Hyperspectral seed detection with supervised learning classification system

Seed planting control

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Project owner:
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Course:
Thesis for the degree M.Sc.E in robotic systems, 40 ECTS points

Project period:
September 1st 2014 - June 1st 2015

Todo list

Abstract

English

Nothing yet

Danish

Nothing yet

Contents

1 Preface

Nothing yet

2 Reading manual

Nothing yet

Indsæt evt et billede af et seed, billede af frø og billede af samlet.

Perhaps some explanation about what is a seed, what is a sprout and what is the whole called when seed and sprout is combined.

3 Introduction

In collaboration between the company ImproSeed ApS and the University of Southern Denmark, ideas for a master thesis project has been developed. The company ImproSeed ApS is working with the forestry planting process to improve the efficiency of fully growing threes. At the moment an efficiency of the planting success lies between 60-75%, i.e. minimum 25% lost in profit. Therefore ImproSeed ApS is interested to maximize the efficiency of the seeds sprouting process, the germination. The idea was to use a vision based solution, where the system is able to differentiate the seeds into three categories as followed:

- *Green*. Seeds are ready for planting. Send to to planting process.
- *Yellow*. Seeds are not ready for planting. Keep them in current process.
- *Red*. Seeds are not valid for planting. Discard the seeds from current process.

Additionally a learning component should be in place for letting the vision system learn how a specific type of seed looks in the different categories.
In this case, it would ideally means that no seeds would be planted in the ground if they where not in a *good* condition. That would contributed to a higher efficiency. Due to uncontrolled environment, like bad soil, wildlife and weather conditions etc. an efficiency of 100% would never be realistic.

3.1 Project description

The setup of the system contains a conveyor belt that runs with a continuous velocity, where a mounted camera from above is sensing the incoming seeds. The image processing system needs to classify the seeds due to the features. One feature would be to look if the seeds is starting sprouting and in this case, how much has the germination reached. An other feature is, if the seed has sprouted, what is the condition of the sprouts. If a sprout is bended or even cracked then this seed should perhaps be sorted out.
A block diagram shown in figure 3.1, is where the different components in the system is indicated.

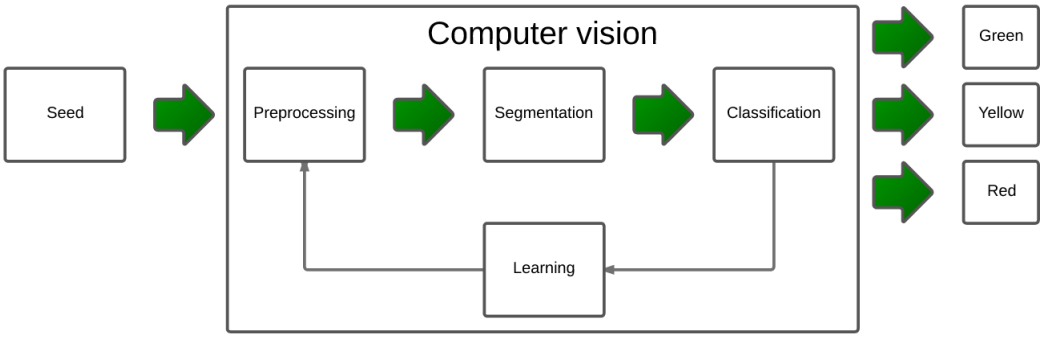


Figure 3.1: Blockdiagram of the computer vision system

- *Seed*. Incoming seeds of a specific type on a conveyor belt is random distributed among the categories. These are monitored by a line spectrometer, that is creating a hyperspectral cube
- *Preprocessing*. Each image from the hyperspectral cube contains important information about the seed

- *Segmentation.* Sorting images and after finding contours, finding central coordinates of each seed.
- *Classification.* Categorize each seed into three buckets due to how their quality and how far their germination is.
- *Learning.* Doing classification, information can be memorized on how a specific seed type looks. This will be used to have a more universal system, which can handle different type of seeds.

3.1.1 Sensor for vision system

By using a normal digital cameras, the option of extracting information outside the spectrum of visible light seems limiting. However from literature search, it is possible to extract information of materials in their near-infrared spectrum (NIF) by using hyperspectral imaging. This techniques has been used in many different application, like detecting the quality of wine-grapes [14], rice cultivar identification [9] and many others like mineral exploration, agriculture, and forest production. [16]. Therefore to classify the seeds into the three categories a line spectrometer will be used. The hypothesis is that there is a significant difference in the reflected wavelength for each pixel, when the objects is seed or a sprout. However if the seeds or sprouts are covered with resin, experiments in how this would change the electromagnetic spectral signature needs to be investigated. Thinking about the water contain can perhaps lead to a feature extraction.

3.1.2 Learn how other type of seeds looks in different categories

The system needs to detect the difference of the seeds, which is related to how far in the sprouting process each has reached. Having a system, that can handle only one kind of seed type is not enough. Therefore the system should be able to learn how different seeds looks like by supervised learning and thereby not only be limited to one kind of seed. The idea is that the user can take a portion of manually sorted seeds in a given condition and use that for training data. The result would be a more universal system, which can classify different types of seeds into the three introduced categories, *Green*, *Yellow*, *Red*.
An example will explain the flow:

- Example 1
  - Manually sorted seeds of type A, category *Green* is placed on a running conveyor belt
  - Each seed is segmented and classified as type A, category *Green*
  - Repeat training with type A, category *Yellow* and *Red*
  - After training procedure, a handful of mixed categories type A seeds is placed on the running conveyor belt. The system should be able to recognize the category for each seeds and thereby sorting the seeds correctly.

3.2 Deliverables

At the end of this Master Thesis project, A MSc. report documenting the following will be delivered:

- A seed detecting method based on computer vision, where the main methods is compared together alternative methods
- A learning method based on AI, where the main methods is compared together with alternative methods

- A description of the project management, i.e. timetable and logbook

3.3 Learning goals

The learnings goals for this Master Thesis project is defined [3]. The learning outcome is:

3.3.1 Knowledge

The student

- is able to account for relevant engineering skills based on the highest level of international research within the subject area of the programme
- has a good understanding of - and be able to reflect on - relevant knowledge within the subject area of the programme
- is able to identify relevant scientific problems within the subject area of the programme

3.3.2 Skills

The student

- is able to assess, select and apply scientific methods, tools and competencies within the subject area of the course
- is able to present novel analysis and problem-solving models
- is able to explain and discuss relevant professional and scientific problems
- is able to communicate in writing in a clear and understandable manner

3.3.3 Competence

The student

- is able to manage work and development situations that are complex and unforeseen and require new solution models
- is able to independently initiate and carry out discipline-specific and crossdisciplinary cooperation and to assume professional responsibility
- is able to independently take responsibility for his/her own professional development and specialization is able to disseminate research-based knowledge

Furthermore the student is able to demonstrate engineering skills in

- Understand and explain how a line spectrometer works.
- Interpret the hyperspectral data from the line spectrometer and create an images that can be handled for segmentation of seeds.
- Implementing a seed detection algorithm that detects seeds out from the image that is created by the data from the line spectrometer
- Implementing a learning algorithm that can use training data for a specific type of seed and be able to classify the seeds based on the training data.

4 Related work

Using hyperspectral imaging, information beyond the visible spectra is extracted. Using a line spectrometer a column of pixel will be ready for processing at each scan. The idea is to extract the information in the near-infrared (NIR) part of the spectrum to get the spectral signature of each image. As the line spectrometer scan across the seeds, many grayscale image can be created, where each grayscale image represent a small wavelength band. All the images is stacked on top of each other to create a hyperspectral cube. This cube is defined at having the x and y axis represent the spatial coordinates and the z axis represent the spectral dimension.
A figure from the reference [7] is illustrating the principle in figure 4.1

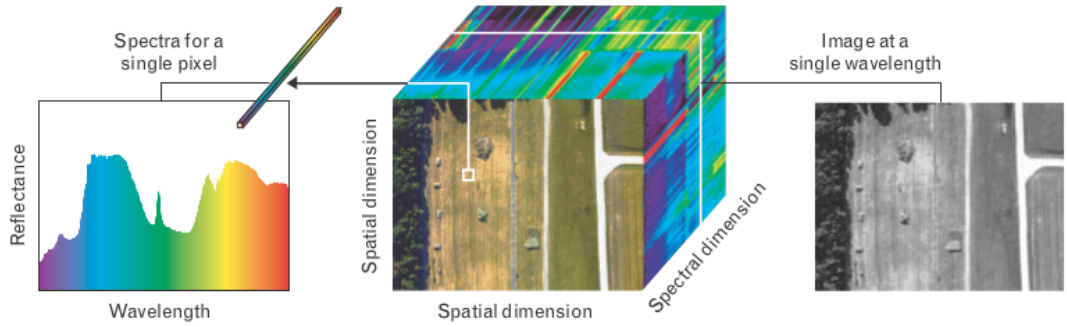


Figure 4.1: Hyper spectral imaging [7]

Evt have referencer her på, hvordan man selv vil kunne lave sit eget hyperspektralt setup

5 Division of work

This chapter gives an overview of how the project was structured from start to end. Decision has been made based on gained experience from implementing different proof of concept. The different proof of concepts is described as followed:

details in chapter **??**. The overall structure in the project is described in section 5.1. A short conclusion for each proof of concept is described in section **??**.

5.1 Project methods

As described in section 3.1, the overall task is to have a vision system that is able to detect, analyse and classify each seed on a moving conveyor belt. The output is a 3D coordinate, which must be calibrated in both intrinsic and extrinsic parameters, before transferred as a motion command to a ABB Flexpicker.

In the start of the project, the author and supervisor agreed that it was important to get the chain of the project with different components up and running first. This is illustrated in figure 5.1. As soon all the component is implemented it is possible to optimize each component individual and independent of the system. Using this approach, compared to start out by interfacing a hyper spectral camera, will lead to faster implementation time. The pitfall by using the other approach, is the risk of not having the data flow establish in time before hand-in of the project. Working with growing seeds is time consuming and can not be fully control. This can lead to time consumption and delay in the project. By using the described project method, this minimize the risk of delays in the project. I.e. if a component is inhibited since seeds are not ready, the possibly of optimizing other component, like the classifier component exist. In this way the project are agile and is not locked on hold.

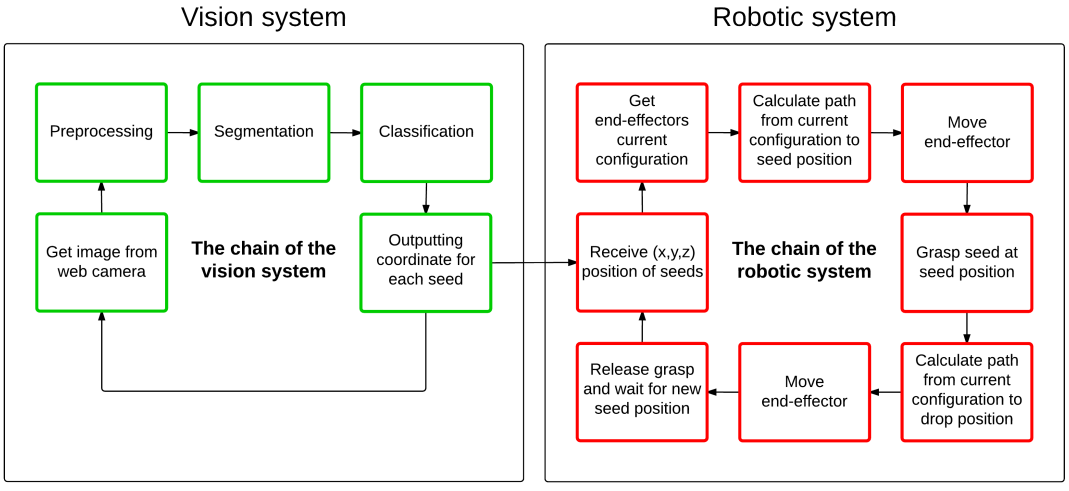


Figure 5.1: The chain of the project

The start of figure 5.1 goes with feeding image into the system, which is handled by the *Get image* component. From there each image will go through the components *Preprocessing*, *Segmentation*, *Classification* and finally the *Outputting coordinate for each seed* component in that given order. Then a new image will be loaded and the same process repeats.

Here a short description of the different concept and then reference it to the appendix

Also write something about how the program was seperated into input, preprocessing, segmentation, classification. Perhaps also write in discussion part, that the feature extraction, which is included in the segmentation part could have its own Python file

Perhaps change this figure,

After the structure for the working process was setted, the implementing of the chain of the project could begin. The implementation would be based on proof of concept. The different implementations is described further in chapter **??**.

5.2 Change of direction in the project

write some here about the argument for chosen the cheap webcamera compaired to the expensice hyperspectral camera.

5.3 Optimization of components

write somehere here about going from the Perceptron classifier to support vector machine.

6 Computer vision system

In this chapter, the computer vision system is described separately in more details. This system contains different components, which is illustrated in figure 6.1. These component are further described in the following sections.

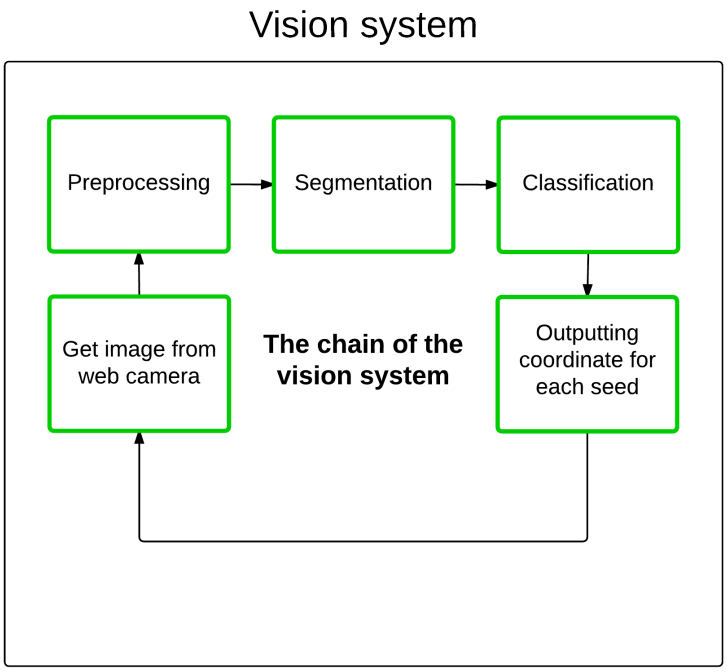


Figure 6.1: The chain of the project for the vision system

6.1 Get image from web camera

In this section, the process of getting the image from the web camera is described. The web camera used in this project is the Logitech C930e. Argument for choosing this web camera is described in . By using the OpenCV library in, it is possible to load RGB images from the web camera into the Python script, which is shown in the code listing 6.1.

where I put the argument for choosing this webcamera

```
1 import cv2
2
3 # Create the VideoCapture instantiation.
4 cap = cv2.VideoCapture(cameraIndex)
5
6 # Read the image, img.
7 ret, img = self.cap.read()
```

Listing 6.1: Get image from web camera

The argument *cameraIndex* needs to be corrected to the proper number, i.e. 0, 1, 2 ... depending on how many video devices the computer running the Python script is connected to. A simple method in Ubuntu to verify the index for the USB web camera is to launch the VLC media player and go to the *Capture Device* menu. Here select the proper index under *Device Selection* by testing the video output of the selected video device.

6.2 Preprocessing

When an input RGB images from the web camera is loaded into the system, within the preprocessing component, a *front ground* image, a *sprout* image and a combined *seed and sprout* image is produced as three outputs images. The flow is shown in figure 6.2.

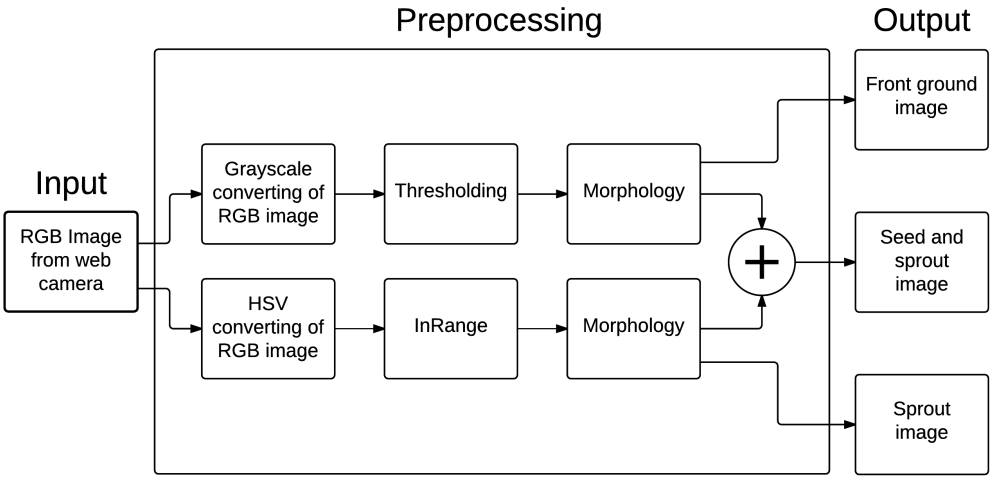


Figure 6.2: Preprocessing flow in order to generate the front ground, sprout and the combined seed and sprout image.

The front ground image is produced by converting the input image to grayscale, threshold it and finally apply the morphology process *closing* in order to repair the seed structures after the threshold. The conveyor belt, i.e. the background is relatively darker than the seeds and sprouts, which make a simple threshold sufficient. The threshold value was chosen to be 128. A sprout image is produced by converting the RGB image to a HSV image, filter out pixels using the inRange function from the OpenCV library and finally use morphology to repair the sprout structures. At the end the seed and sprout image is produced by adding the sprout image with the front ground image. The *Closing* morphology process is applied in order to close the gabs within each seed. This is performed by first dilate the image which expand the front ground pixel and thereby fills out holes and afterwards shrink the structure back to original state by erosion. A dense 3 x 3 kernel is used. In figure 6.7 and figure 6.8 shows an example of a front ground image before and after the morphology respectively.

An example of an RGB input image is shown in figure 6.3. Within this image, a red and a green rectangle are placed. This is not part of the original image, but is added in order to indicate the regions of interest (ROIs), which is described in subsection 6.2.1.The three output images is described as followed:

- Front ground image, figure 6.4 is a binary image, where a whole seed with sprout has pixels intensity values of 128. The rest of the pixels are black.
- Sprout image, figure 6.5 is a binary image, where the sprout pixels has intensity value of 255. The rest of the pixels are black.
- Seed and sprout image, figure 6.6 is the combination of the front ground image, figure 6.4 and the sprout image, figure 6.5. The result is an image where background pixels are black, seed pixels are gray and sprout pixels are white.

Ideally all gray pixels belongs to the seed and all white pixels belongs to the sprout. However scenarios happens, where seed pixels is is processed as sprout pixels. This is discussed further in section **??**. .

Ref to where we discuss the fact that there is some uner-tainscy

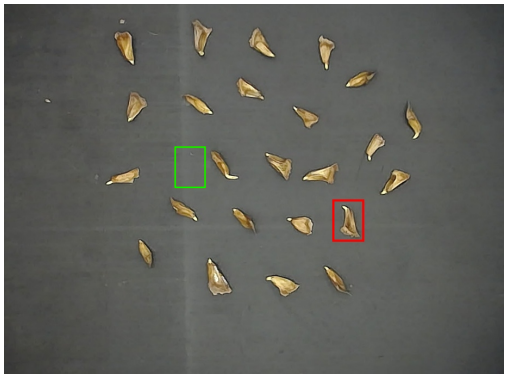


Figure 6.3: Input RGB image

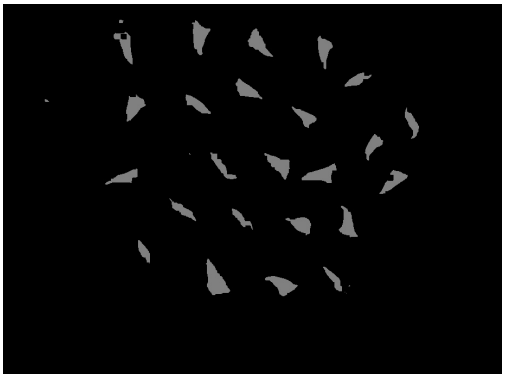


Figure 6.4: Front ground image

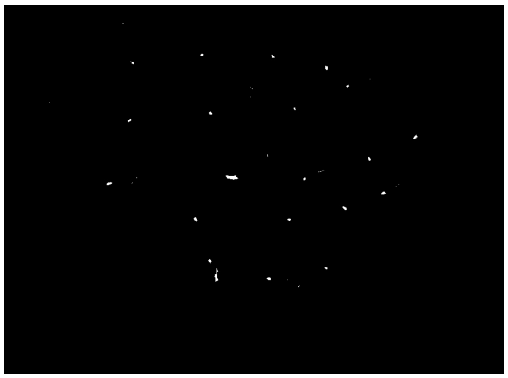


Figure 6.5: Sprout image

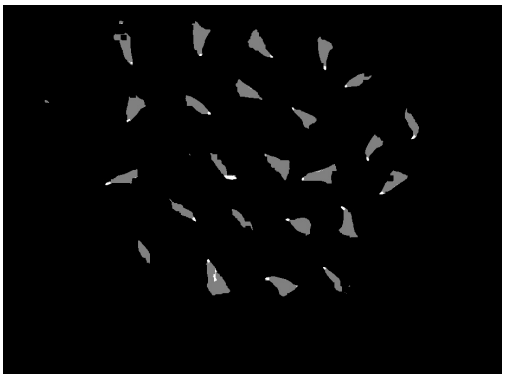


Figure 6.6: Seed and sprout image

Figure 6.7: Front ground before morphology

Figure 6.8: Front ground after morphology

6.2.1 Choice of using HSV compared to RGB method

As described in section 6.2, the RGB pixel was converted to the HSV colormap in order to find the sprout pixels. Instead of using HSV, the sprout pixels could be extracted by setting the RGB parameters directly. In order to see if this makes any difference, a HSV vs RGB test was initiated. For simplification a ROI of a single seed with sprout was cropped out of the test image. The dimension is 55 x 74 pixels. In order to have a portion of background pixels, another ROI of the background was created. These ROIs are indicated by a red and a green rectangle respectively in figure 6.3. The test included the following images:

- ROI of seed with sprout, figure 6.9
- ROI of background, figure 6.10:
- Seed image, where non-seed pixels was set to 0, figure 6.11
- Sprout image, where non-sprout pixels was set to 0, figure 6.12

A 3D plot in figure 6.14 and figure 6.13 shows the color map of RGB and HSV respectively. The result heavily depends on the accuracy in the pixel selection. From the 3D plots non of the color mapping approaches can be claimed to perform better than the other. From literature [15], the HSV method separate the intensity from the color information and makes the HSV colormapping invariant to certain types of highlights, shading, and shadow in the image. This makes the HSV more practical for the human interpretation [8]. Therefore the HSV method is the chosen approach in the preprocessing part.

Figure 6.9: Cropped image

Figure 6.10: Cropped background image

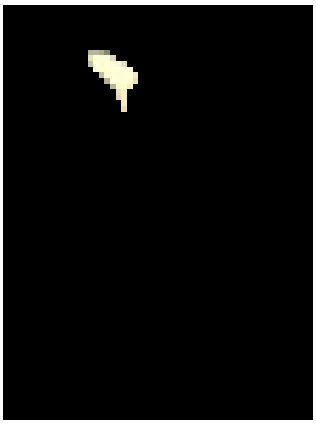


Figure 6.11: Sprout pixels only

Figure 6.12: Seed pixels only

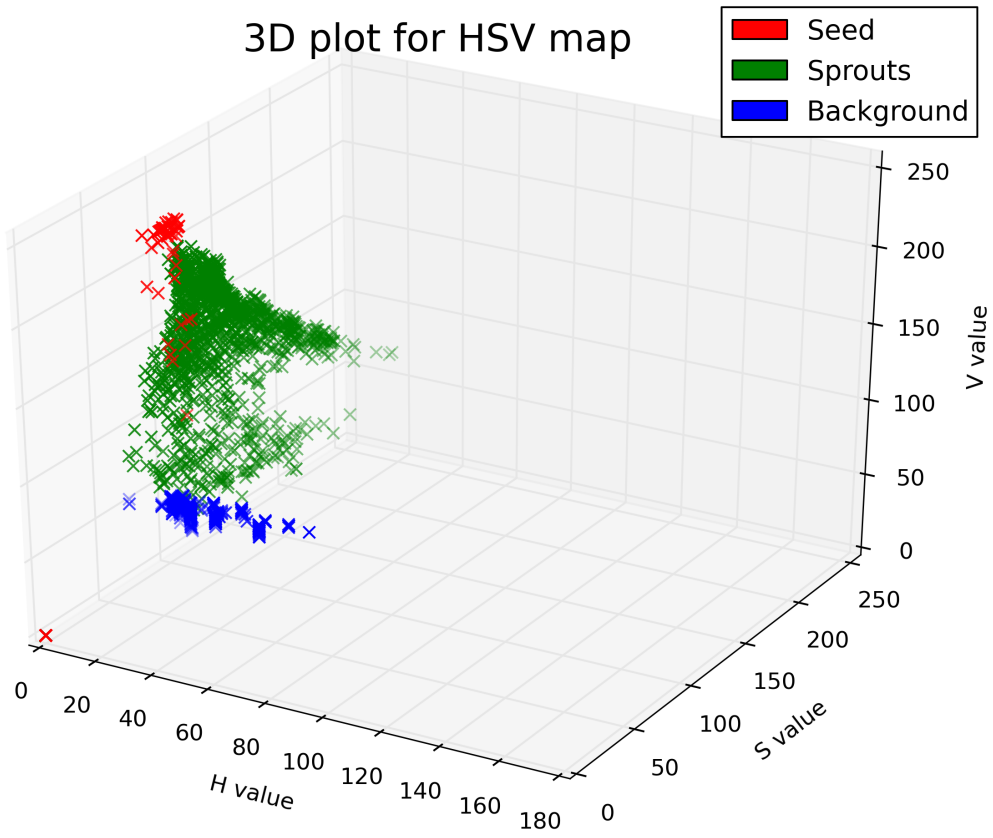


Figure 6.13: Preprocessing flow in order to generate the frontground , sprout and the combined seed and sprout image

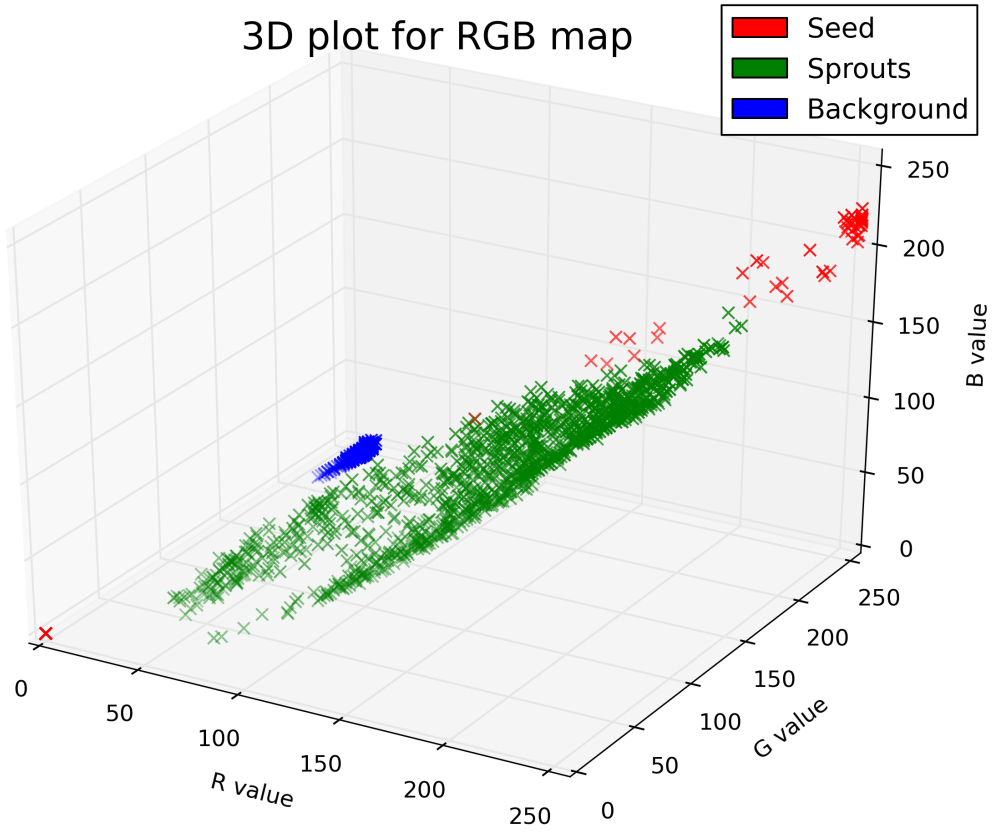


Figure 6.14: Preprocessing flow in order to generate the frontground , sprout and the combined seed and sprout image

6.3 Segmentation

When a front ground image, sprout image and the combined seed and sprout image is from the preprocessing component is loaded into the segmentation component a list with features is extracted for each object in the RGB image. An object is referred to a seed with or without sprout. The flow of the segmentation process is shown in figure 6.15.

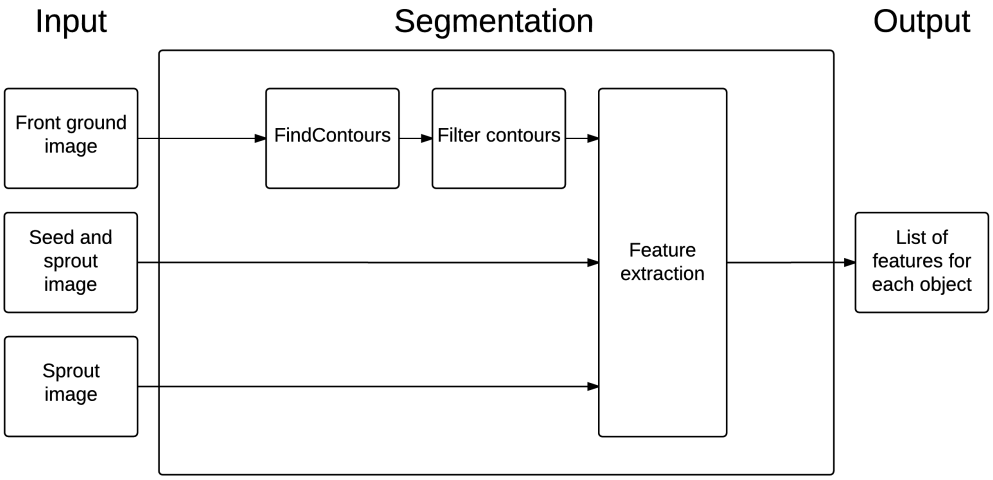


Figure 6.15: Segmentation flow in order to generate the list of features for each object in the RGB image.

The front ground image is segmented using the function FindContours from the OpenCV library. This function segment a binary image into contours and returns a list of all the contours found in the binary image, including any left over noise blobs, which was not removed by morphology in the preprocessing component, described in section 6.2. A contour contains the (x,y) location of edge pixels for any given shape. To filter out the noise contours, which e.g. could be an artefact or a piece of any material from the conveyor belt, a contour area threshold is implemented. This is done by using the findContourArea function from the OpenCV library.

In order to find a threshold value of minimum and maximum contourarea, a test image was analysed, which is shown in figure 6.41. This test image has been produced and edited in Gimp (GNU Image Manipulator Program) in order to have a mix of different types of objects, i.e. some objects with long sprout, some with small sprouts and last some without sprouts.

Figure 6.16: Test image with a mix of objects.

To analyse the test image, a histogram of the contour area for all contours in the test image is shown in figure 6.17. By inspecting the histogram in the left lower corner, it is expected that noise blobs are the reason for five detected contours with a contour area from 0 to 157 square pixels. The maximum contour area is 1574 square pixels. A minimum 200 square pixels seems reasonable for cutting off the noise contours in the images. A upper threshold is set to 2000 square pixels.

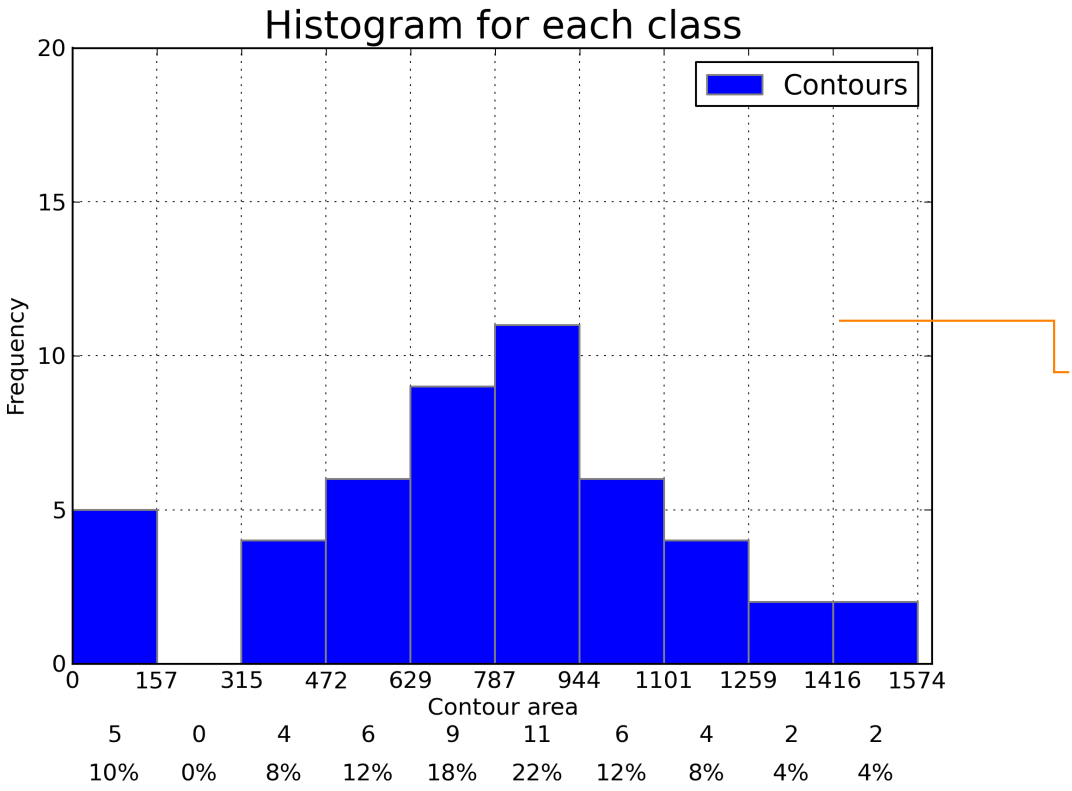


Figure 6.17: Histogram of contour area in the test image

ref this: http://answ of-a-single-pixel-object-in-opencv/

Regarding the histogram in figure 6.17, five noise blobs were found in the test image which goes into the bin between 0 and 157 square pixels. In order to visualize these objects that were below the 200 minimum contour area threshold, the noise contours is illustrated in figure 6.18. The list of countour areas is: 2.0, 18.5, 0.0, 127.5, 29.5 square pixels. The result is by calling the *findContourArea* from the OpenCV library. From the reference, the area return from the function will almost always differ from number of white pixels. From the reference, if a contour area is 0.0, it means that the given contour has only one pixel. If a contour has an area of 0, the center of mass coordinate is placed in the (0,0), i.e. the upper left location in the image.

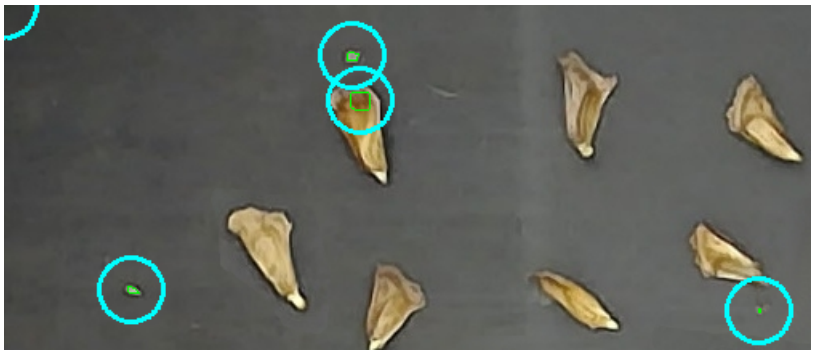


Figure 6.18: Indication of contours with area below 200 square pixels

In order to test the effect see the effect of the min and max contour area threshold threshold range, a test was carried out. For better visualization the effect of the min and max contour area threshold, a ROI of For better visualization the effect of the min and max contour area threshold was cropped out from the input images in figure **??**. The test included the following images:

- ROI of input image, figure 6.19
- ROI of front ground image after the morphology process, figure 6.20
- ROI of drawn contours before filtering, figure 6.21
- ROI of drawn contours after filtering, 6.22

The test shows how the smaller noise contours is removed, by setting the minimum contour area to 200 square pixels. The effect of having a maximum contour area of 2000 is not illustrated in the test. However from the histogram in figure 6.17 the maximum contour area from the input image is 1574 square pixels, hence the upper threshold is set to 2000 square pixels given the current camera setup. Is the camera mounted closer to the conveyor belt, this maximum threshold needs to be adjusted. Additionally if two objects are touching each other, the contour that covers two or more objects will be filtered out. This topic is further discussed in the section

Here disucss that 2000 square pixels are perhaps a little to little if e.g two objects are touching each other. Or we have the camera mounted closer to the conveyor belt. Important topics!

6.3.1 Feature extraction

Finally the feature extraction in the segmentation component is performed for each object in the input image. The input for the feature extraction is a list of filtered contours, the sprout image and the combined seed and sprout image. The output is a list of features for each contour. This is illustrated in figure 6.15
It is a difficult task to categorizing an object, i.e. a seed with or without as either good or bad. There exist uncertainty in the classification even for a human supervisor. However the classification is based on rules of thump which are described as followed:

- An object is categorized as bad if:
  - No sprout exist within the object, figure 6.23.
  - The length of the sprout is longer than 3 mm, figure 6.24.
  - The sprout is curved or twisted, figure 6.25.
  - The color of the sprout is yellow or brownish, figure 6.26.
- An object is categorized as good if:
  - The length of the sprout is between 1 to 3 mm, figure 6.27
  - The color of the sprout is white, figure 6.28

If a condition which categorize an object as good is present while a condition which categorize the object as bad, the object is categorized as bad. E.g. if the sprout of an object is white, but longer than 3 mm, then the object is bad. A problem in defining when a sprout is yellow exist. This problem is discussed in the section

Here describe the problem with seeds that should be brown is sampled as white pixels. Perhaps make a plot between pixel that are "brown" and pixel that are white. It would be two histograms

Figure 6.19: ROI of input image

Figure 6.20: ROI of thresholded image

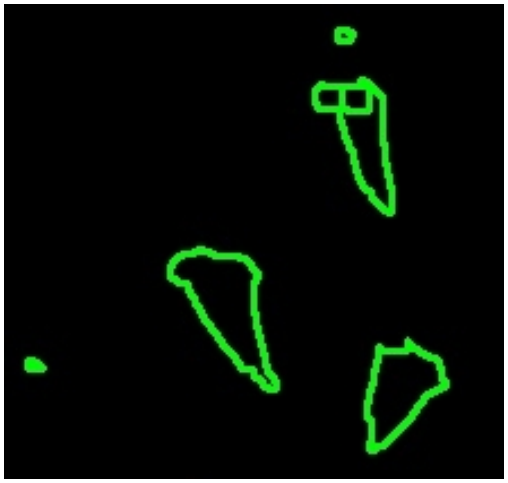


Figure 6.21: Founded contours with min contour area is zero

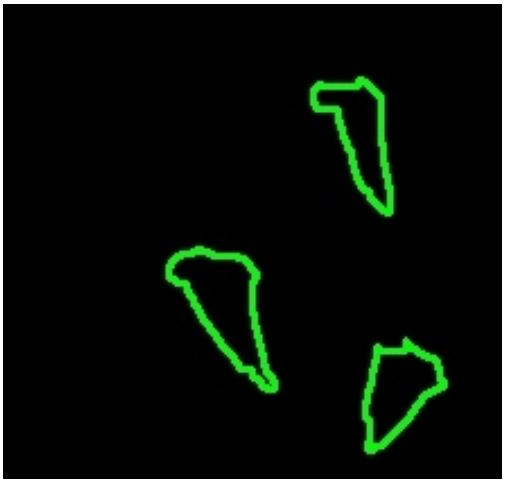


Figure 6.22: Founded contours with min contour area is 200

Figure 6.23: No sprout

Figure 6.24: Sprout too long

Figure 6.25: Curved sprout

Figure 6.26: Brownish sprout

Figure 6.27: Sprout OK

Figure 6.28: Sprout OK

Picking the right features is a hard task. However the main factor in deciding the category for an object is to analyse the sprout. The sprout information is collected by finding the oriented boundingbox (OBB) of the sprout pixels. In the following figures 6.29, a ROI has been cropped out for better visualization. In figure 6.30 the OBB around the sprout pixels is drawn. The red pixels is not a part of the image data.

Figure 6.29: Cropped out object from RGB input image

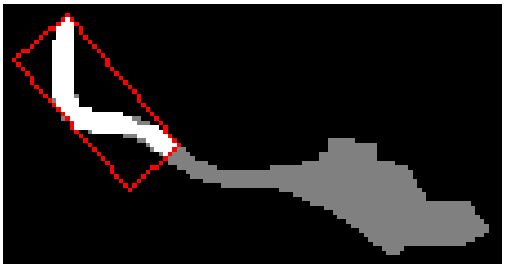


Figure 6.30: A red OBB drawn around the sprout pixels

For each OBB, the length, width, ratio and number of sprout pixel is extracted. In order to differentiate between sprout that has a white nuance compared to yellow or brownish nuance, the mean and standard deviation of the sprout pixels is analysed. All in all it boils down to the following list of features, that is extracted within the segmentation component:

- Length of OBB
- Width of OBB
- Ratio $\frac{Width_{OBB}}{Length_{OBB}}$
- Number of sprout pixels within the OBB
- The mean hue value for the sprout pixels
- The standard deviation for the sprout pixels

The OBB is found by using the *minAreaRect* function from OpenCV library. This function returns the center of mass (COM), the width, the height and the orientation of a contour. The attributes are not invariant due to rotation, hence extra functionality is implemented to insure the attributes *length* and *width* is always the longest and shortest side of a bonding box respectively. The COM coordinate is available within the attributes of the function *minRectArea*. However calculating the center of mass is available through the use of moments. To see the difference between the two methods, a comparison is shown in figure 6.31. The red dots in the figure indicate the contours COM using the *minRectArea* and the green dots indicate the COM calculated by using moments. Taking into account, that the objects in the image is between 10-15 mm long, the difference between red and green COM do not play any important role. It all comes down to the type of grasping, which in this case will be performed by an pneumatic suction end-effector. At the moment the methods of using moments is used, since this was implemented before using the *minRectArea* function. Argument for using the the *minRectArea* would be to save the computational time by using moments. However this is a is a task for future work.

I really dont have any arguments for stick with the moments. So at the end write that I change to use use COM from the minRectArea function and that saved this amount of time

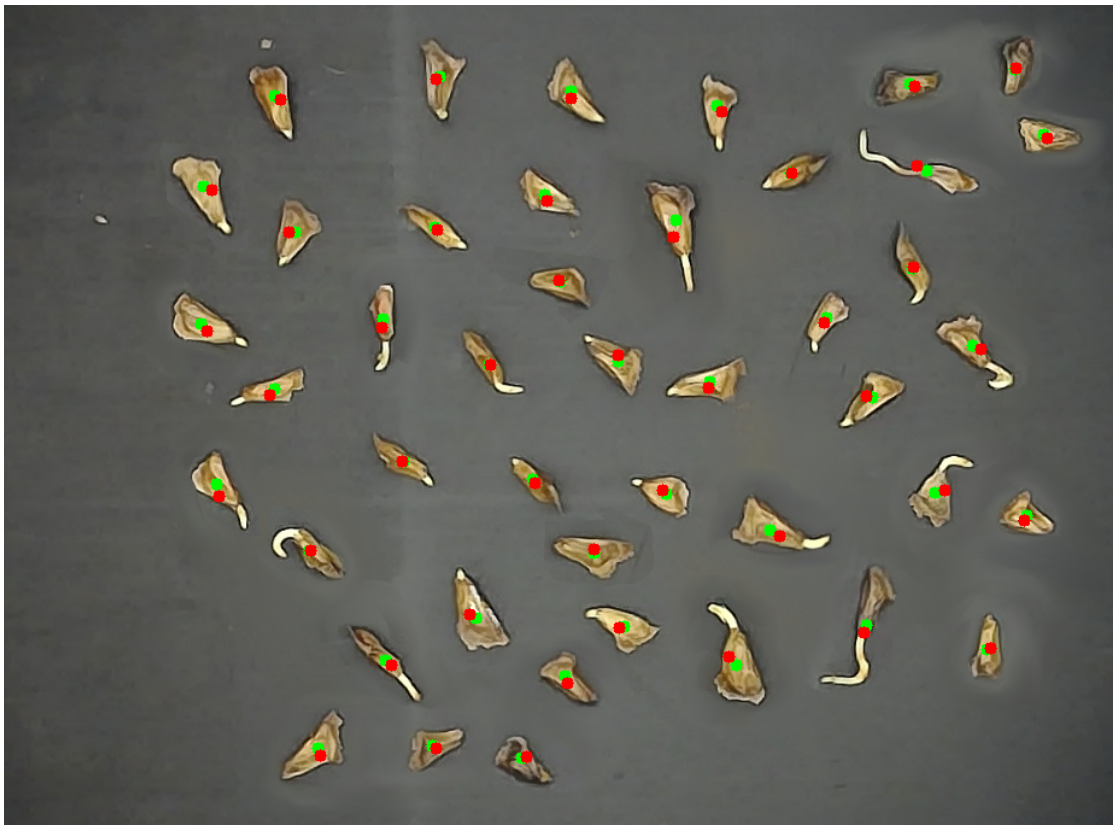


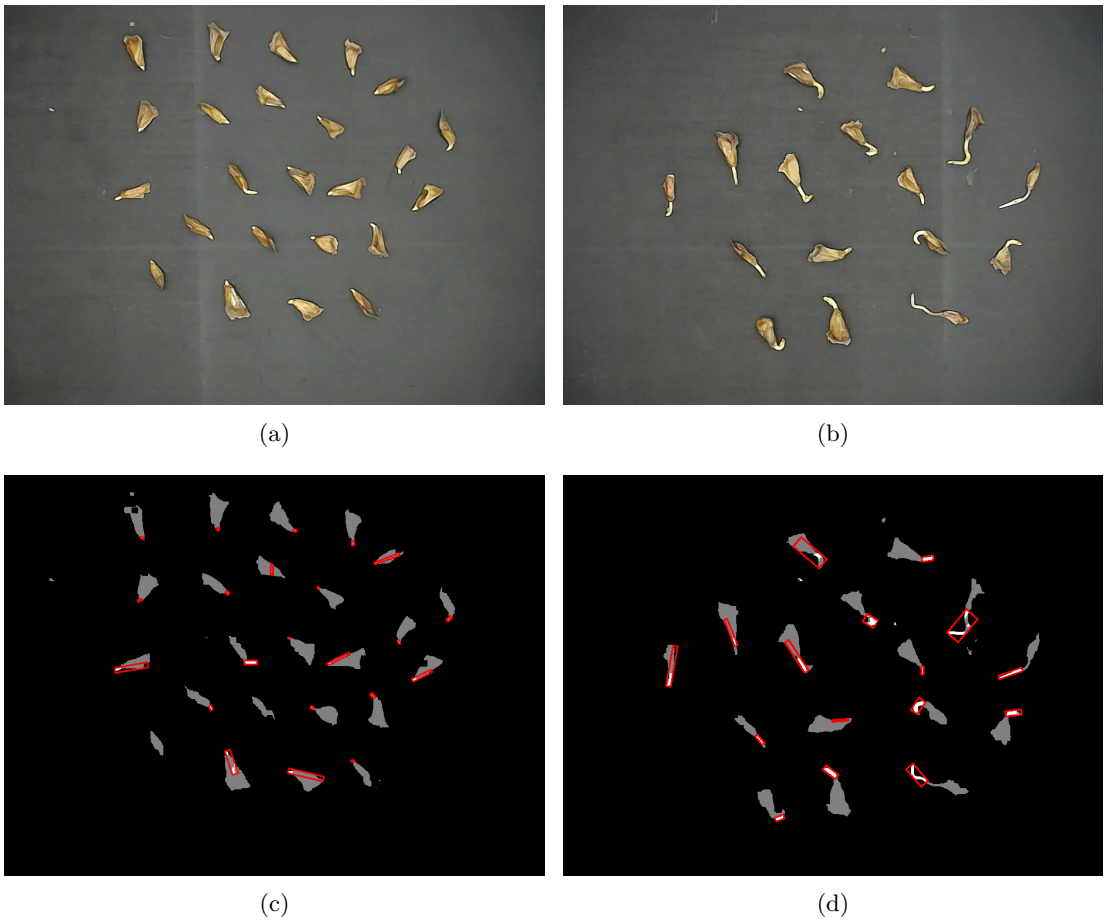
Figure 6.31: Red dots indicate COM using *minRectArea*. Green dots indicate COM using moments

Write a little about moments here. See doc from Summerkursus or individual projects

6.3.2 Clustering

As described in section 6.3.1 the feature extraction is based on the OBB that span the sprout pixels for each contour. The data from the feature extraction is later used in the classification module in section 6.4. In order to maximize the classification rate, it is important to minimize the false negatives and false positive, i.e .type I and type II errors. It is hypothesized that each object in a image is good. A type I error will occur if an object is classified as bad, but confirmed by a supervisor as good. Vice versa a type II error will occur if an object is classified as good, but the supervisor confirms the object is bad.

In order to measure the type I and type II errors, two tests is carried out. Test 1 contains an RGB image with good objects. Test 2 contains an RGB image with bad objects. These are shown respectively as (a) and (b) in figure 6.32. Both dimensions of the images is 920 x 680 pixels. Doing the test, each image (a) and image (b) was preprocessed. The preprocessing component is described in section 6.2. The result of the preprocessing component of image (a) and (b) is shown in the same figure as image (c) and (d) respectively.



(a) (b)

(c) (d)

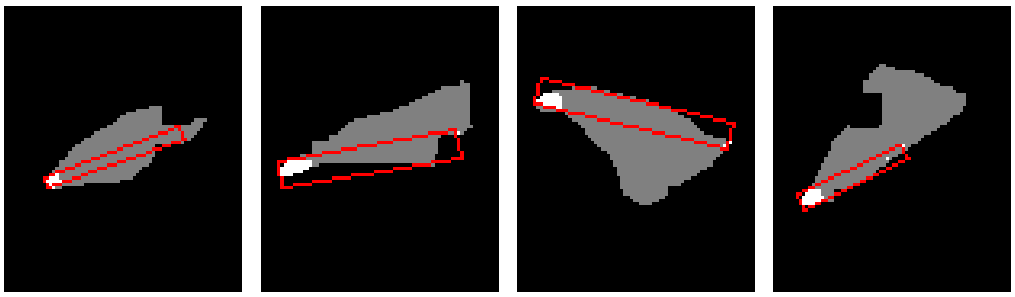
Figure 6.32: Two RGB images. The left image (a) contains good seeds and the right image (b) contains bad seeds, since the sprouts are too long

Perhaps (c) and (d) should be removed or placed in the appendix together with (a) and (b) since a big image needs big space to see the details. This is not true with (c) and (d)

Doing analyse of the sprouts for each object, the bounding boxes is extracted and drawn with a red rectangle. The drawing is performed by using the *drawContours* from the OpenCV libray. In figure 6.30 the OBB is fitted correctly around the sprout pixels by comparing the white sprout pixels with the RGB image, i.e. no type I or type II error. However this is not always the case. An example with four images in figure 6.33 shows

incorrectly OBB. All the images is size 74 x 89 pixels and is cropped out from an original *Seed and sprout* image . By observing the OBB is spanning white pixel, that do not belong to the sprout area of an object.

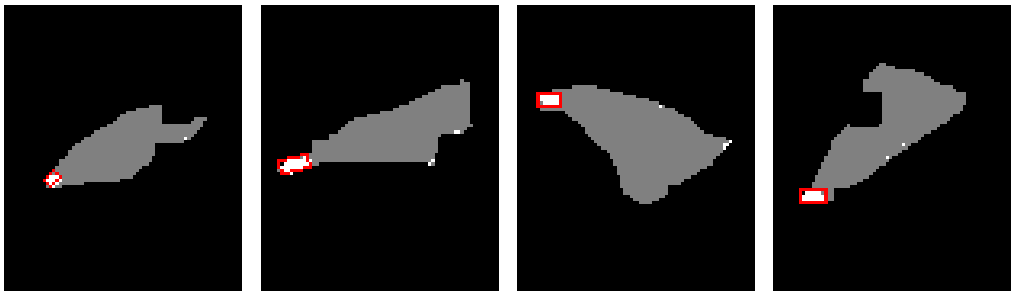
Store all the big images in appendix, that we dont show but still is referred to



(a) (b) (c) (d)

Figure 6.33: Main figure caption

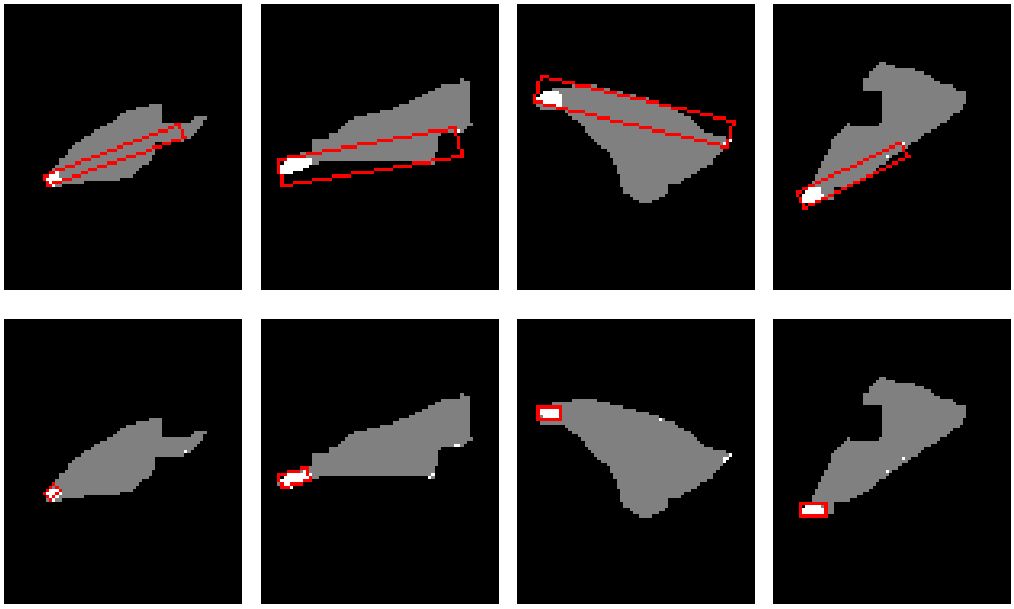
By observing the drawing of the bounding box, sometimes an extracted bounding box is spanning white pixel, that do not belong to the sprout area of an object. This is shown in the following figure



(a) (b) (c) (d)

Figure 6.34: Main figure caption

The image in **??** show how the potential errors will accor, if the seeds look like as above. Here a more sophisticated algorithm is needed. An extra check on how the neiboorhood is. figure **??** If the founded "real" sprout list is surrounded only or almost by gray pixel then take the other. It is hard to tell what the solution should be.



(e) Angry Smiley (f) Angry Smiley (g) Angry Smiley (h) Angry Smiley

Figure 6.35: Main figure caption

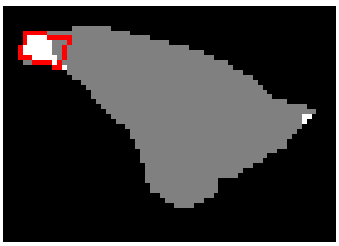


Figure 6.36: Class 1

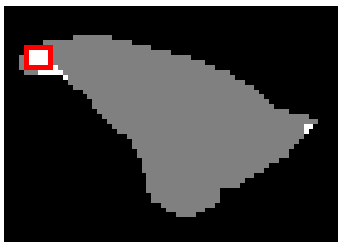


Figure 6.37: Class -1

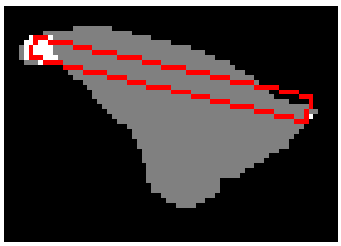


Figure 6.38: Class 0

6.4 Classification

here add some part of the AI stuff with training data etc

Three images, where the first two are training data and the last is testing data, has been analysed to find a proper minimum contour area threshold. Each image is explained as followed:

- Training data, class 1: Seeds with optimal sprouts, figure 6.39
- Training data, class -1: Seeds with too long sprouts, figure 6.40
- Testing data, class 0: Seeds with different sprout length, figure 6.41

Figure 6.39: Class 1

Figure 6.40: Class -1

Figure 6.41: Class 0

6.5 Outputting coordinates

7 Robotic system

8 Final implementation of vision system

This is the section, where the focus is on test and results. How good did we do classification? What is the procentance. How good was it compaired to the old system? Which classifier was best? Random Forrest vs, SVM?

Is that really important? There is a lot of papers out there that has investigated this before....

9 Robotics

An future extension of the Master Thesis is to interface the ABB Flexpicker robot, which is shown in figure 9.1, with the computer vision system. The task of the ABB Flexpicker is to grasp each of the classified seed and place them physically in a place according to their category. At the moment the focus in the Master Thesis is the computer vision and AI component. These components needs to complete the final test, before any more time can be invested in the robotic part.

Figure 9.1: The ABB Flexpicker robot that do the pick-and-place task after seeds has been classified by the vision system

10 System test

Nothing yet

11 Discussion

Nothing yet

12 Conclusion

Nothing yet

13 Future work

This is the future work section

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A Title of Appendix A

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B Title of Appendix B

Text of Appendix B is Here