had the most perfectly reconstructed clusters in the first part. The optimal cut for

the second part, based on the selected parameters, was inactive pixels combined with fill percentage. The third optimal cut, for 300-500 clusters, was the asymmetric cut combined with fill percentage cut. The third optimal cut can have up to approximately 350 clusters in the detector to obtain at least 96% perfectly reconstructed clusters.

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Acronyms

ALICE	A Large Ion Collider Experiment
ALPIDE	Alice Pixel Detector
CERN	the European Organization for Nuclear Research
СТ	Computed Tomography
DTC	Digital Tracking Calorimeter
HIT	Heidelberg Ion-Beam Therapy Center
HVL	Western Norway University of Applied sciences
IMPT	Intensity Modulated Proton Therapy
MAPS	Monolithic Active Pixel Sensor
Proton CT or pCT	Proton Computed Tomography
RSP	Relative Stopping Power
UiB	University of Bergen

Contents

	Abs	tract	i
	Ack	nowledgements	iii
	Acr	onyms	iv
1	Intr	oduction	1
	1.1	Background and motivation	1
	1.2	Problem description	4
	1.3	Goal and research question	5
	1.4	Evaluation and expected result	5
	1.5	Report outline	6
2	Bac	kground	7
	2.1	Medical background	7
	2.2	Software	9
3	Imp	lementation	11
	3.1	Creating a data collection of clusters $\ldots \ldots \ldots \ldots \ldots$	11
		3.1.1 Data acquisition \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots	12
		3.1.2 How the database of clusters is created \ldots \ldots \ldots	16
		3.1.3 Final collection of cluster shapes	22
	3.2	Simulation	25
		3.2.1 Method for simulation \ldots \ldots \ldots \ldots \ldots \ldots	25
		3.2.2 Method for finding clusters	27

		3.2.3	Method for analysing results	33					
4	Res	ults ar	nd evaluation	35					
	4.1 Results from the basic method								
		4.1.2	Results from different beam sizes	40					
	4.2	Result	s from cut 1 - fill percentage	41					
		4.2.1	Misclassified clusters	45					
	4.3	Result	s from cut 2 - Asymmetric	47					
		4.3.1	Misclassified clusters	49					
	4.4	Result	s from cut 3 - Inactive pixels	51					
		4.4.1	Misclassified clusters	52					
	4.5	Comb	inations of different cuts	54					
		4.5.1	Misclassified clusters	55					
	4.6	The of	ptimal cuts	56					
		4.6.1	How many clusters the optimal cuts identified \ldots .	57					
5	Cor	nclusio	n and future work	59					
	5.1	Conclu	usion	59					
	5.2	Future	ework	61					
	Bib	liograp	\mathbf{p}	62					
	App	pendix	Α	65					
	App	pendix	В	71					
	App	pendix	С	77					
	App	pendix	D	79					
	App	pendix	Ε	81					

List of Figures

Proton CT prototype [2].	2
Demonstration of one particle passing through multiple detec-	
tors and stops.	3
Illustration of how the protons and photons deposit dose during	
proton and x-ray therapies.	8
Illustration the beam test setup [14]	13
Cluster with event id 32 and plane id 1	14
Double cluster on plane id 1 and event id 3135	17
Distribution of size, height and width of clusters in the raw	
dataset	17
The 9 first clusters on plane 0. The 3 red dashed rectangles	
shows which clusters where combined	18
Examples of hole in clusters. The active pixel is coloured green	
and the white pixels are inactive	19
Illustration of method for removing holes	20
Illustration of how a cluster is stored in a binary array	20
Illustration of two clusters which does not fulfil the definition of	
a single cluster. The "count $= 1$ " means that only one element	
of each exists in the data collection	22
Distribution of size, height and width.	23
16 most frequent clusters in the data collection	24
Distribution of randomly picked x and y pixel positions	26
	Proton CT prototype [2]

3.13	Simulation of helium particles hitting the ALPIDE chip. The	
	beam size is a sigma of 4 mm in both x and y directions and 1000	
	particles are hitting the layer. There are used 1000 particles in	
	the detector to clearly see the distribution of clusters. \ldots .	27
3.14	Algorithms which separate on two different terms when finding	
	cluster in simulated chip.	28
3.15	Distribution of fill percentage calculated with both square and	
	rectangular box for clusters in data collection	29
3.16	Distribution of cluster projected onto x and y axis	31
3.17	A double cluster which will be separated by the method used	
	in approach 3 - inactive pixels	32
4.1	Results finding clusters with and without diagonal directions	
	using a beam size of 4 mm	38
4.2	The average errors of misclassified clusters in the simulation. $\ .$	39
4.3	How many extra pixels each misclassified clusters had, using the	
	basic method	39
4.4	Results from simulation with different sigma values using the	
	basic method - where pixels are adjacent in x and y directions.	40
4.5	Results tuning the parameters for the fill percentage square ap-	
	proach using 200 clusters in the detector	42
4.6	Results from combining different variants of minimum size and	
	fill percentage calculated with rectangular box approach using	
	200 clusters in detector. \ldots \ldots \ldots \ldots \ldots \ldots \ldots	43
4.7	Results from simulations with fill percentage calculated using	
	square and rectangular box approaches compared with the ba-	
	sic method. The fill percentage calculated with a square box	
	approach is 55% and minimum size of 13, and the fill percent-	
	age calculated with a rectangular box is 72% and minimum size	
	of 14	45
4.8	Types of misclassified clusters for the fill percentage cuts	46

4.9	Distribution of how many extra pixels each misclassified cluster	
	had, using different fill percentage cuts	47
4.10	Results from asymmetric cut compared with the basic method.	49
4.11	Average errors of misclassified in simulation for the asymmetric	
	cut	50
4.12	Distribution of how many extra pixels each misclassified cluster	
	had, using the asymmetric cut.	50
4.13	Results from inactive pixels cut compared with the basic method.	52
4.14	Average errors of misclassified clusters in simulation. \ldots .	53
4.15	Distribution of how many extra pixels each misclassified cluster	
	had, using the inactive pixels cut	53
4.16	Results from simulation using different cuts with a beam size of	
	143 pixels and an average result of 200 simulations per point	55
4.17	The inactive pixels cut - Illustration of how many clusters the	
	cut was able to find versus how many perfectly reconstructed	
	clusters which was found with error margins	57
4.18	The inactive pixels and the fill percentage cuts - Illustration of	
	how many clusters the cut was able to find versus how many per-	
	fectly reconstructed clusters which was found with error margins.	58
4.19	The asymmetric and the fill percentage cuts - Illustration of how	
	many clusters the cut was able to find versus how many perfectly	
	reconstructed clusters which was found with error margins	58

List of Tables

3.1	Raw data for one particle hit in one plane	14
4.1	Summarised results for combining different minimum sizes and	
	fill percentage (square box) with different amount of clusters in	
	the detector. There are two combinations which performs best	
	aggregated. The combinations are fill percentage 54% and 55%	
	combined with a minimum size of 13	42
4.2	Summarised results for combining different minimum sizes and	
	fill percentage (rectangle box) with different amount of clusters	
	in the detector. The best combination is fill percentage 72%	
	combined with a minimum size of 14	44
4.3	Average results from simulation of asymmetric cut with differ-	
	ent minimum size values (Appendix C, Table 11). The minimum	
	size of 13 gave the highest score	48
4.4	The average result from simulation of inactive pixels cut with	
	different minimum size values (Appendix D, Table 12). The	
	minimum size values resulted in nearly the same results. $\ .$.	51
4.5	Results of optimal cuts depending on the number of clusters in	
	detector	56

1	Results from combining different variants of minimum sizes and	
	fill percentage square approach. The simulation uses 100 cluster	
	in the detector and beam size 4mm, which results in the high-	
	est perfectly reconstructed cluster to be 97.265%. There are 2	
	combination which results in the same highest score, both with	
	minimum size 13, and fill percentage of 49% and 50%. Each	
	value is an average of 100 simulations.	66
2	Results from combining different variants of minimum sizes and	
	fill percentage square approach. The simulation uses 150 cluster	
	in the detector and beam size 4mm, which results in the highest	
	perfectly reconstructed cluster to be 97.8%. There are 10 com-	
	bination which results in the same highest score, including fill	
	percentage 55% and minimum size 13. Each value is an average	
	of 100 simulations.	67
3	Results from combining different variants of minimum sizes and	
	fill percentage square approach. The simulation uses 200 cluster	
	in the detector and beam size 4mm, which results in the highest	
	perfectly reconstructed cluster to be 97.265% . There are 2 com-	
	bination which results in the same highest score, including fill	
	percentage 55% and minimum size 13. Each value is an average	
	of 100 simulations.	68
4	Results from combining different variants of minimum sizes and	
	fill percentage square approach. The simulation uses 250 cluster	
	in the detector and beam size 4mm, which results in the highest	
	perfectly reconstructed cluster to be 96.896% . There are 2 com-	
	bination which results in the same highest score, including fill	
	percentage 55% and minimum size 13. Each value is an average	
	of 100 simulations.	69

6

- 5 Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 300 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 96.457%. The best combination was fill percentage 56% and minimum size 13. Each value is an average of 100 simulations.
 - Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 100 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 98.300%. The
- 7 Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 150 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 97.580%. The best score is a combination of fill percentage 72% and minimum size 17. Each value is an average of 100 simulations.

70

73

74

75

10	Results from combining different variants of minimum sizes and	
	fill percentage rectangle approach. The simulation uses 300	
	cluster in the detector and beam size 4mm, which results in	
	the highest perfectly reconstructed cluster to be 95.967% . The	
	best combination was fill percentage 72% and minimum size 14.	
	Each value is an average of 100 simulations	76
11	Results from simulation of the asymmetric cut using different	
	minimum sizes. Each value is an average of 100 simulations. $% \left({{{\bf{n}}_{{\rm{s}}}}} \right)$.	78
12	Results from simulation of the inactive pixels cut using different	
	minimum sizes. Each value is an average of 100 simulations. $% \left({{{\bf{n}}_{{\rm{s}}}}_{{\rm{s}}}} \right)$.	80
13	Results from simulation with mixtures of all cuts. Each value is	
	an average of 200 simulations. The values have the following ab-	
	breviation: A=Asymmetric, I=Inactive pixels, F=fill percent-	
	age square approach, and B=basic method	82

Chapter 1

Introduction

1.1 Background and motivation

A research team with members in Bergen in collaboration with others [1] is working to develop a Proton Computed Tomography (proton CT) prototype based on high energy physics technology. The technology has been developed for A Large Ion Collider Experiment (ALICE) project at the European Organization for Nuclear Research (CERN). The development of a Proton CT system in Bergen is a collaboration between the University of Bergen (UiB), Western Norway University of Applied sciences (HVL) and Haukeland University Hospital.

Proton CT is an imaging modality. It measures the composition of the tissue by transmitting protons through the patient and measuring the energy remaining in the protons when they exit the patient. By measuring how much energy the protons have lost while penetrating the patient, it is possible to create an accurate volume map or an image of the patient. To create the Computed Tomography (CT) image, repeated measurements from different angles will be needed.



Figure 1.1: Proton CT prototype [2].

Figure 1.1 is a schematic setup of the proton CT system from Bergen. It consists of the beam itself, the patient and a calorimeter. The Digital Tracking Calorimeter (DTC) [3] consists of layers of sensors and energy absorbers. The technology behind the sensor is the Alice Pixel Detector (ALPIDE) chip, which is a Monolithic Active Pixel Sensor (MAPS) with a 1-bit digital "hit-or-no-hit" readout [4]. It is a 1024 x 512 pixel grid of 28 x 28 μ m² pixels.

The setup shows a beam line that shoots proton particles or heavier ions such as carbon or helium. The particles pass through the patient and into the tracking calorimeter. The tracking calorimeter is divided into different layers of sensors and energy absorbers and the protons will stop in one of them. It is important to have a signal from all the layers such that the track reconstruction can be done.

The particles will start with the same initial energy. Thereafter each proton will lose different amounts of energy in the patient depending on the paths it takes through the patient, determined by the multiple Coulomb scattering. Different types of tissue result in different energy loss, hence the particles will stop in different layers of the tracking calorimeter depending on the energy lost in the patient. Each layer in the calorimeter consists of 9 x (10-12) ALPIDE-chips connected and aluminium absorbers between the planes, with a total area of 27 cm x (15-18 cm). This results in a grid of (1024 x 9) x (512 x 10-12) pixels.



Figure 1.2: Demonstration of one particle passing through multiple detectors and stops.

As shown in Figure 1.2, a particle will deposit energy in multiple pixels as it goes through a sensor chip. This is because a proton will eject electronhole pairs from the Si semiconducting layer of the ALPIDE chips. The many electron-hole pairs will diffuse randomly into nearby pixels, causing neighbouring pixels to activate as well. Pixels where a minimum charge is reached, corresponding to the pre-set threshold value, are activate [5].

Figure 1.2 illustrates a particle passing through layers in the calorimeter. Each layer shows only a section of one detector in order to see how the pixels are activated (dark green pixels) once the particle passes through. The number of pixels activated depends on the energy deposited by the particle. The group of pixels in each layer corresponding to a single particle is called a cluster. The figure shows that the first 4 layers have the same cluster size. Thereafter one can see a rapid increase in the cluster size in the next two layers, followed by no clusters in the last two layers. This is due to the characteristics of a charged particle. The particle will emit a low amount of energy in the first layers, and right before it stops, it will emit a high amount of energy, resulting in a rapid increase in cluster size in the last layers. This is further discussed in subsection 2.1.

Figure 1.2 shows how one particle hit the detectors, but in reality, each detector per readout cycle will have up to \sim 500 particle tracks. The readout includes information about which pixel is activated (X and Y positions) in the detector and the time-frame. Therefore, the information must be processed and track reconstruction methods used to find the correct path for each particle.

1.2 Problem description

The master thesis will contribute to simulation of the track reconstruction part of the proton CT system, more specifically, to simulation of particles hitting a pixel plane. The contribution involves two parts.

The first part is the creation of a collection of pixel cluster shapes from a Heidelberg experiment. This requires analysing and filtering the data from a test beam experiment and will be further discussed in subsection 3.1.2. This data collection is created in order obtain realistic cluster shapes in the simulation, and in addition, so that it can be used for other simulations for track reconstruction in proton CT as well, as has been done in [6].

The second part includes creating a toy Monte Carlo simulation procedure to randomly pick cluster shapes from the collection and adding this to the detector. This is done with a Gaussian distribution mimicking the data resulting from an Intensity Modulated Proton Therapy (IMPT) scenario. The challenge when reconstructing the clusters is that the more clusters there are in the detector, the more the clusters will overlap and be more difficult to reconstruct. Methods will be needed to distinguish between overlapping clusters and single clusters. Different methods have therefore been developed in order to separate the clusters and thereafter each method is analysed.

1.3 Goal and research question

The goal of the master thesis is to create a filtered pixel cluster library and develop and implement different methods to separate the simulated clusters and compare them in terms of particles per pencil beam and efficiency. Particles per pencil beam in this context is defined as how many particles which can hit the detector. Efficiency means how many clusters it is possible to perfectly reconstruct. This means that if 100 particles are shot from the beam into the detector, and the method can reconstruct 96 of them, the efficiency is 96%. If the beam intensity is too high, it will be difficult to separate the clusters from each other and reconstruct them. The number of particle hits per detector in this thesis have been between 0 and 500 because a higher particles per pencil beam will result an efficiency that is too low.

A high efficiency is needed to obtain the best precision and decrease the radiation to the patient when conducting the proton CT. This is further discussed in Chapter 4. The effect of having as many particles per pencil beam as possible, with a acceptable efficiency, is making the duration for taking a proton CT shorter for the patient.

This work aims to answer the research question of which method provide the best result in terms of efficiency compared to particle per pencil beam.

1.4 Evaluation and expected result

The final result is the choice of which method will give best results in terms of efficiency and particles per pencil beam. In addition, the second expected result is a filtered pixel cluster shape library. The data collection will be used in other simulations as well, as has been done in [6]. Quantitative methods and case studies using both comparative study and simulations will be used to achieve the expected results.

1.5 Report outline

This thesis is divided into the following chapters.

Chapter 2 - Background is divided into two subsections and contains a brief background for the relevant domains of this thesis. These are the medical background and the software that was used. The medical background gives a short introduction to cancer, proton therapy, and how proton CT is related to this. The Software subsection gives a presentation of the framework ROOT, and why it was used.

Chapter 3 - Implementation is divided into two parts. Firstly, creating a data collection of pixel cluster shapes and secondly simulating particle hits on a single detector and using methods to reconstruct the clusters.

Chapter 4 - Results and evaluation contains the results from reconstructing clusters using the different methods described in chapter 3. Additionally, it contains an evaluation of the results.

Chapter 5 - Conclusion and future work involves a summary of the results achieved and a proposal for further work based on the findings of this thesis.

Chapter 2

Background

This chapter contains the theory of the relevant domains of this thesis. It will give a brief introduction to the medical aspect of the thesis and then present the software framework ROOT that was used to develop the project.

2.1 Medical background

Cancer is a common term for the uncontrolled growth and spread of cells [7]. It can occur in every organ or tissue in the human body. There are three main types of treatment for cancer, including surgery, radiation therapy and chemotherapy. Which one to use is determined by several factors such as cancer type, stage, organs at risk adjacent to the tumour and progression [2].

The last decades have been characterised by a significant increase in the number of patients treated with proton therapy, which is a type of radiation therapy. There are 92 facilities worldwide which offer proton therapy and several more are under construction or at a planning stage, including two facilities in Bergen and Oslo [8].



(a) Dose distribution in x-ray therapy and proton therapy [9].

Figure 2.1: Illustration of how the protons and photons deposit dose during proton and x-ray therapies.

Proton therapy uses protons to irradiate the diseased tissue as demonstrated in figure 2.1a. The protons are shot through the patient with a high amount of energy and the proton will deposit almost all its energy right before it stops. The goal is therefore to concentrate the majority of the energy from the proton in the diseased tissue of the patient.

The Bragg curve is illustrated in Figure 2.1b showing how much energy protons lose in the tissue and how much photons are absorbed. Protons have high energy and lose minimum energy before the Bragg peak, which results in low damages to the surrounding tissues in front of the tumour. Then all the remaining energy is deposited in the tumour. Photons (used in traditional xray), on the other hand, deposits a higher dose to the surrounding tissue before the tumour, and after the tumour as well. Figure 2.1a shows how the radiation is distributed to the surrounding tissue for both x-ray therapy and proton therapy. Proton therapy is preferred for some cancer treatment because of the limited amount of dose to surrounding healthy tissue. However, it requires detailed planning and preparation prior to performing the treatment. X-ray CT can be used to plan the exact dose calculation for proton therapy treatment. An x-ray CT is an image modality which combines a series of x-rays measurements from different angles, to produce cross-sectional slices [11]. Using the datasets generated by the CT scans, the electron density of the tissue can be calculated [12].

As mentioned in subsection 1.1, a proton CT system in Bergen is in development. Using a proton CT system rather than an x-ray CT it can potentially lead to a more precise dose calculation for the proton therapy treatment. By using proton CT instead of x-ray CT the relative stopping power (RSP) directly from the proton CT scans can be used. RSP is today calculated based on the data from the x-ray CT scans. The RSP defines how much energy the protons will deposit in the patient, which is crucial knowledge in calculating the dose for the proton therapy treatment.

2.2 Software

The ROOT framework [13] developed by CERN was used during the project for the master thesis. ROOT is a scientific software framework which is based on the programming language C++. However, there is integration with other languages such as R, Mathematica or Python as well. The framework provides good possibilities for managing statistical analysis, visualisation, storage and large data processing.

The framework uses the Cling C++ interpreter to compile the program. ROOT offers a library of objects such as histograms for visualisation and trees for data storage, in addition to the standard C++. One of the main advantages of ROOT is that it is easy to visualise results in histograms. Histograms may be created by code or different ROOT objects such as TTree may be used to draw histograms.

ROOT is frequently used in the Proton CT research team, and this framework was therefore suggested to develop the master project. This will also make it easier to integrate the solution with other programs that will be developed in the future. In addition it will be easy for the research group to use the program because they know the framework.

Chapter 3

Implementation

This chapter will provide a deeper understanding of how the solution was implemented. The implementation was divided into two parts. The first part was creating a representative data collection of pixel cluster shapes which would then be used for further simulation. The second part was simulating particle hits on the detector by using the data collection. Different methods were then used to reconstruct the clusters. The methods were thereafter analysed in terms of efficiency and particles per pencil beam.

3.1 Creating a data collection of clusters

A data collection of clusters was created using data from a beam test in Heidelberg [14]. The data was used to obtain a good, representative collection of real pixel cluster shapes.

An alternative solution to creating a representative data collection would have been to create a mathematical model which generated a data collection of pixel cluster shapes. However, the experimental data from the beam test were a good, representative and realistic data collection and were therefore used instead of generating a mathematical model.

In order to create the collection, a few pre-processing steps were applied to the data from the beam test. The steps included analysing and filtering the data to obtain a usable collection. The filtering methods removed apparent double clusters, clusters which lasted over multiple readouts, clusters including holes, and separated the remaining double clusters.

3.1.1 Data acquisition

A beam test was conducted at the Heidelberg Ion-Beam Therapy Center (HIT) in July 2018 where helium and proton particles were used [14]. The test was performed with 3 ALPIDE chips in a telescopic layout as shown in Figure 3.1. The purpose of the experiment was to examine the readout efficiency of the chips and view the cluster lifetime, shape, etc. of each particle hitting the detectors. As a result, the system was able to read out 220138 activated pixels during one of the runs. The data for that exact run were written to a single file, which is referred to as the raw data file in this thesis.

The helium particle data were used in the project for the master thesis. The reason why helium particles were used instead of proton particles is that helium has a larger cluster size than protons. It is therefore, more difficult to use the helium particles in the simulation because a larger cluster size results in more overlapping of clusters in the detector, and therefore makes it harder to conduct cluster reconstruction. A more difficult cluster reconstruction was therefore preferred to make sure the reconstruction can be done for even larger cluster sizes than protons. In addition, a model was created which shows the correlation between the deposited energy (measured in keV/ μ m) and cluster sizes [15]. It is therefore possible to use this data collection for protons-like cluster sizes, if a subset of the cluster size distribution is selected. The Bragg peak has a even narrower width and needs more energy to reach the same



Figure 3.1: Illustration the beam test setup [14].

destination.

Each line in the raw data file corresponded to information about one single activated pixel in a detector with a given event id. A section of the data is given in Table 3.1 and illustrated in Figure 3.2. This is the information given from a readout of plane id 1 and event id 32. The cluster is read out from approximately the center of the chip.

The raw data includes, among other variables, an index, plane id, hit id, x and y positions, time-stamp, run and event id. The index is a counter from 0 to the last readout event in a single run, which was up to approximately 220000 in this dataset. The plane id is a value between 0,



Figure 3.2: Cluster with event id 32 and plane id 1.

Index	Plane id	Hit id	X pos.	Y pos.	Time-stamp	Run	Event id
0	1	0	492	310	21600	425	32
1	1	1	493	310	21600	425	32
2	1	2	493	311	21600	425	32
3	1	3	492	311	21600	425	32
4	1	4	493	312	21600	425	32
5	1	5	493	313	21600	425	32
6	1	6	495	311	21600	425	32
7	1	7	494	311	21600	425	32
8	1	8	494	312	21600	425	32
9	1	9	495	312	21600	425	32
10	1	10	495	313	21600	425	32
11	1	11	494	313	21600	425	32
12	1	12	494	314	21600	425	32
13	1	13	495	314	21600	425	32
14	1	14	496	312	21600	425	32
15	1	15	496	313	21600	425	32

 Table 3.1: Raw data for one particle hit in one plane.

1 or 2 depending on the plane the data was read out from. The hit id is a counter of activated pixels for a single event on a plane. Each activated pixel on a single plane at a given time-stamp, has an hit id, starting at 0 and counting up towards the number of activated pixel in that plane. However, the hit id is not serialised throughout the entire run, it is just unique in that exact readout from one plane. This is to enumerate the pixel in the cluster. The x and y position identify the position of the activated pixels in the chip, with a maximum of 511 for y position and 1023 for x position. Time-stamp is the time when the chip was read out and are in units of 25 ns, and the run is a number describing that exact run in order to distinguish the different runs. The event id is similar to the time-stamp, it is a value for one readout, and can be the same for multiple planes. It is not a unique number for one single cluster or plane.

The system was configured such that it read out data from the chip every 20 µs in a given period of time if the chip contained any data. For each time it read out from the 3 planes, an event id is given. The event id starts at 0 and increased by one for every readout. The frequency was lower than the readout speed in order to capture each cluster. A cluster could "live" over multiple events in the chip. If a readout did not contain any data, it incremented the event id and the time-stamp. Therefore, event ids will not have sequential numbers and and it will vary which plane containing data. Therefore, one will not get sequential numbers of event id's and it will vary which plane containing data.

The data from event id 32 on plane id 1, as shown in Table 3.1, is one single cluster. However, the readout of one event on one plane does not always include a single cluster. Therefore, filtering and analysing steps were performed in order to obtain a representative data collection of single clusters, which will be further discussed in the next subsection.

3.1.2 How the database of clusters is created

The raw data from the beam test in Heidelberg included double clusters in single events, clusters with holes in them and clusters which had a lifetime in same plane over two events, etc. Therefore, a couple of filtering and analysing steps were conducted.

Removal of some apparent double clusters

A simple method was used in order to filter out apparent double clusters, illustrated in Figure 3.3. The method consists of looping through all the data and for each event in a single plane, the size, height and width of the clusters are checked. The information on each event in a single plane was treated as one cluster in this method, in order to remove double clusters. The double cluster will usually have a higher value in height, width or size, than a single cluster. This is because the height in every cluster is defined as:

$Height = Maximum \ y \ pixel - Minimum \ y \ pixel$

The width was calculated the same way but using x pixel values instead. The size of the cluster is defined as how many pixels there are in the data, such as 16 in Table 3.1.

By looking at the distribution of the size, width and height in Figure 3.4, a value to separate on can be determined. That is to say, the value which represents the barrier for abnormal clusters. The distribution of cluster sizes shows that the tail of the graph starts around 25-30. The cluster size of 30 was therefore chosen to be the barrier for the size of a single cluster. Figure 3.4 shows that height and width of the cluster was quite similar. The barrier for those two values are therefore equal and defined as the value 10. If either the height, width or size was greater than the barrier values, the cluster was discarded. The double cluster method removed 1058 elements from the dataset.



Figure 3.3: Double cluster on plane id 1 and event id 3135.



Figure 3.4: Distribution of size, height and width of clusters in the raw dataset.

As a result, there were 22 773 remaining clusters to work with within the next method.

Combining clusters

Another challenge with all the datasets from the ALPIDE chip was that some of the clusters last over two events. Multiple examples are given in Figure 3.5. For instance, **event id** 56 and 57 (top two clusters to the right) have approximately the same x and y pixels activated, with only one pixel less in the second cluster.



Figure 3.5: The 9 first clusters on plane 0. The 3 red dashed rectangles shows which clusters where combined.

The solution was to compare each cluster to the subsequent cluster. If the cluster's event id only differs by one and they were on the same plane, then the two clusters probably originated from he same track. To determine if they should be merged, the larger cluster was compared with the smaller cluster. If the pixels in the small cluster were a subset of the large cluster, excepting a given number of additional pixels in the smaller one, then the clusters are merged. The exception was given in order to allow a slight change in the cluster shape from the two different readouts. The difference was set to 2 in this implementation but could easily have been adjusted if needed for another

dataset. The value was chosen after a quick analysis in which all of the smaller clusters had no more than two pixels that were not part of the bigger cluster.

The analysis was conducted to find similarities in a range of 1500 clusters. It was conducted to understand how long the "lifetime" of a particle lasted in the detector and how the shape changed. The conclusion from the analysis was that all the clusters lasted a maximum of 2 readout frames in the readout from the detector. This is consistent with the readout settings which were explained earlier, since the readout period (strobe window) is 20 µs. Additionally, the two clusters which appeared to be the same were compared. All the compared clusters had one smaller cluster which was a subset of the larger cluster, with an exception of 2 pixels. As a result, it was decided to combine all clusters with subsequent event ids, where one of the clusters was a subset of the other with an exception of 2 pixels.

Removed clusters with holes

Another method for filtering unwanted clusters is the removal of clusters with holes thus removing some additional double clusters. A couple of examples of clusters with holes are shown in Figure 3.6.



Figure 3.6: Examples of hole in clusters. The active pixel is coloured green and the white pixels are inactive.

Figure 3.6 shows 4 examples of clusters with holes. A hole is defined as one or multiple inactive pixels between two active pixels, either in the x or y direction.



Figure 3.7: Illustration of method for removing holes.

The exception is if the inactive pixel is on one of the outer edges of the cluster. Then the cluster does not include the inactive pixel as a hole. The method is illustrated in Figure 3.7.

In addition to remove holes, the method will simultaneously remove some remaining double clusters. Each cluster is stored in a binary list as a bit pattern, which means that the cluster in Figure 3.8a, will be stored as the list to the right in 3.8b.



2 ⁸	2 ⁷	2 ⁶	2 ⁵	2 ⁴	2 ³	2 ²	2 ¹	2 ⁰	
256	128	64	32	16	8	4	2	1	384
256	128	64	32	16	8	4	2	1	384
256	128	64	32	16	8	4	2	1	0
256	128	64	32	16	8	4	2	1	6
256	128	64	32	16	8	4	2	1	15
256	128	64	32	16	8	4	2	1	15
256	128	64	32	16	8	4	2	1	15
256	128	64	32	16	8	4	2	1	2

(b) Illustration of how the cluster is calculated to a binary array containing only a list of numbers. The dimensions of the array are the same as the height and the width of the double cluster, which is 8x9.

Figure 3.8: Illustration of how a cluster is stored in a binary array.

The cluster is placed in a 2-dimensional array with the same height and width as the cluster. Each column represents a value in the base 2 system. These values are calculated by the index, such that index 0 has the value $2^0 = 1$. The index starts at the end of the array and increases moving to the left as seen in Figure 3.8b. To calculate the value for a row, the pixel position on each column is added to the value of the column. An example is how the value 384 is calculated. The index of activated pixels in that row, which is at index 7 and 8 is determined. Then the values from these two columns are added together, $2^7 + 2^8 = 384$. This procedure is done for every row in the array and results in the list [384, 384, 0, 6, 15, 15, 15, 2].

If the list contains the number 0, it means that a double cluster exists, since there are no pixels in that row. Figure 3.8a is a good example of this. Therefore, are all binary lists containing 0, are removed from the data collection.

The last pre-processing step

A last pre-processing step was conducted in order to obtain a good, representative collection of clusters without errors. A single cluster is here defined as a group of active pixels that are next to each other in the x and y directions, not in a diagonal direction. There were 20 examples in the collection which did not fulfil this definition, and two examples are illustrated in Figure 3.9.

One can clearly see that these two examples contain multiple clusters. However, none of the previous filtering methods was able to remove them. Therefore, a method for separating the remaining double clusters and separately adding them to the collection was developed. The method is also used to separate clusters in simulation in subsection 3.2 and will therefore discuss this in detail there.





(a) A cluster which is separated into two stored clusters.

(b) A cluster which is separated into three stored clusters.

Figure 3.9: Illustration of two clusters which does not fulfil the definition of a single cluster. The "count = 1" means that only one element of each exists in the data collection.

As a result of the method, Figure 3.9a is added as two clusters in the collection, and Figure 3.9b is added as three clusters. 20 wrongly defined clusters resulted in 47 clusters in the data collection.

Consequently, all clusters containing only a single pixel were removed. These pixels were most likely noise in the chip. There were approximately 500 single pixels.

3.1.3 Final collection of cluster shapes

The final cluster collection contains approximately 13500 clusters. Each cluster in the collection contains information about mean x and y values, size, positions of the cluster, height, width, cluster shape, event id and if the cluster was combined.

The collection has the following distribution of size, height and width as shown in Figure 3.10. The size has a mean value of 9.7 pixels, the height has a mean value of 3.5 pixels and the width has a mean value of 3.3 pixels.


Figure 3.10: Distribution of size, height and width.

Additionally, the collection contains around 550 distinct cluster shapes. The most frequent 16 cluster shapes are shown in Figure 3.11. The clusters here have a count between 235 and 1093.

CHAPTER 3. IMPLEMENTATION



Figure 3.11: 16 most frequent clusters in the data collection.

3.2 Simulation

Simulation is used in order to imitate a function of a system or process in the real world by means of the use of another system. It is an important tool used in scientific research to mimic the behaviour of a system. Monte Carlo simulation is a type of simulation where one uses a computer program to represent a system based on a mathematical description, or model. The simulation also makes it possible to test each component of a system separately and simulate a system which does not yet exist [16].

In this project, simulation is used to study the pixel cluster reconstruction part of the proton CT system. The "toy Monte Carlo" simulated system is used to imitate a beam shooting helium particles at a given beam size towards an idealised pixel detector. Thereafter, different methods are used to reconstruct as many clusters in the chip as possible. Finally, an analysis is performed to evaluate how many correct clusters the algorithm was able to find.

3.2.1 Method for simulation

The method for simulation consists of generating particle hits on the ALPIDE chip. In order to conduct the simulation, parameters such as the lateral beam size and the count of particles hitting the chip are selected. Thereafter, random x and y points from a Gaussian distribution are selected as shown in Figure 3.12. The mean values for the x and y positions are 512 and 256, respectively. Both Figure 3.12 and Figure 3.13 show examples of a simulation with 1000 hits and a beam size corresponding to a circular Gaussian with a standard deviation of 4 mm, or approximately 143 pixels.

Figure 3.12 shows the x distribution on the left, and y distribution on the right. The standard deviation for the two figures is slightly different. The left graph has a standard deviation of 146.8 pixels, and the right graph have

a value of 119.5 pixels. This is because the simulated ALPIDE chip has a dimension of $1024 \ge 512$, where the y range of the chip is smaller than the beam size, and therefore will result in a slightly lower standard deviation than the x distribution.



Figure 3.12: Distribution of randomly picked x and y pixel positions.

Figure 3.13a shows how the points are placed in the chip. Arbitrary clusters from the collection are placed onto random points as shown in Figure 3.13b. As a result, one will get a chip with 1000 clusters, and a chip occupancy of approximately 1.7%. In this example, the Gaussian beam size is set to 143 pixels in each lateral direction, which is approximately 4 mm.

Each pixel simulated in the detector will contain some information. This includes information about the position in the chip, and if one pixel is part of a multiple clusters. This information is not used in the method for finding a cluster, but in analysing the results of the cluster reconstruction.



Figure 3.13: Simulation of helium particles hitting the ALPIDE chip. The beam size is a sigma of 4 mm in both x and y directions and 1000 particles are hitting the layer. There are used 1000 particles in the detector to clearly see the distribution of clusters.

3.2.2 Method for finding clusters

The method for finding clusters include going through the entire chip, pixel by pixel. When an active pixel is found, two approaches could be used. These are demonstrated in Figure 3.14. Figure 3.14a will find all activated pixels which are adjacent to one another in x, y, and diagonal directions. This means it will

consider one pixel (the red one) and find all activated pixels around that pixel. It will keep doing this until there are no more adjacent activated pixels. Then, it classifies all the found pixels as one cluster. The approach shown in Figure 3.14b is similar, except it excludes the diagonal direction. This will result in the first approach classifying the simulated cluster as one cluster, and the other as two clusters in Figure 3.13. The method without diagonally adjacent clusters provides a better overall result, which is discussed in subsection 4.1.





(a) Find all activated pixels which are adjacent to one another in x, y and diagonal directions. Results in one cluster.

(b) Find all activated pixels which are adjacent to one another in x and y directions, not in a diagonal direction. Results in two clusters.

Figure 3.14: Algorithms which separate on two different terms when finding cluster in simulated chip.

The methods discussed above are simple techniques to reconstruct the clusters in the detector. The methods may be used to find the clusters in the detector when there is apparently no overlap between the clusters. However, when there are multiple overlaps among the clusters, the method will perform poorly. The source for misclassified clusters is the overlapping of two or more single clusters. In order to classify some of these overlapping clusters correctly, several cuts to recognise double clusters were developed. All the cuts use the above method without diagonal direction and will therefore be referred to as the basic method in this thesis.

Cut 1 - Fill percentage

The first cut uses the fill percentage to distinguish whether a cluster identified by means of the basic method, should be divided into two clusters. The fill percentage means placing the cluster in a square or a rectangular box, and then calculating the percentage of active pixels that exist inside the box. In order to calculate the square box, one would take the largest height or weight and multiply it by itself. The rectangular box is calculated by multiplying height and width.

Fill percentage = Activated pixels / box

A separator value is thereafter chosen to distinguish when a cluster should be divided into two clusters. The fill percentage can be adjusted to a preferred value between 0 and 100%. When the cluster's fill percentage is less than the chosen value, the method will classify the identified cluster as two clusters instead of one. The double cluster will not be separated from each other, but they will be marked as two clusters.



Figure 3.15: Distribution of fill percentage calculated with both square and rectangular box for clusters in data collection.

The distribution of the fill percentage in the data collection are presented in Figure 3.15. The square approach is shown in the left graph and the rectangular approach in the right. The graph on the left shows a broader spread in fill percentage and an average of 73.7%. The right graph, on the other hand, has a narrower distribution of the fill percentage and an average of 82.4%.

Cut 2 - Asymmetry

The second method is to make a cut based on the asymmetry of the cluster shape, where the distribution of pixels in the cluster is viewed in either the x or y direction. An example is shown in Figure 3.16. Figure 3.16a shows a double cluster in the detector created in simulation, which should be classified as two clusters. Figure 3.16b shows the distribution of pixels in x direction, and Figure 3.16c shows the distribution of pixels in a y direction. The method looks for deviations in the distribution in both directions, which results in asymmetric cluster shapes. The deviation can be:

- 1. Two clusters which are adjacent to one another where there exists a high pixel peak among lower ones in either the x or y distribution. The high pixel peak needs to be at least 2 pixels higher on both sides. An example of this is shown in Figure 3.16c. The peak contains 5 pixels, and the count of pixels on both sides of the peak contains 3 pixels. Since the difference in the count of pixels on both sides of a peak is 2, this fulfils the condition. The method will always compare 3 and 3 counts of pixels next to each other sequentially and look for a peak. If the peak is more than 1 pixel wide, it will not detect it.
- 2. Opposite of the previous one, two clusters which are adjacent to one another where there exists a low pixel count among higher ones. Also here, 3 and 3 values of pixels are compared, if the first and the third value differ by at least 2 pixels to the second value, the condition is fulfilled.

3. Two clusters which are adjacent to one another with only one pixel in the middle of the distribution. For example, the distribution in y direction containing the following values: [3, 3, 2, 1, 3, 3, 2]. The middle value contains 1, which fulfils this condition.

If at least one of these conditions for deviation in the distribution is fulfilled, the simulated cluster is marked as two clusters.





(a) A double cluster simulated in the detector.





Figure 3.16: Distribution of cluster projected onto x and y axis.

Cut 3 - Inactive pixels

Cut 3 uses almost the same method as used to remove clusters with holes as was described in subsection 3.1.2. It looks for continuously active pixels in both x and y direction. This method includes the outer edges of the cluster, in contrast to the method for removing holes in the cluster. An example of a double cluster which will be marked as two clusters is shown in Figure 3.17. When the method goes through column x_1 row by row, it will find an inactive pixel among active pixels at y_5 . Therefore, the method will mark this cluster as a double cluster.



Figure 3.17: A double cluster which will be separated by the method used in approach 3 - inactive pixels.

Barrier (Separator) values

The three different cuts will also recognise a double cluster if the cluster exceeds the values for maximum size, height and width which were specified in subsection 3.1.2. The size is 30 pixels, and the height and width are 10 pixels. If the cluster exceeds these values, they will be classified as two different clusters.

Some clusters exist in the data collection which will be classified as 2 clusters by one of the cutting approaches, even though they are single clusters. To reduce this misclassification of clusters, a separator value is defined for the minimum size of a cluster. The cluster size will therefore need to exceed this value in order to use one of the cutting approaches on the cluster.

For example, if the fill percentage separator is set to 56%, then there are over 1100 single clusters which will be misclassified as two clusters in the data collection. However, if a minimum size separator value exists, of for example 9, the misclassified clusters will be significantly reduced. As a result, there will be around 150 clusters which will be misclassified in the data collection. Even though a few single clusters are misclassified, more double clusters will be able to be separated by the cut and the score of reconstructed clusters increased.

3.2.3 Method for analysing results

An analysis must be conducted to evaluate the results from the reconstructed clusters. The analysis determines which simulated clusters are perfectly classified and which are incorrectly classified.

The first analysis is performed on the method for reconstructing clusters with and without diagonal pixels. The method looks at each classified cluster. All the pixels in the cluster contain information from the simulation which will be used here. If one of the pixels in the cluster contains information about multiple clusters, or if the pixels belong to a different original cluster, then the entire cluster will be classified as an error. However, if all the pixels belong to the same cluster, and the size of the cluster is also the same as the original, it is classified as a perfectly reconstructed cluster.

The second analysis was performed on the extended method of reconstructed clusters with filter. If the method has classified a cluster as one cluster, it will go through the same procedure as above. However, if the method has classified the cluster as two clusters, it will look for only two original clusters in that exact cluster. If it is able to find only two clusters, it will be classified as two perfectly reconstructed clusters. On the other hand, if the cluster contains more than two clusters or only one cluster, it will be categorised as an error.

The analysis will in both cases classify the cluster as either a perfectly reconstructed cluster or a misclassified cluster. It will not take into account whether the cluster is nearly perfectly reconstructed, meaning that there are only one or a few pixels more than the origin cluster.

Chapter 4

Results and evaluation

This chapter will answer the research question about which method will perform best in terms of efficiency compared to particles per pencil beam. The efficiency is defined to be the radio of perfectly reconstructed clusters to total number of cluster in the detector. The basic method identified clusters which were adjacent in x and y directions, and then different cuts were tested in order to distinguish single clusters from overlapping clusters in the detector.

The result of each cut was thereafter evaluated by looking at how many perfectly reconstructed clusters were found and how many clusters there were in the detector. The desired perfectly reconstructed clusters percentage is as high as possible, and at least 96%. The percentage needs to be high because there are a lot of hits in the calorimeter in the planned proton CT system in Bergen. The calorimeter contains approximately 40 layers, and if around 4% are lost in every detector layer, then the effective per-track efficiency would be $96\%^{40} \simeq 20\%$. This is a high total loss, which would results in a significantly reduced precision and increase the radiation dose to the patient. However, methods have been developed to mitigate the loss in the track reconstruction part of Proton CT. If 100 particles hit the calorimeter, it is expected that there will be 88% correctly reconstructed proton paths without taking the effective per-track efficiency into account, and 85% when considering them[6]. This is before applying the filters discussed in chapter 3. Therefore, we will fortunately get much better than 20% per-track clustering efficiency.

The effect of having as many particles per pencil beam as possible, with a acceptable efficiency, is making the duration for taking a proton CT shorter for the patient.

In addition, in order to to evaluate the performance of the different cuts in terms of particles per pencil beam and efficiency, the misclassified clusters from each cut were analysed. The misclassified clusters are, as described before, discarded clusters which did not fulfil the criteria for perfectly reconstructed clusters (subsection 3.2.3). The misclassified clusters were divided into 3 categories:

- Category 1 Found 2, was 3+: The cut classified the cluster found using the basic method as 2 clusters, but there were at least 3 clusters originally.
- Category 2 Found 2, was 1: The cut classified the cluster found using the basic method as 2 clusters, but there was only a single cluster originally.
- Category 3 Found 1, was 2+: The cut found only 1 cluster, but there were at least 2 clusters originally.

All the different cuts will only distinguish between a single cluster and 2 clusters. Therefore 3 or more overlapping clusters will never be classified with these cuts. These discarded clusters will fall into category 1. Category 2 contains single clusters which were misclassified as 2 double clusters because it met the criteria for abnormal clusters for that cut. The last category, category 3, is the division into which most misclassified clusters fall. The cut was not able to classify each cluster as an abnormal cluster and therefore only found a single cluster.

The misclassified clusters from each cut are also analysed where one looks at how many extra pixels each cluster contains. This information tells us how many clusters were nearly perfectly reconstructed.

The following subsection will present the step-by-step results of each cut described in subsection 3.2.2. Firstly, how the different parameter values were chosen. Followed by the results of each cut. Thereafter which type of misclassified clusters the cut had. Finally, all the cuts are combined in different variants to compare which combinations perform best.

Each of the simulations contains the following settings if nothing else is specified. The beam size correspond to a circular Gaussian with a standard deviation of 4 mm, or approximately 143 pixels. The simulation is conducted with 0-500 clusters placed in a detector layer, with a step of 25. Each step shows an average of 100 simulations in order to get better statistical significance. The graphs of misclassified clusters include these settings as well.

4.1 Results from the basic method

The results from the first two methods described in subsection 3.2.2 are presented in Figure 4.1. The methods identified clusters either by finding pixels in the detector which were adjacent in x, y and diagonal directions or only x and y directions (basic method). The graph shows how many clusters the two methods were able to reconstruct with an increase in the number of clusters in the detector. The y axis shows the percentage of perfectly reconstructed clusters. The x axis shows how many clusters there were in the detector in each simulation.



Figure 4.1: Results finding clusters with and without diagonal directions using a beam size of 4 mm.

Figure 4.1 shows that the basic method resulted in the best score of perfectly reconstructed clusters. The difference in percentages between the two methods increases slightly with the clusters' occupancy in the detector. Figure 4.1 shows that in order to have a minimum of 96% given a beam size of 4 mm, there cannot be more than approximately 175-200 clusters in the detector depending on the method.

4.1.1 Misclassified clusters

Figure 4.2 illustrates the average errors of all the misclassified clusters using the basic method with increasing clusters in the detector. The method has no cuts to distinguish a single cluster from multiple clusters, and therefore it will only have errors of category 3.

The misclassified clusters were also analysed in terms of how many extra pixels each cluster had, which is shown in Figure 4.3. The graph shows around



Figure 4.2: The average errors of misclassified clusters in the simulation.

35 000 misclassified clusters out of 525 000 clusters in the entire simulation, which is approximately 6.67% errors. The x axis shows how far from perfectly reconstructed each cluster was. One can see that there are approximately 2000 misclassified clusters which fall into 0-2 extra pixels. These errors can be considered as nearly perfectly reconstructed clusters. Over 500 clusters with 0 extra pixels have either a fully overlapping cluster, or it is a larger cluster which covers the overlapping cluster completely. The shape of the graph (figure 4.3) is quite similar to the size distribution of size in the cluster collection (Figure 3.16a), and both of the graphs have an average of around 9 pixels.



Figure 4.3: How many extra pixels each misclassified clusters had, using the basic method.

4.1.2 Results from different beam sizes

The size of the beam determines how centred or spread the clusters are placed in the detector. A smaller beam size will centre the clusters and result in more overlap between clusters than a larger beam size. The beam size is normally set to a range between 71 pixels and 214 pixels in x and y directions, which is the same as 2 mm and 6 mm. There is not much difference in cluster overlapping when the beam size exceeds approximately 6 mm (214 pixels). The result of different beam sizes is shown in Figure 4.4 where one can see a cluster range from 0-500 with a step of 25. The beam sizes presented in the graph are 2-6 mm and the basic method was used.



Figure 4.4: Results from simulation with different sigma values using the basic method - where pixels are adjacent in x and y directions.

One can see that the result of perfectly reconstructed clusters varies depending on the beam size. A beam size of 2 mm, which is the dark blue line on the graph, decreases rapidly compared to the others. This is due to a lot of overlapping of clusters in the detector, which may be difficult to separate from one another. Additionally, the graph shows that a bigger beam size results in a higher fraction of perfectly reconstructed clusters which is due to a higher spread of clusters in the detector. This simulation was conducted to examine the effect of different beam sizes and the performance was found to vary.

4.2 Results from cut 1 - fill percentage

The fill percentage cut which is described in subsection 3.2.2, uses the fill percentage of a cluster placed in a square or rectangular box to determine if the cluster should be defined as two clusters. Additionally, one has the minimum cluster size barrier value, which decides the size a found cluster must be in order to be classified as two clusters by the fill percentage cut.

Both the fill percentage approaches have their parameters selected according to the following conditions: Simulations with 100, 150, 200, 250 and 300 clusters in the detector were conducted with various fill percentages and minimum sizes. The simulations are carried out using a beam size of 143 pixels (4mm) and minimum size of 0, 7-17. The fill percentage varied depending on the approach. The square box approach had a fill percentage between 40-70%, and the rectangular approach had between 55-80%. Each value in the tables is an average result of 100 simulations with different clusters placed in the detector.

The results from the square box approach are shown in details in Appendix A including Table 1, 2, 3, 4 and 5 with 100-300 clusters in the detector. The results are summarised in Table 4.1. Figure 4.5 demonstrate the results when changing the parameters with 200 clusters in the detector. The figure shows that if the fill percentages are increased, the minimum size value should also be increased.



Figure 4.5: Results tuning the parameters for the fill percentage square approach using 200 clusters in the detector.

Summarised results				
Cluster in	Fill per-	Minimum	Highest	Difference from
detector	centage	size	score	next highest score
100	49	13	98.520%	0.010%
	50	13		
150	51	13	97.800%	0.007%
	52	13		
	53	13		
	54	13		
	55	13		
	51	15		
	52	15		
	53	15		
	54	15		
	55	15		
200	54	13	97.265%	0.015%
	55	13		
250	54	13	96.896%	0.016%
	55	13		
300	56	13	96.457%	0.014%

Table 4.1: Summarised results for combining different minimum sizes and fill percentage (square box) with different amount of clusters in the detector. There are two combinations which performs best aggregated. The combinations are fill percentage 54% and 55% combined with a minimum size of 13.

Table 4.1 shows that all the best scores had a minimum value of either 13 or 15, and a fill percentage between 49%-56%. Recurrent combinations were fill percentages of 54% and 55% combined with a minimum size of 13. To determine which combination to use, a further simulation was conducted. It consisted of simulations with a beam size of 143, 0-500 clusters in the detector, with a step of 25 clusters, and each step shows an average of 100 simulations. The result of the different fill percentages was identical. New simulations were also conducted with an average of 200 simulations instead of 100, which resulted in the same results. Since both of the fill percentage values performed identically, one of them was simply chosen. The parameters for the fill percentage square approach were therefore chosen to be a fill percentage of 55% and a minimum size of 13.

The results from each simulation run for selecting the fill percentage rectangular approach are presented in Appendix B. This includes details from Table 6 (100 clusters), 7 (150 clusters), 8 (200 clusters), 9 (250 clusters), 10 (300 clusters), and are summarised in Table 4.2. An illustration of the results from 200 clusters in the detector is also presented in Figure 4.6.



Figure 4.6: Results from combining different variants of minimum size and fill percentage calculated with rectangular box approach using 200 clusters in detector.

Summarised results					
Cluster in	Fill per-	Minimum	Highest	Difference from	
detector	centage	size	score	next highest score	
100	68	15	98.300%	0.020%	
150	72	14	97.580%	0.070%	
200	72	14	96.930%	0.015%	
	68	13			
250	72	14	96.572%	0.024%	
300	72	14	95.967%	0.037%	

Table 4.2: Summarised results for combining different minimum sizes and fill percentage (rectangle box) with different amount of clusters in the detector. The best combination is fill percentage 72% combined with a minimum size of 14.

Table 4.2 shows all the best scores from various counts of clusters in the detector. The best scores had a fill percentage of either 72% or 68% and minimum sizes of 13, 15 or 17. The most recurrent combination was a fill percentage of 72% and minimum size of 14, and was therefore selected as the best parameter for this cut.

The two best combinations between fill percentage and the minimum size are compared with the basic method in Figure 4.7. The basic method is better using between 0-50 clusters in the detector, and the fill percentage cuts perform better with 50 and more clusters in the detector. The graph also shows that the square approach performs slightly better than the rectangular approach. The reason why the square approach is better than the rectangular approach is that most clusters have a circular shape. Therefore, the square approach will more easily detect when two clusters are overlapping. The cut with the square approach can have nearly 350 clusters in the detector in order to obtain a result higher than 96% of perfectly reconstructed clusters. The rectangular approach, on the other hand, can only have approximately 300 clusters in the detector.



Figure 4.7: Results from simulations with fill percentage calculated using square and rectangular box approaches compared with the basic method. The fill percentage calculated with a square box approach is 55% and minimum size of 13, and the fill percentage calculated with a rectangular box is 72% and minimum size of 14.

4.2.1 Misclassified clusters

Figure 4.8 shows which categories the different fill percentage cuts divide the misclassified clusters into. Category 1 and category 3 are not far from identical in Figure 4.8a and 4.8b. Category 2 on the other hand, varies a lot more. The rectangular cut results in approximately twice as many average errors for category 2 than the square cut. This is why the square cut performs slightly better at finding perfectly reconstructed clusters.

An illustration of how many extra pixels each misclassified cluster had using the two cuts is shown in Figure 4.9. In contrast to the basic method, both of the fill percentage cuts have a high peak at 0 extra pixels in the cluster. This is the result of misclassifying single clusters, which were shown in Figure 4.8, category 2. In other words, the peak includes mostly clusters which were classified by the cut as two clusters but were only one cluster.



Figure 4.8: Types of misclassified clusters for the fill percentage cuts.

As described earlier, the basic method had around 35 000 misclassified clusters out of a total of 525 000. Both of the fill percentage cuts have significantly lower total misclassified clusters. The cut with the square approach beats the rectangular approach with approximately 1800 fewer misclassified clusters.



Figure 4.9: Distribution of how many extra pixels each misclassified cluster had, using different fill percentage cuts.

4.3 Results from cut 2 - Asymmetric

The asymmetric cut which is discussed in subsection 3.2.2, looks at each identified cluster and views the distribution of pixels in x and y direction to determine if the cluster should be classified as one or two clusters. The results from this cut are presented in Figure 4.10, along with the basic method and the asymmetric cut combined with a minimum size value. The minimum size value was determined by combining cut 2 and different minimum sizes. It was conducted with a minimum size values of 0 and 7-17. The results of how many perfectly reconstructed clusters the different combinations had are presented in Table 11 in Appendix C. The minimum size values 11 to 15 gave very similar results. In order to determine the best combination of these minimum size values, the average for each minimum value is calculated, and the value which gave the highest percentage result was chosen. The results are presented in Table 4.3. The value which gave the highest percentage of perfectly reconstructed clusters were 13.

Minimum size value	Average result (%)	
0	92.076	
7	92.563	
8	95.970	
9	96.059	
10	96.301	
11	96.401	
12	96.451	
13	96.501	
14	96.481	
15	96.445	
16	96.272	
17	96.146	

Table 4.3: Average results from simulation of asymmetric cut with different minimum size values (Appendix C, Table 11). The minimum size of 13 gave the highest score.

Figure 4.10 shows that the asymmetric cut performs poorly without the minimum size value, even worse than the basic method. The basic method is best with 0-50 clusters in the detector, and thereafter the asymmetric cut combined with a minimum size value of 13 performs better. The best method (blue line) can have up to around 275 clusters in the detector in order to have a higher percentage than 96% of perfectly reconstructed clusters.



Figure 4.10: Results from asymmetric cut compared with the basic method.

4.3.1 Misclassified clusters

The misclassified clusters are presented in different categories in Figure 4.11. The cut results in a few errors of category 1 and 2, and a higher amount of category 3 errors. If one compares category 3 in this figure with the errors for the fill percentage cuts, one can see that this cut has a higher number of misclassified clusters than both of the fill percentage cuts. However, this cut has fewer misclassified clusters of category 2 than the fill percentage cuts.

Figure 4.12 shows the distribution of extra pixels on each misclassified cluster which was due to overlapping or wrongly classifying single clusters. There were approximately 24 400 misclassified clusters out of 525 000 simulated clusters. This is higher than both of the fill percentage cuts, but still significantly better than the basic method. The asymmetric cut also has a high peak at 0 extra pixels, as both of the fill percentage cut had. However, the peak is much lower than the fill percentage peaks and are on the same level as the second peak on the graph. This is due to fewer misclassification of single clusters in this cut in comparison to the fill percentage cuts.



Figure 4.11: Average errors of misclassified in simulation for the asymmetric cut.



Figure 4.12: Distribution of how many extra pixels each misclassified cluster had, using the asymmetric cut.

4.4 Results from cut 3 - Inactive pixels

The inactive pixels cut, which is described in subsection 3.2.2, looks for continuously active pixels in both x and y directions in each cluster. When it finds inactive pixels among the active ones, the cluster is classified as two clusters. This cut was also tested together with the minimum size value, similar to the asymmetric cut. The simulation was the same as in subsection 4.3, except that the inactive pixels cut were used instead. However, the minimum size value seemed to have little effect on this cut, as can be seen in Table 4.4. The table is calculated in the same way as Table 4.3, and the full table of the simulation is available in Appendix D - Table 12. Since the minimum size value had a very small effect on the method, the value 0 was chosen.

Minimum size value	Average result(%)
0	96.261
7	96.264
8	96.264
9	96.264
10	96.261
11	96.253
12	96.118
13	96.252
14	96.215
15	96.180
16	96.106
17	95.984

Table 4.4: The average result from simulation of inactive pixels cut with different minimum size values (Appendix D, Table 12). The minimum size values resulted in nearly the same results.

Figure 4.13 shows the result of inactive pixels cut compared with the basic method. One can see that the inactive pixels cut performs better overall than the basic method. One can have up to 275 clusters in the detector to obtain a higher result than 96% of perfectly reconstructed clusters.



Figure 4.13: Results from inactive pixels cut compared with the basic method.

4.4.1 Misclassified clusters

The misclassified clusters divided into 3 categories are shown in Figure 4.14. The majority of errors falls into category 3, which is clusters that were classified as single clusters, but were at least 2 clusters. This cut has overall higher average errors in this category than the other cuts. However, both of the other categories for this cut have lower average errors than all the other cuts.

Each misclassified cluster is also compared with how many extra pixels it was found with. The distribution is presented in Figure 4.15. The shape of the graph is quite similar to the distribution of the basic method, except that it has fewer errors in total. The cut gave approximately 26 600 misclassified clusters out of 525 000 clusters. This is a higher value than the other cuts, but it is still considerably better than the basic method.



Figure 4.14: Average errors of misclassified clusters in simulation.



Figure 4.15: Distribution of how many extra pixels each misclassified cluster had, using the inactive pixels cut.

4.5 Combinations of different cuts

All the cuts were also combined in different combinations to see if any of the combinations would perform better than each cut separately. The results of these combinations are presented in Figure 4.16, and contains an average result of 200 instead of 100 simulations. This is to determine the optimal cuts with an even higher statistical significance.

The parameters for each combination are not fully optimised, but rather chosen based on the best parameters for each separate cut. The fill percentage value varies depending on the minimum size value, and therefore these settings are chosen over the settings of other cuts when combined with the fill percentage cut. In addition, the minimum value for the asymmetric cut is chosen when combining this cut and the inactive pixels cut. This is because the inactive pixels did not vary much in the results when using different values, but the asymmetric cut, on the other hand, improved significantly when setting the minimum size value.

Figure 4.16 shows the results of 8 different ways to cut clusters. After passing 150 clusters in the detector the different combinations roughly fall into 3 groups. The superior group includes different combinations of cuts combined with the fill percentage cut. In order to have a perfectly reconstructed clusters percentage of above 96%, one can have approximately up to 350 clusters in the detector by choosing one of them. The intermediate group includes the inactive pixels cut, asymmetric cut and a combination of these two. These, on the other hand, can have up to 250-275 clusters in the detector to have a score of at least 96%. The last group, which performed poorest, was the basic method and cannot have more than 200 clusters in the detector to reach above 96%. The different cuts will result in a variation of 200-350 clusters in the detector to obtain at least 96% perfectly reconstructed clusters. Even 200 clusters in the detector will give a higher efficiency than the track reconstruction conducted in [6] by the Bergen proton CT research team.



Figure 4.16: Results from simulation using different cuts with a beam size of 143 pixels and an average result of 200 simulations per point.

4.5.1 Misclassified clusters

A lot of the combinations resulted in similar graphs for misclassified clusters. All cuts combined with the fill percentage cut resulted in nearly identical graphs as the fill percentage graphs (Figures 4.8 and 4.9) for misclassified clusters. In addition, the combination of the asymmetric and inactive pixels cut has almost identical graphs for misclassified clusters as the asymmetric cut (Figures 4.11 and 4.12).

4.6 The optimal cuts

The inactive pixels cut gave the best score of all the combinations of cuts presented in this thesis from 0-100 clusters in the detector, which was shown in Figure 4.16. Subsequently, all the combinations of the fill percentage cut performed quite similarly with 100-500 clusters in the detector, but there were some minor differences. Figure 4.16 together with Table 13 presented in Appendix E, shows that the optimal cut for 100-300 clusters is the combination of the inactive pixels cut and the fill percentage cut. The optimal cuts for 300-500 clusters are the combination of the asymmetric cut and the fill percentage cut, and all cuts, which performs identically. There is no effect when including the inactive pixels cut, with the fill percentage and asymmetric cuts. Therefore, the optimal cut for 300-500 clusters is the combination of the fill percentage and the asymmetric cuts. The optimal cuts for different clusters in the detector are summarised in Table 4.5.

All the cuts combined with the fill percentage cut were not fully optimised by parameter tweaking for each combination. The differences are very small, and the optimal result could be different if the parameters were tuned for each combination.

Combination of optimal cuts	Clusters in detector	
Inactive pixels	0-100	
Fill percentage and inactive pixels	100-300	
Fill percentage and asymmetric	300-500	

 Table 4.5: Results of optimal cuts depending on the number of clusters in detector.

4.6.1 How many clusters the optimal cuts identified

Figure 4.17, 4.18 and 4.19 shows how many clusters the optimal cuts identified in the detector (blue line). Additionally, the graph includes how many perfectly reconstructed clusters (red line) it found, with error bars of 1 standard deviation.

Both of the combined cuts (Figure 4.18 and 4.19) classifies several original single clusters as two clusters (category 2). As a result, the cuts found more than 100% of clusters in the detector. The inactive pixels cut, on the other hand, classified fewer of these errors. This is the reason why the inactive pixels cut performs better with few clusters in the detector.



Figure 4.17: The inactive pixels cut - Illustration of how many clusters the cut was able to find versus how many perfectly reconstructed clusters which was found with error margins.



Figure 4.18: The inactive pixels and the fill percentage cuts - Illustration of how many clusters the cut was able to find versus how many perfectly reconstructed clusters which was found with error margins.



Figure 4.19: The asymmetric and the fill percentage cuts - Illustration of how many clusters the cut was able to find versus how many perfectly reconstructed clusters which was found with error margins.
Chapter 5

Conclusion and future work

This chapter contains a summary of the achieved results and further work based on the findings of the thesis.

5.1 Conclusion

The objective of this project was to simulate particle hits on an ALPIDE chip using a realistic data collection of pixel cluster shapes and then use different approaches to reconstruct the clusters. The challenge when reconstructing the clusters was to find a satisfying approach to separate the overlapping clusters. The reconstruction was done by experimenting with various cuts, which had different ways to distinguish abnormal clusters.

The basic method was a template for all the cuts when reconstructing clusters. 3 different cuts were tested: fill percentage cut, asymmetric cut and inactive pixels cut. The different cuts had various parameters to optimise in order to improve the percentage of perfectly reconstructed clusters. The identified clusters were additionally classified as two clusters if they exceeded the barrier (separator) values for height, width and size. All the simulations contained a beam size corresponding to a circular Gaussian with a standard deviation of 4 mm, and an average of 100-200 simulation per step in the graph to obtain a reasonably good statistical significance.

The optimal cut, based on the cuts tested in this thesis, was divided into 3 parts. These include the optimal solution for 0-100 clusters, 100-300 clusters and 300-500 clusters, respectively, in the detector. The inactive pixels cut had the most perfectly reconstructed clusters in the first part. The second and the third parts had 4 combinations of cuts which performed quite similarly, all different combinations containing the fill percentage square cut. Since all the 4 combinations of cuts maintained the settings from the fill percentage parameters and were not tuned individually, the optimal solution could differ slightly. However, there were some combinations which performed slightly better then the others in each part. The optimal cut for the second part, based on the selected parameters, was the inactive pixels cut combined with fill percentage cut. The third optimal cut, for 300-500, was the asymmetric cut combined with the fill percentage cut. The third optimal cut could have up to 350 clusters in the detector to get at least 96% perfectly reconstructed clusters. To obtain at least 98%, the maximum number of clusters is 125.

The different cuts developed in this thesis will result in a variation of 200-350 clusters in the detector to obtain at least 96% perfectly reconstructed clusters. Even 200 clusters in the detector will give a higher efficiency than the track reconstruction conducted in [6] by the Bergen proton CT research team.

5.2 Future work

The program which was developed in the thesis is not a final solution for the cluster reconstruction part of proton CT, only the beginning. Several extensions could be done to this simulation as further work:

- Cluster collection: The last method for separating clusters (section 3.1.2) could have been used on all the removed double clusters to get a larger cluster collection.
- Optimise all the parameter for each cut, beam size, particle thoroughly.
- Add noise and dead pixels in the detector and modify the basic method or the cuts to handle it.
- Apply cuts to multiple layers in path reconstruction part of proton CT.
- Develop other cuts to detect abnormal clusters.

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Appendix A

Fill p.	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20
17	98.140	98.150	98.150	98.190	98.190	98.270	98.290	98.290	98.290	98.330	98.330	98.280	98.300	98.310	98.310	98.310	98.170	98.170	98.170	98.100	98.100	98.100	98.070	98.070	98.060	98.060	98.060	98.020	98.020	98.020	98.000
16	98.160	98.170	98.170	98.210	98.210	98.290	98.310	98.310	98.350	98.390	98.390	98.340	98.360	98.370	98.370	98.370	98.230	98.230	98.230	98.160	98.160	98.160	98.130	98.130	98.120	98.120	98.120	98.080	98.080	97.550	97.530
15	98.160	98.170	98.170	98.210	98.210	98.410	98.430	98.430	98.470	98.510	98.510	98.460	98.480	98.490	98.490	98.490	98.350	98.350	98.350	98.280	98.280	98.280	98.250	98.250	98.240	97.200	97.200	97.160	97.160	96.630	96.610
14	98.160	98.170	98.150	98.190	98.190	98.390	98.410	98.410	98.450	98.490	98.490	98.440	98.460	98.470	98.470	98.470	98.330	98.330	98.330	98.260	98.260	97.200	97.170	97.170	97.160	96.120	96.120	96.080	96.080	95.550	95.530
13	98.190	98.200	98.180	98.220	98.220	98.420	98.440	98.440	98.480	98.520	98.520	98.470	98.490	98.500	98.500	98.500	98.360	97.850	97.850	97.780	97.780	96.720	96.690	96.690	96.680	95.640	95.640	95.600	95.600	95.070	95.050
12	98.180	98.190	98.170	98.210	98.210	98.410	98.430	98.430	98.470	98.510	98.510	98.460	98.480	98.280	98.280	98.280	98.140	97.630	97.630	97.560	97.560	96.500	96.470	96.470	96.460	95.420	95.420	95.380	95.380	94.850	94.830
11	98.180	98.190	98.170	98.210	98.210	98.410	98.430	98.430	98.470	98.430	98.430	98.380	98.400	98.200	98.200	98.200	98.060	97.550	97.550	97.480	97.480	96.420	96.390	96.390	96.380	95.340	95.340	95.300	95.300	94.770	94.750
10	98.180	98.190	98.170	98.210	98.210	98.380	98.400	98.400	98.440	98.400	98.400	98.350	98.370	98.170	98.170	98.170	98.030	97.520	97.520	97.450	97.450	96.390	96.360	96.360	96.350	95.310	95.310	95.270	95.270	87.020	87.000
6	98.180	98.190	98.170	98.210	98.210	98.380	98.400	98.400	98.440	98.400	98.400	98.350	98.370	98.170	98.170	98.170	98.030	97.520	97.520	97.450	97.450	96.390	96.360	82.540	82.530	81.490	81.490	81.450	81.450	73.200	73.180
×	98.180	98.190	98.170	98.210	98.210	98.380	98.400	98.400	98.440	98.400	98.400	98.350	98.370	98.170	98.170	98.170	98.030	88.490	88.490	88.420	88.420	87.360	87.330	73.510	73.500	72.460	72.460	72.420	72.420	64.170	64.150
2	98.180	98.190	98.170	98.210	98.210	98.380	98.400	98.400	98.440	98.400	98.400	94.610	94.630	94.430	94.430	94.430	94.290	84.750	84.750	84.680	84.680	83.620	83.590	69.770	69.760	68.720	68.720	68.680	68.680	60.430	60.410
0	98.170	98.180	98.160	98.200	98.150	97.660	97.680	97.680	97.720	97.680	97.680	93.490	93.510	93.310	93.310	93.310	90.620	81.080	81.080	81.010	81.010	79.950	79.920	66.100	66.090	65.050	65.050	60.850	60.850	52.600	52.580

Table 1: Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 100 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 97.265%. There are 2 combination which results in the same highest score, both with minimum size 13, and fill percentage of 49% and 50%. Each value is an average of 100 simulations.

Fill p.	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	60	20
17	97.293	97.380	97.380	97.480	97.480	97.533	97.547	97.567	97.567	97.633	97.633	97.647	97.647	97.647	97.647	97.647	97.587	97.587	97.587	97.547	97.547	97.547	97.527	97.527	97.533	97.533	97.533	97.487	97.487	97.487	97.500
16	97.307	97.393	97.393	97.493	97.493	97.547	97.560	97.580	97.633	97.700	97.700	97.713	97.713	97.713	97.713	97.713	97.653	97.653	97.653	97.613	97.613	97.613	97.593	97.593	97.600	97.600	97.600	97.553	97.553	96.913	96.927
15	97.307	97.393	97.393	97.493	97.493	97.633	97.647	97.667	97.720	97.787	97.787	97.800	97.800	97.800	97.800	97.800	97.740	97.740	97.740	97.700	97.700	97.700	97.680	97.680	97.687	96.647	96.647	96.600	96.600	95.960	95.973
14	97.307	97.393	97.380	97.480	97.480	97.620	97.633	97.653	97.707	97.773	97.773	97.787	97.787	97.787	97.787	97.787	97.727	97.727	97.727	97.687	97.687	96.740	96.720	96.720	96.727	95.687	95.687	95.640	95.640	95.000	95.013
13	97.320	97.407	97.393	97.493	97.493	97.633	97.647	97.667	97.720	97.787	97.787	97.800	97.800	97.800	97.800	97.800	97.740	97.360	97.360	97.320	97.320	96.373	96.353	96.353	96.360	95.320	95.320	95.273	95.273	94.633	94.647
12	97.313	97.400	97.387	97.487	97.487	97.627	97.640	97.660	97.713	97.780	97.780	97.793	97.793	97.633	97.633	97.633	97.573	97.193	97.193	97.153	97.153	96.207	96.187	96.187	96.193	95.153	95.153	95.107	95.107	94.467	94.480
11	97.313	97.400	97.387	97.487	97.487	97.627	97.640	97.660	97.713	97.707	97.707	97.720	97.720	97.560	97.560	97.560	97.500	97.120	97.120	97.080	97.080	96.133	96.113	96.113	96.120	95.080	95.080	95.033	95.033	94.393	94.407
10	97.313	97.400	97.387	97.487	97.487	97.613	97.627	97.647	97.700	97.693	97.693	97.707	97.707	97.547	97.547	97.547	97.487	97.107	97.107	97.067	97.067	96.120	96.100	96.100	96.107	95.067	95.067	95.020	95.020	86.813	86.827
6	97.313	97.400	97.387	97.487	97.487	97.613	97.627	97.647	97.700	97.693	97.693	97.707	97.707	97.547	97.547	97.547	97.487	97.107	97.107	97.067	97.067	96.120	96.100	82.580	82.587	81.547	81.547	81.500	81.500	73.293	73.307
×	97.327	97.413	97.400	97.500	97.500	97.627	97.640	97.660	97.713	97.707	97.707	97.720	97.720	97.560	97.560	97.560	97.500	88.067	88.067	88.027	88.027	87.080	87.060	73.540	73.547	72.507	72.507	72.460	72.460	64.253	64.267
2	97.327	97.413	97.400	97.500	97.500	97.627	97.640	97.660	97.713	97.707	97.707	94.087	94.087	93.927	93.927	93.927	93.867	84.433	84.433	84.393	84.393	83.447	83.427	69.907	69.913	68.873	68.873	68.827	68.827	60.620	60.633
0	97.320	97.407	97.393	97.493	97.460	96.967	96.980	97.000	97.053	97.047	97.047	92.987	92.987	92.827	92.827	92.827	90.353	80.920	80.920	80.880	80.880	79.933	79.913	66.393	66.400	65.360	65.360	61.160	61.160	52.953	52.967

Table 2: Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 150 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 97.8%. There are 10 combination which results in the same highest score, including fill percentage 55% and minimum size 13. Each value is an average of 100 simulations.

Fill p.	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20
17	96.325	96.440	96.440	96.550	96.580	96.670	96.700	96.725	96.725	96.805	96.805	96.865	96.875	96.935	96.950	96.950	96.925	96.925	96.925	96.900	96.910	96.910	96.895	96.895	96.920	96.920	96.920	96.885	96.885	96.885	96.890
16	96.355	96.470	96.470	96.580	96.610	96.700	96.730	96.755	96.875	96.955	96.955	97.015	97.025	97.085	97.100	97.100	97.075	97.075	97.075	97.050	97.060	97.060	97.045	97.045	97.070	97.070	97.070	97.035	97.035	96.430	96.435
15	96.385	96.500	96.500	96.610	96.640	96.825	96.855	96.880	97.000	97.080	97.080	97.140	97.150	97.210	97.225	97.225	97.200	97.200	97.200	97.175	97.185	97.185	97.170	97.170	97.195	96.185	96.185	96.150	96.150	95.545	95.550
14	96.385	96.500	96.520	96.630	96.660	96.845	96.875	96.900	97.020	97.100	97.100	97.160	97.170	97.230	97.245	97.245	97.220	97.220	97.220	97.195	97.205	96.285	96.270	96.270	96.295	95.285	95.285	95.250	95.250	94.645	94.650
13	96.405	96.520	96.540	96.650	96.680	96.865	96.895	96.920	97.040	97.120	97.120	97.180	97.190	97.250	97.265	97.265	97.240	96.975	96.975	96.950	96.960	96.040	96.025	96.025	96.050	95.040	95.040	95.005	95.005	94.400	94.405
12	96.395	96.510	96.530	96.640	96.670	96.855	96.885	96.910	97.030	97.110	97.110	97.170	97.180	97.110	97.125	97.125	97.100	96.835	96.835	96.810	96.820	95.900	95.885	95.885	95.910	94.900	94.900	94.865	94.865	94.260	94.265
11	96.395	96.510	96.530	96.640	96.670	96.855	96.885	96.910	97.030	97.035	97.035	97.095	97.105	97.035	97.050	97.050	97.025	96.760	96.760	96.735	96.745	95.825	95.810	95.810	95.835	94.825	94.825	94.790	94.790	94.185	94.190
10	96.395	96.510	96.530	96.640	96.670	96.835	96.865	96.890	97.010	97.015	97.015	97.075	97.085	97.015	97.030	97.030	97.005	96.740	96.740	96.715	96.725	95.805	95.790	95.790	95.815	94.805	94.805	94.770	94.770	86.470	86.475
6	96.395	96.510	96.530	96.640	96.670	96.835	96.865	96.890	97.010	97.015	97.015	97.075	97.085	97.015	97.030	97.030	97.005	96.740	96.740	96.715	96.725	95.805	95.790	82.445	82.470	81.460	81.460	81.425	81.425	73.125	73.130
×	96.400	96.515	96.535	96.645	96.675	96.840	96.870	96.895	97.015	97.020	97.020	97.080	97.090	97.020	97.035	97.035	97.010	87.580	87.580	87.555	87.565	86.645	86.630	73.285	73.310	72.300	72.300	72.265	72.265	63.965	63.970
2	96.400	96.515	96.535	96.645	96.675	96.840	96.870	96.895	97.015	97.020	97.020	93.540	93.550	93.480	93.495	93.495	93.470	84.040	84.040	84.015	84.025	83.105	83.090	69.745	69.770	68.760	68.760	68.725	68.725	60.425	60.430
0	96.390	96.505	96.525	96.635	96.635	96.225	96.255	96.280	96.400	96.405	96.405	92.470	92.480	92.410	92.425	92.425	90.085	80.655	80.655	80.630	80.640	79.720	79.705	66.360	66.385	65.375	65.375	61.400	61.400	53.100	53.105

Table 3: Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 200 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 97.265%. There are 2 combination which results in the same highest score, including fill percentage 55% and minimum size 13. Each value is an average of 100 simulations.

Fill p.	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20
17	95.620	95.776	95.776	95.920	95.952	96.080	96.104	96.152	96.152	96.232	96.232	96.296	96.336	96.444	96.460	96.460	96.444	96.444	96.444	96.440	96.456	96.456	96.460	96.460	96.480	96.480	96.480	96.452	96.452	96.452	96.472
16	95.660	95.816	95.816	95.960	95.992	96.120	96.144	96.192	96.360	96.440	96.440	96.504	96.544	96.652	96.668	96.668	96.652	96.652	96.652	96.648	96.664	96.664	96.668	96.668	96.688	96.688	96.688	96.660	96.660	96.144	96.164
15	95.684	95.840	95.840	95.984	96.016	96.276	96.300	96.348	96.516	96.596	96.596	96.660	96.700	96.808	96.824	96.824	96.808	96.808	96.808	96.804	96.820	96.820	96.824	96.824	96.844	95.900	95.900	95.872	95.872	95.356	95.376
14	95.684	95.840	95.864	96.008	96.040	96.300	96.324	96.372	96.540	96.620	96.620	96.684	96.724	96.832	96.848	96.848	96.832	96.832	96.832	96.828	96.844	95.976	95.980	95.980	96.000	95.056	95.056	95.028	95.028	94.512	94.532
13	95.732	95.888	95.912	96.056	96.088	96.348	96.372	96.420	96.588	96.668	96.668	96.732	96.772	96.880	96.896	96.896	96.880	96.632	96.632	96.628	96.644	95.776	95.780	95.780	95.800	94.856	94.856	94.828	94.828	94.312	94.332
12	95.724	95.880	95.904	96.048	96.080	96.340	96.364	96.412	96.580	96.660	96.660	96.724	96.764	96.744	96.760	96.760	96.744	96.496	96.496	96.492	96.508	95.640	95.644	95.644	95.664	94.720	94.720	94.692	94.692	94.176	94.196
11	95.724	95.880	95.904	96.048	96.080	96.340	96.364	96.412	96.580	96.576	96.576	96.640	96.680	96.660	96.676	96.676	96.660	96.412	96.412	96.408	96.424	95.556	95.560	95.560	95.580	94.636	94.636	94.608	94.608	94.092	94.112
10	95.724	95.880	95.904	96.048	96.080	96.332	96.356	96.404	96.572	96.568	96.568	96.632	96.672	96.652	96.668	96.668	96.652	96.404	96.404	96.400	96.416	95.548	95.552	95.552	95.572	94.628	94.628	94.600	94.600	86.496	86.516
6	95.724	95.880	95.904	96.048	96.080	96.332	96.356	96.404	96.572	96.568	96.568	96.632	96.672	96.652	96.668	96.668	96.652	96.404	96.404	96.400	96.416	95.548	95.552	82.340	82.360	81.416	81.416	81.388	81.388	73.284	73.304
×	95.728	95.884	95.908	96.052	96.084	96.336	96.360	96.408	96.576	96.572	96.572	96.636	96.676	96.656	96.672	96.672	96.656	87.292	87.292	87.288	87.304	86.436	86.440	73.228	73.248	72.304	72.304	72.276	72.276	64.172	64.192
2	95.728	95.884	95.908	96.052	96.084	96.336	96.360	96.408	96.576	96.572	96.572	93.096	93.136	93.116	93.132	93.132	93.116	83.752	83.752	83.748	83.764	82.896	82.900	69.688	69.708	68.764	68.764	68.736	68.736	60.632	60.652
0	95.716	95.872	95.896	96.040	96.040	95.720	95.744	95.792	95.960	95.956	95.956	92.012	92.052	92.032	92.048	92.048	89.724	80.360	80.360	80.356	80.372	79.504	79.508	66.296	66.316	65.372	65.372	61.360	61.360	53.256	53.276

Table 4: Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 250 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 96.896%. There are 2 combination which results in the same highest score, including fill percentage 55% and minimum size 13. Each value is an average of 100 simulations.

Fill p.	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20
17	94.647	94.850	94.850	95.043	95.090	95.250	95.270	95.327	95.327	95.420	95.420	95.590	95.623	95.763	95.787	95.787	95.827	95.827	95.840	95.853	95.867	95.867	95.873	95.873	95.913	95.913	95.913	95.900	95.900	95.900	95.917
16	94.707	94.910	94.910	95.103	95.150	95.310	95.330	95.387	95.610	95.703	95.703	95.873	95.907	96.047	96.070	96.070	96.110	96.110	96.123	96.137	96.150	96.150	96.157	96.157	96.197	96.197	96.197	96.183	96.183	95.680	95.697
15	94.733	94.937	94.937	95.130	95.177	95.530	95.550	95.607	95.830	95.923	95.923	96.093	96.127	96.267	96.290	96.290	96.330	96.330	96.343	96.357	96.370	96.370	96.377	96.377	96.417	95.563	95.563	95.550	95.550	95.047	95.063
14	94.747	94.950	95.010	95.203	95.250	95.603	95.623	95.680	95.903	95.997	95.997	96.167	96.200	96.340	96.363	96.363	96.403	96.403	96.417	96.430	96.443	95.617	95.623	95.623	95.663	94.810	94.810	94.797	94.797	94.293	94.310
13	94.800	95.003	95.063	95.257	95.303	95.657	95.677	95.733	95.957	96.050	96.050	96.220	96.253	96.393	96.417	96.417	96.457	96.250	96.263	96.277	96.290	95.463	95.470	95.470	95.510	94.657	94.657	94.643	94.643	94.140	94.157
12	94.790	94.993	95.053	95.247	95.293	95.647	95.667	95.723	95.947	96.040	96.040	96.210	96.243	96.267	96.290	96.290	96.330	96.123	96.137	96.150	96.163	95.337	95.343	95.343	95.383	94.530	94.530	94.517	94.517	94.013	94.030
11	94.790	94.993	95.053	95.247	95.293	95.647	95.667	95.723	95.947	95.953	95.953	96.123	96.157	96.180	96.203	96.203	96.243	96.037	96.050	96.063	96.077	95.250	95.257	95.257	95.297	94.443	94.443	94.430	94.430	93.927	93.943
10	94.790	94.993	95.053	95.247	95.293	95.647	95.667	95.723	95.947	95.953	95.953	96.123	96.157	96.180	96.203	96.203	96.243	96.037	96.050	96.063	96.077	95.250	95.257	95.257	95.297	94.443	94.443	94.430	94.430	86.487	86.503
6	94.790	94.993	95.053	95.247	95.293	95.647	95.667	95.723	95.947	95.953	95.953	96.123	96.157	96.180	96.203	96.203	96.243	96.037	96.050	96.063	96.077	95.250	95.257	82.243	82.283	81.430	81.430	81.417	81.417	73.473	73.490
×	94.800	95.003	95.063	95.257	95.303	95.657	95.677	95.733	95.957	95.963	95.963	96.133	96.167	96.190	96.213	96.213	96.253	86.960	86.973	86.987	87.000	86.173	86.180	73.167	73.207	72.353	72.353	72.340	72.340	64.397	64.413
2	94.800	95.003	95.063	95.257	95.303	95.657	95.677	95.733	95.957	95.963	95.963	92.587	92.620	92.643	92.667	92.667	92.707	83.413	83.427	83.440	83.453	82.627	82.633	69.620	69.660	68.807	68.807	68.793	68.793	60.850	60.867
0	94.787	94.990	95.050	95.243	95.260	95.033	95.053	95.110	95.333	95.340	95.340	91.510	91.543	91.567	91.590	91.590	89.380	80.087	80.100	80.113	80.127	79.300	79.307	66.293	66.333	65.480	65.480	61.613	61.613	53.670	53.687

Table 5: Results from combining different variants of minimum sizes and fill percentage square approach. The simulation uses 300 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 96.457%. The best combination was fill percentage 56% and minimum size 13. Each value is an average of 100 simulations.

Appendix B

Fill p.	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
17	97.980	97.980	98.000	98.100	98.080	98.100	98.110	98.110	98.120	98.140	98.180	98.230	98.180	98.200	98.200	98.180	98.140	98.150	97.930	97.900	97.920	97.880	97.680	97.680	97.740	97.730
16	97.980	97.980	98.050	98.150	98.130	98.150	98.160	98.160	98.170	98.190	98.230	98.280	98.230	98.250	98.100	98.080	98.030	98.040	97.820	97.790	97.810	97.770	97.570	97.570	97.630	97.620
15	97.980	97.980	98.050	98.150	98.130	98.150	98.160	98.160	98.170	98.190	98.190	98.240	98.280	98.300	98.150	98.130	98.080	98.090	97.870	97.840	97.860	97.820	97.620	97.620	97.680	97.670
14	97.980	97.980	98.050	98.150	98.130	98.150	98.150	98.150	98.140	98.160	98.160	98.210	98.250	98.270	98.120	98.100	98.050	98.060	97.840	97.810	97.830	96.740	96.540	96.540	96.600	96.590
13	97.980	97.980	98.050	98.150	98.130	98.150	98.150	98.150	98.140	98.160	98.160	98.210	98.250	98.270	98.120	98.100	97.650	97.660	97.440	97.410	97.430	96.340	96.140	96.170	96.230	96.220
12	97.980	97.980	98.050	98.150	98.130	98.150	98.150	98.150	98.140	98.160	98.160	97.990	98.030	98.050	97.900	97.880	97.430	97.440	97.210	97.180	97.200	96.110	95.910	95.940	96.000	95.990
11	98.000	98.000	98.070	98.170	98.150	98.170	98.090	98.090	98.080	98.100	98.100	97.930	97.970	97.990	97.840	97.820	97.370	97.380	97.150	97.120	97.140	86.750	86.550	86.580	86.640	86.630
10	98.000	98.020	98.090	98.190	98.170	98.190	98.110	98.110	98.100	98.120	98.120	97.950	97.990	98.010	92.940	92.920	92.470	92.480	92.250	92.170	92.190	81.800	81.600	81.630	81.690	81.680
6	98.000	98.020	98.090	98.190	98.170	98.190	98.110	98.110	96.850	96.870	96.870	96.700	96.740	96.760	91.690	91.670	91.220	91.230	91.000	90.920	90.940	80.550	80.350	80.380	80.440	80.430
×	98.000	98.020	98.000	98.100	98.080	98.100	98.020	98.020	96.760	96.780	96.780	96.610	96.650	96.670	91.600	91.580	91.130	91.140	90.910	90.830	90.850	71.520	71.320	71.350	71.410	71.400
7	98.000	98.020	98.000	98.100	98.080	98.100	98.020	98.020	96.760	96.780	96.780	96.610	92.910	92.930	87.860	87.840	87.390	87.400	87.170	87.090	87.110	67.780	67.580	67.610	67.670	67.660
0	98.000	97.440	97.420	97.520	97.500	97.520	97.440	97.440	96.180	96.200	96.200	96.030	90.660	90.680	85.610	85.590	85.140	85.150	84.920	84.840	84.860	64.660	64.460	57.120	57.180	57.170

Table 6: Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 100 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 98.300%. The best score is a combination of fill percentage 68% and minimum size 15. Each value is an average of 100 simulations.

Fill p.	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20	71	72	73	74	75	76	27	78	62	80
17	97.133	97.160	97.173	97.293	97.273	97.273	97.353	97.360	97.367	97.400	97.440	97.473	97.460	97.487	97.540	97.553	97.527	97.580	97.360	97.320	97.333	97.360	97.160	97.160	97.200	97.180
16	97.133	97.160	97.200	97.320	97.300	97.300	97.380	97.387	97.393	97.427	97.467	97.500	97.487	97.513	97.373	97.387	97.387	97.440	97.220	97.180	97.193	97.220	97.020	97.020	97.060	97.040
15	97.133	97.160	97.200	97.320	97.300	97.300	97.380	97.387	97.393	97.427	97.453	97.487	97.547	97.573	97.433	97.447	97.447	97.500	97.280	97.240	97.253	97.280	97.080	97.080	97.120	97.100
14	97.133	97.160	97.200	97.320	97.300	97.300	97.373	97.380	97.360	97.393	97.420	97.453	97.513	97.540	97.400	97.413	97.413	97.467	97.247	97.207	97.220	96.287	96.087	96.087	96.127	96.107
13	97.133	97.160	97.213	97.333	97.313	97.313	97.387	97.393	97.373	97.407	97.433	97.467	97.527	97.553	97.413	97.427	97.113	97.167	96.947	96.907	96.920	95.987	95.787	95.800	95.840	95.820
12	97.147	97.173	97.227	97.347	97.327	97.327	97.400	97.407	97.387	97.420	97.447	97.313	97.373	97.400	97.260	97.273	96.960	97.013	96.787	96.747	96.760	95.827	95.627	95.640	95.680	95.660
11	97.160	97.187	97.240	97.360	97.340	97.340	97.353	97.360	97.340	97.373	97.400	97.267	97.327	97.353	97.213	97.227	96.913	96.967	96.740	96.700	96.713	86.493	86.293	86.307	86.347	86.327
10	97.160	97.200	97.253	97.373	97.353	97.353	97.367	97.373	97.353	97.387	97.413	97.280	97.340	97.367	92.347	92.360	92.047	92.100	91.873	91.807	91.820	81.600	81.400	81.413	81.453	81.433
6	97.160	97.200	97.253	97.373	97.353	97.353	97.367	97.373	96.147	96.180	96.207	96.073	96.133	96.160	91.140	91.153	90.840	90.893	90.667	90.600	90.613	80.393	80.193	80.207	80.247	80.227
×	97.160	97.200	97.167	97.287	97.267	97.267	97.293	97.300	96.073	96.107	96.133	96.000	96.060	96.087	91.067	91.080	90.767	90.820	90.593	90.527	90.540	71.353	71.153	71.167	71.207	71.187
7	97.160	97.200	97.167	97.287	97.267	97.267	97.293	97.300	96.073	96.107	96.133	96.000	92.427	92.453	87.433	87.447	87.133	87.187	86.960	86.893	86.907	67.720	67.520	67.533	67.573	67.553
0	97.160	96.680	96.647	96.767	96.747	96.747	96.773	96.780	95.553	95.587	95.613	95.480	90.207	90.233	85.213	85.227	84.913	84.967	84.740	84.673	84.687	64.633	64.433	57.107	57.147	57.127

Table 7: Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 150 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 97.580%. The best score is a combination of fill percentage 72% and minimum size 17. Each value is an average of 100 simulations.

						<u> </u>	1	1	1	1	1	1	T	T	1						1		<u> </u>	I	1	
Fill p.	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20	71	72	73	74	75	76	27	78	62	80
17	96.190	96.205	96.215	96.335	96.330	96.340	96.455	96.465	96.510	96.585	96.625	96.690	96.695	96.710	96.790	96.805	96.805	96.835	96.605	96.570	96.580	96.650	96.505	96.505	96.565	96.570
16	96.190	96.205	96.250	96.370	96.365	96.375	96.490	96.500	96.545	96.620	96.660	96.725	96.730	96.745	96.650	96.665	96.745	96.775	96.545	96.510	96.520	96.590	96.445	96.445	96.505	96.510
15	96.200	96.215	96.260	96.400	96.395	96.405	96.520	96.530	96.575	96.650	96.720	96.785	96.865	96.880	96.785	96.800	96.880	96.910	96.680	96.645	96.655	96.725	96.590	96.590	96.650	96.655
14	96.200	96.215	96.260	96.400	96.395	96.405	96.540	96.550	96.595	96.670	96.740	96.805	96.885	96.900	96.805	96.820	96.900	96.930	96.700	96.665	96.675	95.795	95.660	95.660	95.720	95.725
13	96.200	96.215	96.280	96.420	96.425	96.435	96.570	96.580	96.625	96.700	96.770	96.835	96.915	96.930	96.835	96.850	96.695	96.725	96.495	96.460	96.470	95.590	95.455	95.465	95.525	95.530
12	96.220	96.235	96.300	96.440	96.445	96.455	96.590	96.600	96.645	96.720	96.790	96.705	96.785	96.800	96.705	96.720	96.565	96.595	96.345	96.310	96.320	95.440	95.305	95.315	95.375	95.380
11	96.230	96.245	96.310	96.450	96.455	96.465	96.540	96.550	96.595	96.670	96.740	96.655	96.735	96.750	96.655	96.670	96.515	96.545	96.295	96.260	96.270	86.330	86.195	86.205	86.265	86.270
10	96.230	96.255	96.320	96.460	96.465	96.475	96.550	96.560	96.605	96.680	96.750	96.665	96.745	96.760	91.655	91.670	91.515	91.545	91.295	91.230	91.240	81.300	81.165	81.175	81.235	81.240
6	96.230	96.255	96.320	96.460	96.465	96.475	96.550	96.560	95.400	95.475	95.545	95.460	95.540	95.555	90.450	90.465	90.310	90.340	90.090	90.025	90.035	80.095	79.960	79.970	80.030	80.035
×	96.230	96.255	96.230	96.370	96.375	96.385	96.470	96.480	95.320	95.395	95.465	95.380	95.460	95.475	90.370	90.385	90.230	90.260	90.010	89.945	89.955	70.940	70.805	70.815	70.875	70.880
2	96.230	96.255	96.230	96.370	96.375	96.385	96.470	96.480	95.320	95.395	95.465	95.380	91.915	91.930	86.825	86.840	86.685	86.715	86.465	86.400	86.410	67.395	67.260	67.270	67.330	67.335
0	96.230	95.720	95.695	95.835	95.835	95.845	95.930	95.940	94.780	94.855	94.925	94.840	89.765	89.780	84.675	84.690	84.535	84.565	84.315	84.250	84.260	64.435	64.300	57.260	57.320	57.325

Table 8: Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 200 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 96.930%. There are 2 combination which results in the highest score, including fill percentage 72% and minimum size 14. Each value is an average of 100 simulations.

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Fill p.	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	20	71	72	73	74	75	76	27	78	62	80
17	95.356	95.368	95.392	95.544	95.552	95.568	95.676	95.704	95.796	95.900	95.980	96.076	96.092	96.128	96.208	96.236	96.252	96.312	96.112	96.088	96.096	96.196	96.068	96.068	96.140	96.160
16	95.356	95.368	95.468	95.620	95.628	95.644	95.760	95.788	95.880	95.984	96.064	96.160	96.176	96.212	96.192	96.220	96.312	96.372	96.172	96.148	96.156	96.256	96.128	96.128	96.200	96.220
15	95.372	95.384	95.484	95.652	95.660	95.676	95.792	95.820	95.912	96.016	96.136	96.232	96.352	96.388	96.368	96.396	96.488	96.548	96.348	96.324	96.332	96.432	96.312	96.312	96.384	96.404
14	95.372	95.384	95.484	95.652	95.660	95.676	95.816	95.844	95.936	96.040	96.160	96.256	96.376	96.412	96.392	96.420	96.512	96.572	96.372	96.348	96.356	95.556	95.436	95.436	95.508	95.528
13	95.372	95.384	95.496	95.664	95.696	95.712	95.852	95.880	95.972	96.076	96.196	96.292	96.412	96.448	96.428	96.456	96.328	96.388	96.188	96.164	96.172	95.372	95.252	95.276	95.348	95.368
12	95.380	95.392	95.504	95.672	95.704	95.720	95.860	95.888	95.980	96.084	96.204	96.156	96.276	96.312	96.292	96.320	96.192	96.252	96.036	96.012	96.020	95.220	95.100	95.124	95.196	95.216
11	95.388	95.400	95.512	95.680	95.712	95.728	95.800	95.828	95.920	96.024	96.144	96.096	96.216	96.252	96.232	96.260	96.132	96.192	95.976	95.952	95.960	86.180	86.060	86.084	86.156	86.176
10	95.388	95.420	95.532	95.700	95.732	95.748	95.820	95.848	95.940	96.044	96.164	96.116	96.236	96.272	91.356	91.384	91.256	91.316	91.100	91.048	91.056	81.276	81.156	81.180	81.252	81.272
6	95.388	95.420	95.532	95.700	95.732	95.748	95.820	95.848	94.744	94.848	94.968	94.920	95.040	95.076	90.160	90.188	90.060	90.120	89.904	89.852	89.860	80.080	79.960	79.984	80.056	80.076
×	95.388	95.420	95.456	95.624	95.656	95.672	95.752	95.780	94.676	94.780	94.900	94.852	94.972	95.008	90.092	90.120	89.992	90.052	89.836	89.784	89.792	70.972	70.852	70.876	70.948	70.968
7	95.388	95.420	95.456	95.624	95.656	95.672	95.752	95.780	94.676	94.780	94.900	94.852	91.428	91.464	86.548	86.576	86.448	86.508	86.292	86.240	86.248	67.428	67.308	67.332	67.404	67.424
0	95.388	94.900	94.936	95.104	95.128	95.144	95.224	95.252	94.148	94.252	94.372	94.324	89.300	89.336	84.420	84.448	84.320	84.380	84.164	84.112	84.120	64.504	64.384	57.472	57.544	57.564

Table 9: Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 250 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 96.572%. The best combination was fill percentage 72% and minimum size 14. Each value is an average of 100 simulations.

Fill p.	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	27	78	79	80
17	94.393	94.417	94.437	94.570	94.567	94.580	94.753	94.783	94.893	95.007	95.113	95.220	95.273	95.317	95.403	95.427	95.467	95.557	95.390	95.373	95.393	95.567	95.453	95.453	95.540	95.573
16	94.393	94.417	94.503	94.637	94.633	94.647	94.840	94.870	94.980	95.093	95.200	95.307	95.360	95.403	95.393	95.417	95.583	95.673	95.507	95.490	95.510	95.683	95.570	95.570	95.657	95.690
15	94.413	94.437	94.523	94.677	94.673	94.687	94.880	94.910	95.020	95.133	95.283	95.390	95.593	95.637	95.627	95.650	95.817	95.907	95.740	95.723	95.743	95.917	95.810	95.810	95.897	95.930
14	94.413	94.437	94.523	94.677	94.673	94.687	94.913	94.943	95.067	95.180	95.330	95.437	95.640	95.683	95.673	95.697	95.863	95.967	95.800	95.783	95.803	95.097	94.990	94.990	95.077	95.110
13	94.413	94.437	94.533	94.687	94.717	94.730	94.957	94.987	95.110	95.223	95.373	95.480	95.683	95.727	95.717	95.740	95.733	95.837	95.670	95.653	95.673	94.967	94.860	94.880	94.967	95.000
12	94.413	94.437	94.533	94.687	94.717	94.730	94.957	94.987	95.110	95.223	95.373	95.360	95.563	95.607	95.597	95.620	95.613	95.717	95.533	95.517	95.537	94.830	94.723	94.743	94.830	94.863
11	94.420	94.443	94.540	94.693	94.723	94.737	94.880	94.910	95.033	95.147	95.297	95.283	95.487	95.530	95.520	95.543	95.537	95.640	95.457	95.440	95.460	85.993	85.887	85.907	85.993	86.027
10	94.420	94.460	94.557	94.710	94.740	94.753	94.897	94.927	95.050	95.163	95.313	95.300	95.503	95.547	90.750	90.773	90.767	90.870	90.687	90.653	90.673	81.207	81.100	81.120	81.207	81.240
6	94.420	94.460	94.557	94.710	94.740	94.753	94.897	94.927	93.863	93.977	94.127	94.113	94.317	94.360	89.563	89.587	89.580	89.683	89.500	89.467	89.487	80.020	79.913	79.933	80.020	80.053
×	94.420	94.460	94.460	94.613	94.643	94.657	94.813	94.843	93.780	93.893	94.043	94.030	94.233	94.277	89.480	89.503	89.497	89.600	89.417	89.383	89.403	70.947	70.840	70.860	70.947	70.980
7	94.420	94.460	94.460	94.613	94.643	94.657	94.813	94.843	93.780	93.893	94.043	94.030	90.690	90.733	85.937	85.960	85.953	86.057	85.873	85.840	85.860	67.403	67.297	67.317	67.403	67.437
0	94.420	93.983	93.983	94.137	94.157	94.170	94.327	94.357	93.293	93.407	93.557	93.543	88.597	88.640	83.843	83.867	83.860	83.963	83.780	83.747	83.767	64.510	64.403	57.557	57.643	57.677

Table 10: Results from combining different variants of minimum sizes and fill percentage rectangle approach. The simulation uses 300 cluster in the detector and beam size 4mm, which results in the highest perfectly reconstructed cluster to be 95.967%. The best combination was fill percentage 72% and minimum size 14. Each value is an average of 100 simulations.

Appendix C

Clusters	0	25	50	75	100	125	150	175	200	225	250	275	300	325	350	375	400	425	450	475	500
17	100.00	99.560	98.880	98.733	98.280	97.872	97.587	97.086	96.730	96.493	96.188	95.851	95.437	95.108	94.717	94.336	93.978	93.581	93.273	92.811	92.564
16	100.00	99.520	98.900	98.747	98.320	97.912	97.620	97.149	96.820	96.582	96.324	96.007	95.597	95.271	94.894	94.544	94.207	93.826	93.536	93.091	92.854
15	100.00	99.680	99.000	98.867	98.410	98.016	97.720	97.246	96.935	96.720	96.464	96.164	95.783	95.480	95.106	94.797	94.465	94.115	93.818	93.396	93.172
14	100.00	99.560	98.980	98.800	98.360	97.992	97.680	97.217	96.920	96.702	96.456	96.178	95.840	95.566	95.197	94.920	94.603	94.249	93.960	93.564	93.348
13	100.00	99.480	98.900	98.760	98.340	98.000	97.673	97.206	96.925	96.711	96.476	96.189	95.880	95.622	95.271	94.995	94.668	94.325	94.027	93.646	93.422
12	100.00	99.320	98.780	98.680	98.270	97.928	97.627	97.166	96.875	96.653	96.416	96.127	95.823	95.569	95.223	94.955	94.645	94.304	94.027	93.655	93.434
11	100.00	99.280	98.740	98.667	98.210	97.880	97.580	97.097	96.815	96.596	96.356	96.051	95.747	95.498	95.154	94.891	94.590	94.256	93.991	93.625	93.398
10	100.00	99.080	98.560	98.520	98.050	97.760	97.453	96.977	96.695	96.480	96.248	95.953	95.660	95.431	95.089	94.821	94.522	94.191	93.922	93.568	93.348
6	100.00	98.920	98.260	98.213	97.720	97.440	97.160	96.674	96.415	96.209	95.996	95.705	95.423	95.203	94.854	94.595	94.305	93.969	93.691	93.352	93.132
×	100.00	98.840	98.200	98.160	97.630	97.344	97.073	96.600	96.325	96.124	95.912	95.615	95.327	95.102	94.751	94.488	94.190	93.852	93.576	93.242	93.018
2	100.00	94.800	94.380	94.427	93.890	93.720	93.453	92.989	92.800	92.627	92.392	92.102	91.807	91.588	91.231	90.987	90.688	90.369	90.102	89.813	89.652
0	100.00	94.360	93.820	93.880	93.310	93.200	92.933	92.469	92.265	92.098	91.868	91.596	91.327	91.089	90.746	90.488	90.185	89.878	89.613	89.320	89.146

Table 11: Results from simulation of the asymmetric cut using differentminimum sizes. Each value is an average of 100 simulations.

Appendix D

Clusters	0	25	50	75	100	125	150	175	200	225	250	275	300	325	350	375	400	425	450	475	500
17	100.000	99.680	98.840	98.800	98.330	97.808	97.540	97.051	96.695	96.431	96.096	95.687	95.267	94.889	94.420	93.971	93.582	93.195	92.891	92.415	92.078
16	100.00	99.680	98.880	98.827	98.370	97.856	97.580	97.131	96.795	96.529	96.216	95.847	95.427	95.068	94.614	94.168	93.793	93.393	93.104	92.642	92.298
15	100.00	99.760	98.940	98.867	98.410	97.904	97.620	97.166	96.855	96.582	96.272	95.920	95.503	95.151	94.709	94.267	93.910	93.518	93.222	92.766	92.432
14	100.00	99.720	98.920	98.853	98.410	97.904	97.607	97.177	96.865	96.591	96.296	95.956	95.550	95.212	94.783	94.352	94.000	93.607	93.311	92.867	92.528
13	100.00	99.720	98.960	98.880	98.450	97.936	97.647	97.234	96.935	96.662	96.376	96.029	95.617	95.268	94.840	94.405	94.050	93.664	93.364	92.918	92.584
12	100.00	99.680	98.920	98.853	98.420	97.912	97.627	97.217	96.910	96.649	96.364	96.015	95.610	95.268	94.834	94.405	94.055	93.668	93.369	92.922	92.588
11	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.644	96.360	96.011	95.607	95.265	94.831	94.403	94.062	93.680	93.389	92.941	92.606
10	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.653	96.368	96.018	95.620	95.277	94.843	94.419	94.078	93.694	93.402	92.958	92.622
6	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.653	96.368	96.018	95.620	95.283	94.849	94.429	94.088	93.704	93.411	92.971	92.634
×	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.653	96.368	96.018	95.620	95.283	94.849	94.429	94.088	93.704	93.411	92.971	92.634
7	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.653	96.368	96.018	95.620	95.283	94.849	94.429	94.088	93.704	93.411	92.971	92.634
0	100.00	99.680	98.920	98.853	98.420	97.912	97.620	97.211	96.905	96.649	96.364	96.015	95.617	95.277	94.843	94.424	94.080	93.696	93.404	92.958	92.622

Table 12: Results from simulation of the inactive pixels cut using differentminimum sizes. Each value is an average of 100 simulations.

Appendix E

Clusters	0	25	50	75	100	125	150	175	200	225	250	275	300	325	350	375	400	425	450	475	500
В	100.000	99.520	98.740	98.387	98.000	97.512	97.090	96.603	96.055	95.647	95.088	94.605	94.092	93.615	93.163	92.672	92.188	91.632	91.211	90.689	90.272
AIF	100.000	99.020	98.610	98.547	98.335	98.032	97.773	97.551	97.332	97.149	96.950	96.758	96.522	96.298	96.096	95.853	95.564	95.296	95.022	94.753	94.548
AI	100.000	99.400	98.840	98.573	98.345	960.76	97.647	97.323	97.010	96.764	96.444	96.147	95.818	95.529	95.263	94.976	94.619	94.247	93.931	93.582	93.331
IF	100.000	99.260	98.810	98.733	98.505	98.156	97.907	97.737	97.465	97.242	97.036	96.807	96.528	96.268	96.043	95.787	95.490	95.188	94.907	94.619	94.376
AF	100.000	99.020	98.610	98.547	98.335	98.032	97.773	97.551	97.332	97.149	96.950	96.758	96.522	96.298	96.096	95.853	95.564	95.296	95.022	94.753	94.548
۲ų	100.000	99.180	98.750	98.680	98.475	98.128	97.873	97.657	97.380	97.167	96.932	96.698	96.398	96.132	95.900	95.645	95.338	95.021	94.736	94.434	94.190
I	100.000	99.620	99.000	98.760	98.485	98.008	97.680	97.320	96.938	96.651	96.274	95.925	95.538	95.194	94.854	94.468	94.093	93.673	93.323	92.933	92.576
Α	100.000	99.400	98.840	98.573	98.345	97.996	97.647	97.323	97.010	96.764	96.444	96.147	95.818	95.529	95.263	94.976	94.619	94.247	93.931	93.582	93.331

Table 13: Results from simulation with mixtures of all cuts. Each value is an average of 200 simulations. The values have the following abbreviation: A=Asymmetric, I=Inactive pixels, F=fill percentage square approach, and B=basic method.